PhD Program in Sport and Health

Analysis of Acceleration Signals Using Non-Linear Tools for the Detection and Quantification of Muscle Fatigue.

Doctoral Thesis by

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The present Doctoral Thesis, entitled *"Analysis of Acceleration Signals Using Non-Linear Tools for the Detection and Quantification of Muscle Fatigue"*, is submitted in the form of a **compendium of** the following **publications**:

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INFORMAN:

Que D. *Fernando García Aguilar* ha realizado bajo nuestra supervisión el trabajo titulado "*Analysis of Acceleration Signals Using Non-Linear Tools for the Detection and Quantification of Muscle Fatigue*" conforme a los términos y condiciones definidos en su Plan de Investigación y de acuerdo con el Código de Buenas Prácticas de la Universidad Miguel Hernández de Elche, cumpliendo los objetivos previstos de forma satisfactoria para su defensa pública como tesis doctoral.

Lo que firmamos para los efectos oportunos, en Elche, el de de 2025.

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Que D. *Fernando García Aguilar* ha realizado bajo la supervisión de nuestro Programa de Doctorado el trabajo titulado "*Analysis of Acceleration Signals Using Non-Linear Tools for the Detection and Quantification of Muscle Fatigue*" conforme a los términos y condiciones definidos en su Plan de Investigación y de acuerdo con el Código de Buenas Prácticas de la Universidad Miguel Hernández de Elche, cumpliendo los objetivos previstos de forma satisfactoria para su defensa pública como tesis doctoral.

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"¿Qué debemos hacer en cada momento?

Lo mejor que esté en nuestras manos,

y desapegarnos del resto"

Epicteto

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List of Abbreviations

ACCL5	Acceleration vector at the lumbar region
ACCBR	Acceleration vector at the barbell
ApEn	Approximate Entropy
BVE	Bivariate Variable Error
CMJ	Countermovement Jump
COP	Center of Pressure
COPM	Center of pressure magnitude
CV	Coefficient of Variation
DFA	Detrended Fluctuation Analysis
EMD	Empirical Mode Decomposition
FM	Force Magnitude
FuEn	Fuzzy Entropy
FOR	Functional Overreaching
HS	Hypertrophy Session
ICC	Intraclass Correlation Coefficient
MS	Maximal Strength Session
MVM	Mean Velocity Magnitude
NLT	Non-Linear Tools
NFOR	Non-Functional Overreaching
PS	Power Session
RQA	Recurrence Quantification Analysis
RFD	Rate of Force Development
RM	One-Repetition Maximum
SaEn	Sample Entropy
SEM	Standard Error of Measurement
SD	Standard Deviation
IMU	Inertial Measurement Unit
VO_2máx	Maximal Oxygen Consumption

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Abstract

Exercise-induced fatigue leads to alterations in performance and motor control mechanisms. Traditionally, its assessment has relied on performance indicators, physiological markers, or subjective tools. However, these approaches present limitations due to their dependence on maximal efforts, high logistical demands, or procedures that are difficult to apply in everyday practice. In this context, motor variability—analyzed through non-linear tools—has emerged as a promising strategy to detect altered functional states of the neuromuscular system. The main objective of this thesis is to examine whether variability in acceleration signals, obtained through inertial measurement units (IMUs), can serve as a valid, reliable, and sensitive indicator for monitoring fatigue.

To address this question, four complementary studies were conducted. First, a systematic review examined the use of non-linear tools in fatigue analysis, identifying a recurring pattern of complexity loss, particularly in isometric tasks. Next, the reliability of variability analysis using IMUs during the squat exercise was evaluated, revealing acceptable levels of consistency in metrics such as sample entropy, fuzzy entropy, and detrended fluctuation analysis. Subsequently, the sensitivity of these measures was analyzed in response to different resistance training protocols (power, hypertrophy, and maximal strength), showing that acute fatigue induced an increase in irregularity and a reduction in autocorrelation within the acceleration signals. Finally, this analysis was replicated in a handstand balance task, where a similar pattern of motor reorganization under fatigue was observed.

Taken together, the results support the utility of non-linear analysis of acceleration signals as a practical and ecologically valid tool for fatigue monitoring. These metrics can detect functional changes even in the absence of external performance impairments, which may be particularly valuable in both sports and clinical contexts. The integration of inertial measurement units with non-linear analytical tools offers an automatable, non-invasive, and task-adaptable approach, opening new avenues for individualized training and the prevention of overtraining or neuromuscular dysfunction.

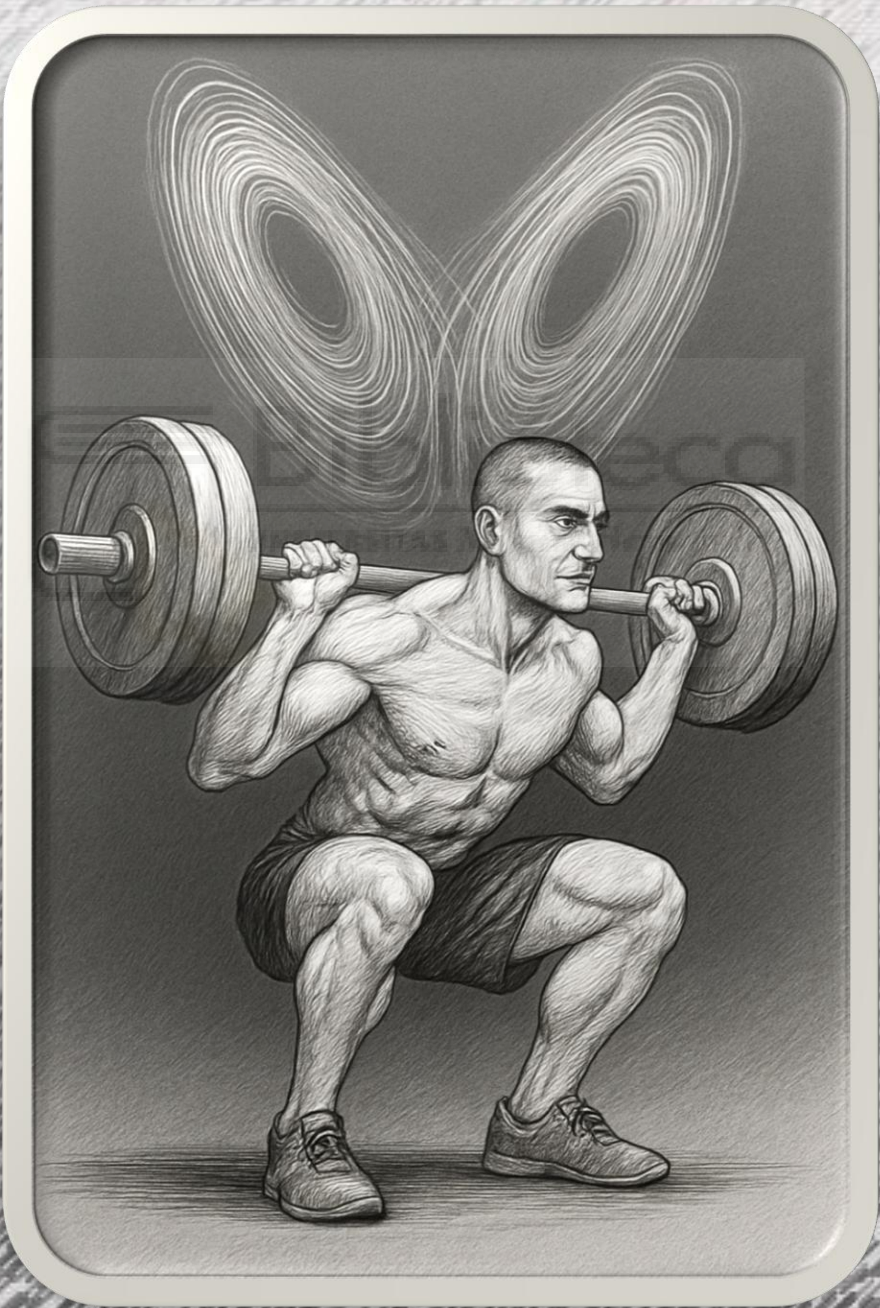
Resumen

La fatiga inducida por el ejercicio produce alteraciones en el rendimiento y en los mecanismos de control motor. Tradicionalmente, su evaluación ha dependido de indicadores de rendimiento, marcadores fisiológicos o herramientas subjetivas. Sin embargo, estas aproximaciones presentan limitaciones asociadas a la necesidad de esfuerzos máximos, elevados requerimientos logísticos o procedimientos de difícil aplicación en el día a día. En este contexto, la variabilidad motora —analizada a través de herramientas no lineales— ha emergido como una estrategia prometedora para detectar estados funcionales alterados del sistema neuromuscular. Esta tesis tiene como objetivo principal analizar si la variabilidad en señales de aceleración, obtenidas mediante unidades de medición inercial, puede constituir un indicador válido, fiable y sensible para monitorizar la fatiga.

Para ello, se desarrollaron cuatro estudios complementarios. En primer lugar, una revisión sistemática examinó el uso de herramientas no lineales en el análisis de la fatiga, observando una pérdida de complejidad como patrón recurrente, especialmente en tareas isométricas. A continuación, se evaluó la fiabilidad del análisis de variabilidad mediante unidades de medida inercial durante la sentadilla, encontrando niveles aceptables de consistencia en métricas como la entropía muestral, la entropía borrosa y el análisis de fluctuaciones sin tendencia. Posteriormente, se analizó la sensibilidad de estas medidas ante diferentes protocolos de entrenamiento de fuerza (potencia, hipertrofia y fuerza máxima), evidenciando que la fatiga aguda inducía un incremento de la irregularidad y una pérdida de autocorrelación en las señales de aceleración. Finalmente, se replicó este análisis en una tarea de equilibrio de manos, observándose un patrón similar de reorganización motora bajo fatiga.

En conjunto, los resultados apoyan la utilidad del análisis no lineal de señales de aceleración como herramienta práctica y ecológica para la monitorización de la fatiga. Estas métricas permiten detectar cambios funcionales incluso en ausencia de alteraciones en el rendimiento externo, lo que podría resultar especialmente útil tanto en contextos deportivos como clínicos. La integración de unidades de medida inercial y herramientas de análisis no lineal ofrece un enfoque automatizable, no invasivo y adaptable a distintas tareas motoras, abriendo nuevas vías para la individualización del entrenamiento y la prevención de estados de sobreentrenamiento o disfunción neuromuscular.

1. General Introduction



1. General Introduction

1.1. Strength training

Strength training can be defined as a systematic and structured intervention aimed at improving various neuromuscular qualities, including maximal strength, power, body composition, and overall physical function (1–5). This type of training relies on the repeated application of mechanical stimuli using different forms of resistance, such as body weight, free weights, resistance machines, elastic bands, or iso-inertial devices, among others (6,7).

Strength training involves a dynamic process that requires carefully planned prescription. This planning must consider key variables such as intensity, volume, frequency, exercise type, and periodization, as well as incorporate continuous assessment systems and clearly defined goals (1). In this regard, the effectiveness of strength training depends both on the program's design and its capacity to adapt to the individual's characteristics and needs.

This type of training can produce adaptations in the neuromuscular system, manifested in increased force production capacity, enlargement of muscle fibers (hypertrophy), and greater activation of motor units. In addition, improvements are observed in nervous system efficiency, such as enhanced motor reflexes, reduced inhibitory mechanisms, increased synchronization of motor unit discharge, and changes in motor control patterns that optimize movement performance (8). Based on these adaptations, the objectives of strength training can vary widely depending on the context and the target population. Among the most common goals are:

1. **Improvement in body composition**, through increased muscle mass and reduced adipose tissue (1,3).
2. **Increase in muscular strength and power**, which are essential both for physical performance across multiple disciplines and for injury prevention and the maintenance of functionality throughout different stages of life (2,9).
3. **Rehabilitation and injury risk reduction**, by improving the body's tolerance to training and competition loads, as well as supporting the rehabilitation process and facilitating more effective recovery following injury (9,10).
4. **Enhancement of health and quality of life**, by counteracting various conditions in which the body's functionality is diminished—such as aging, the presence of certain pathologies, or simply the effects of a sedentary lifestyle. This is achieved through improvements in strength, muscle mass, bone density, metabolic and cardiovascular health, cognitive function, and psychological well-being. These benefits contribute to the maintenance of functional independence and overall

quality of life, particularly in older populations or individuals with chronic conditions (9,11).

Strength training, therefore, is not only an essential tool for enhancing athletic performance but also a key component in health-oriented and rehabilitation programs. Its versatility and effectiveness make it a fundamental pillar in both high-performance athletic preparation and in the general population, including clinical and pathological contexts.

1.1.1. Strength Training and Sports Performance

While the benefits of strength training are evident in sports where performance depends almost exclusively on strength levels—such as weightlifting or powerlifting—there are other types of sports in which its impact on performance may seem less obvious. Contrary to this assumption, an increasing body of scientific evidence (3,12–19) supports its effectiveness in both individual and team sports, as well as in endurance disciplines, due to its positive impact on physical attributes, technical skills, and key performance factors.

Among the most notable benefits is the improvement of fundamental physical qualities such as maximal strength (20,21), power (19,20,22) and speed (14,15). Strength training also enhances the force-time characteristics of the neuromuscular system, significantly improving the rate of force development (RFD) (19,21). Additionally, the increase in muscle mass associated with strength training contributes to greater force-generating capacity and enhanced structural protection against repetitive efforts and/or traumatic events (21).

From the perspective of transfer to specific sport skills, strength training has been shown to significantly improve vertical and horizontal jump performance (2,15,23–25), sprint speed (14,15,23,26), and change of direction ability (2,25). These actions are highly relevant in numerous individual sports—such as track and field—and in team sports, including football, handball, and basketball (15-18). Strength training has also proven effective in improving movement speed in explosive, discrete actions, thereby enhancing performance in sports that involve throwing or striking actions (27–30).

Moreover, although strength training has not traditionally received much attention in endurance disciplines such as running, cycling, or cross-country skiing, scientific evidence increasingly supports its relevance in these sports (19,20,31,32), Studies have reported beneficial effects of strength training on movement economy—that is, the energy cost at a given intensity (20,30,31)—as well as on improvements in speed or power relative to maximal oxygen uptake (VO_2max), and the ability to reach and sustain maximal speed or power (19,20). All of these are critical factors for high-level aerobic performance.

In summary, strength training is an extremely valuable tool for enhancing sports performance and should therefore be implemented by coaches and strength and conditioning professionals in their training programs for athletes of all disciplines.

1.1.2. Strength Training and Health

Beyond improving athletic performance, strength training has proven to be a highly effective and safe tool for enhancing overall health and managing a wide range of medical conditions (33). Regular practice induces favorable adaptations at the muscular, metabolic, cardiovascular, skeletal, neurological, and psychological levels, making it a fundamental intervention for promoting well-being throughout the lifespan (5,12,33–37). Moreover, regular participation in strength training has been associated with reduced all-cause mortality, as well as decreased mortality from cardiovascular disease and cancer—particularly when combined with other forms of physical activity (33).

Among its general benefits, strength training induces adaptations across various physiological systems. Structurally, it increases muscle mass and strength (5,12,33,34), improves bone and joint health (9,12,33), and reduces musculoskeletal pain (4,11,12). These effects are especially relevant for certain populations. For example, in older adults, strength training has been shown to preserve quality of life and functional independence by improving walking speed, enhancing the ability to perform activities of daily living, and reducing the risk of falls and fractures through improved RFD and postural control (5,12,33,37). In oncology patients, it can help preserve muscle mass, improve functional status, and reduce the risk of recurrence and mortality (33,37). Strength training has also shown benefits in occupational settings, particularly for individuals with sedentary or physically demanding jobs, by reducing musculoskeletal pain, enhancing overall function, and decreasing absenteeism (4).

On a metabolic level, strength training contributes to increased resting metabolic rate (12,33) reduced body fat (12,33,37), and improved lipid profile and blood pressure (12,33,35). These adaptations have solidified its role as an essential therapeutic component for individuals with chronic diseases. For instance, in type 2 diabetes, strength training improves insulin sensitivity and reduces visceral fat; in cardiovascular diseases, it enhances functional capacity without increasing hemodynamic risk (12,33). It has also demonstrated benefits in individuals with obesity (12), aiding in body recomposition and improving quality of life.

Regarding cognitive and emotional aspects, strength training has been associated with improvements in cognitive function and mood, including reductions in symptoms of anxiety, depression, and fatigue (5,33,36). These benefits are particularly important in vulnerable populations such as older adults or individuals with chronic illnesses, for whom maintaining psychological well-being is a primary goal (5,33,36).

Taken together, strength training represents an evidence-based, adaptable, safe, and efficient intervention for promoting and maintaining health, as well as for preventing and treating numerous chronic conditions (33).

1.1.3. Strength Training and Injury Prevention

At a point between performance and health, strength training plays an important role in both the prevention and recovery from injuries. In this regard, strength training is a fundamental tool that contributes to reducing the incidence of both acute and overuse injuries, as well as facilitating a safe and effective return after injury (10,11,34–37).

Current scientific literature supports that strength training significantly reduces injury risk, showing a favorable dose-response relationship: the greater the exposure to strength stimuli, the lower the risk of injury (34). This protective effect is explained by the previously mentioned neuromuscular and structural adaptations, as well as improvements in coordination, strengthening of connective tissue, reduction of critical joint loads, and greater postural control in high-risk situations (10,34,37).

In the context of recovery, strength training addresses persistent deficits such as reduced maximal strength, rate of force development, and reactive strength—all of which are key in preventing recurrences and restoring performance. For these reasons, strength training is an essential intervention to reduce injury risk and ensure full functional recovery, provided it is applied with individualized criteria, appropriate load, and professional supervision.

1.2. Fatigue and Strength Training

Among the different variables that must be controlled to design effective, efficient, and safe training programs, fatigue control is essential. Fatigue is a complex and multifactorial phenomenon that involves a reduction in the body's capacity to sustain or generate a given level of force, power, or physical performance, and it can also extend to the cognitive domain. This reduction is not due to a single specific cause but rather results from the interaction between physiological, neuromuscular, metabolic, and psychological factors (38–40). From a functional perspective, it manifests through both objective components—such as measurable performance loss—and subjective ones, including increased perception of effort, feelings of exhaustion, or reduced motivation (8,40,41) .

At the conceptual level, there are various approaches to defining and classifying fatigue. The traditional view divides it into central and peripheral fatigue. Central fatigue is related to alterations in the central nervous system, while peripheral fatigue is attributed to local muscular or metabolic dysfunctions (42,43). However, this dichotomy has been questioned by authors such as Enoka and Duchateau (40), who propose a more integrative definition based on two components: performance fatigability—referring to the objective loss of functional capacity—and perceived fatigability—which includes sensations associated with effort, psychological state, and internal homeostasis. This proposal considers fatigue as task-dependent and suggests that the factors causing it vary depending on the characteristics of the exercise performed.

Other authors highlight complementary nuances. Ament and Verkerke (38) emphasize the psychophysical nature of fatigue, describing it as a protective mechanism that limits the individual's behavior in the face of physiological threat, for example, during excessive effort that may compromise the safety of the organism. Bestwick-Stevenson (39), in turn, expands the definition to the context of cognitive performance and emphasizes its role as a risk factor for injury. However, it must be noted that there is no clear consensus regarding its operational definition when it comes to quantifying fatigue (44), which may lead to limitations in evaluating and comparing results across studies.

Based on the General Adaptation Syndrome proposed by Selye (45), improving a physical quality requires the application of a sufficiently intense stimulus that generates a state of alarm in the organism. Following this alarm state, and after a recovery period, a supercompensation phase occurs in which a functional improvement is produced. In this sense, fatigue is an inherent and necessary component of the training adaptation process, as it reflects the acute impact of the applied stimulus and acts as a catalyst for performance improvement. From this perspective, we can distinguish between acute and chronic fatigue.

Acute fatigue is an expected and even desirable response in the context of training, provided it is properly controlled. This type of fatigue manifests as a temporary reduction in performance that occurs after one or more training sessions, and recovery may take minutes, hours, or even several days, depending on variables such as intensity, volume, type of contraction, environment, and the subject's fitness level (41,46). This form of fatigue affects both peripheral components—such as muscle contractile function or metabolite accumulation—and central components, in which changes may be observed in cortical excitability or in the nervous system's effectiveness in activating the muscles (38,43). Acute fatigue is thus related to the concept of functional overreaching. This concept refers to the fact that after a transient decrease in performance, and following proper recovery, a supercompensation occurs (46), resulting in an improvement in physical condition relative to the pre-fatigue state.

However, if the stimulus is excessive (whether due to intensity or duration) or recovery is insufficient, it is possible to enter a state of chronic fatigue. At the physiological level, this type of fatigue is associated with alterations in the endocrine, immune, and neuromuscular systems and is accompanied by symptoms such as loss of motivation, sleep disturbances, irritability, or depression (39,47). This state is related to the concept of non-functional overreaching. In this case, the stimulus applied to the organism is excessive, and instead of generating beneficial adaptations, a situation arises in which the athlete is unable to assimilate the training load. As a result, performance decreases and the risk of injury increases (1). Bell et al. (46) describe this process as a progression from functional overreaching to non-functional overreaching and, in more severe cases, to overtraining syndrome. When overtraining syndrome occurs, the athlete is considered to be in a critical state, posing a serious risk to both physical and mental health.

Therefore, fatigue control is an essential aspect of training planning, both in programs aimed at sports performance and in those focused on health improvement. In high-performance contexts, appropriate fatigue management allows for the optimization of adaptation processes, reduction of injury risk, and ensures that training stimuli produce sustained improvements without leading to overtraining states. In non-athletic populations, such as individuals with chronic conditions or those participating in preventive or therapeutic exercise programs, excessive fatigue may compromise program adherence, negatively impact general health, and lead to counterproductive effects. Furthermore, within both of these domains, injury prevention and recovery are included. For this reason, identifying early signs of fatigue, adjusting workloads, and respecting recovery processes become key strategies for maximizing the benefits of exercise and protecting the individual's physical and functional integrity, regardless of their level or context.

1.2.1. Methods for Quantifying Fatigue

As previously mentioned, quantifying fatigue is an essential component in the planning, monitoring, and adjustment of training. Measuring fatigue allows for the identification of whether a stimulus has generated an appropriate load, the anticipation of risks such as non-functional overreaching, overtraining syndrome, and/or injury, the optimization of recovery, and ultimately, the individualization of the training process. However, fatigue is a variable that is difficult to measure directly, as it is a multidimensional phenomenon that combines physical, neuromuscular, metabolic, and psychological components (39,40). For this reason, it is recommended to adopt a multifactorial assessment strategy that combines different tools depending on the context, available resources, and the program's objective (44,47). Currently, there are different methods for monitoring fatigue, which are briefly described below.

Subjective Methods

Subjective perception questionnaires, such as the Rate of Perceived Fatigue (RPF) (48), Profile of Mood States (POMS) (49), Daily Analyses of Life Demands for Athletes (DALDA) (50) or the Recovery-Stress Questionnaire (REST-Q) (51), are widely used tools due to their low cost, ease of application, and their capacity to collect relevant information about the athlete's overall condition (52). They are used to assess both perceived effort during training and well-being variables (sleep, energy, muscle soreness, stress, mood). Their main advantage is that they offer a global perspective and are sensitive to small changes, which is especially useful in sports where psychological load plays a relevant role. In addition, they provide insight into how the athlete perceives their own condition. However, their interpretation can be affected by subjectivity, lack of honesty, or the tendency of athletes to downplay their sensations (39,40,47).

Physiological Markers

Biochemical and hormonal biomarkers—such as cortisol, testosterone, creatine kinase (CK), lactate, ammonia, or the testosterone/cortisol (T/C) ratio—make it possible to monitor the body’s response to training from a physiological perspective. Salivary cortisol, for example, has been proposed as a non-invasive indicator of catabolic state, while CK is associated with muscle damage following intense sessions (39,52). Although these markers can provide valuable information on the systemic impact of exercise, their use presents significant limitations: high inter-individual variability, sensitivity to environmental factors (time of day, nutrition, external stress), the need for trained personnel and laboratory equipment, and low specificity in identifying fatigue as the direct cause of training-induced changes (46,47).

Among physiological markers, heart rate variability (HRV) has gained popularity as a tool to assess the state of the autonomic nervous system, particularly the sympathetic-parasympathetic balance, and is used as an indirect indicator of recovery level or chronic fatigue. Decreased HRV may be associated with fatigue, accumulated stress, or low recovery. Its advantages include the possibility of daily monitoring, non-invasiveness, and the use of portable devices. However, it is highly sensitive to external factors (hydration, mental stress, sleep, temperature), requires strict standardized measurement protocols, and its isolated interpretation may lead to errors (39,47).

Performance Loss Indicators

Among the most commonly used methods for quantifying fatigue are physical performance measurements, which allow for the direct evaluation of the functional impact of training on the athlete’s ability to generate force, speed, or power. These measurements provide a practical and specific approximation of the athlete's neuromuscular status and are particularly useful for monitoring acute fatigue (52).

Within performance loss indicators, various tests can be found, such as jump tests or the ability to perform repeated sprints (52). Among these, one of the most widely used tools is the countermovement jump (CMJ), which has been extensively validated due to its simplicity, reliability, and sensitivity to training-induced changes (52,53). It allows for the detection of reductions in jump capacity after demanding sessions, although its sensitivity may be limited in low-load efforts or when analyzing subtle changes (47). Another increasingly widespread strategy is the measurement of execution velocity loss during strength exercises. This is calculated based on the reduction in mean repetition velocity within a set and has been shown to be a reliable and sensitive indicator of neuromuscular fatigue, in addition to enabling the individualization of training dosage (54).

Another metric used is the loss in force production capacity. One of the most common and standardized methods to quantify this loss is through maximal voluntary contraction (MVC) (44). This involves isometric tests, such as the isometric mid-thigh pull or the isometric squat, where the athlete attempts to produce maximum force. From these tests, variables such as maximal force, RFD, or impulse can be obtained under stable and reproducible conditions. These tests are useful for detecting peripheral fatigue and have shown some sensitivity in intense efforts, although they may not fully reflect the demands of dynamic tasks, and their interpretation depends on the protocol, timing post-exercise, and the specific variable analyzed (41,44,55).

The advantages and limitations of the aforementioned methods have been discussed, but it is important to highlight a limitation common to all these performance-based tests: they require maximal efforts, which impose high physical and psychological demands on the individual. This requirement may not be feasible at certain stages of the training process—for example, after particularly demanding sessions or during high-load phases—as well as in clinical populations, older adults, or during injury recovery, where such efforts may be counterproductive. Additionally, in such situations, the individual's inability to express their maximal potential could obscure the true fatigue state of the organism, thus compromising the validity of the assessment. Therefore, the use of these tests must be carefully considered based on the athlete’s profile, the phase of the season, and the application context.

In summary, there are multiple tools available to monitor fatigue, each with its strengths and limitations, and their selection must be adapted to the context, available resources, and the individual being evaluated. Nevertheless, all of these methods present, to varying degrees, limitations related to measurement subjectivity, physical demand, the need for specialized equipment—which implies high cost or implementation difficulty—or sensitivity to external factors. In this context, the need arises to explore new strategies that allow fatigue to be quantified in a less invasive, more automatable manner and that can be applied during the actual execution of the exercise without requiring maximum effort on the part of athletes or patients.

To overcome the aforementioned limitations, a promising research direction is the analysis of motor control as a means of detecting fatigue. In practical settings, fatigue is consistently observed to alter movement patterns—affecting technique, rhythm, and stability—which suggests that changes in the organization of motor control may serve as a potential marker of fatigue. Yet, these alterations have not been objectively or systematically quantified. Accordingly, the present thesis examines motor variability as an indicator of the internal processes governing motor control that are modified under conditions of fatigue.

In recent years, motor variability has emerged as a potential alternative indicator capable of reflecting subtle neuromuscular changes associated with fatigue. The next section will address what motor variability is, how it can be measured, and its relationship with fatigue processes, in line with the main objective of this thesis: to analyze its usefulness as a functional monitoring tool.

1.3. Motor Variability

Motor variability refers to the natural fluctuations that occur in motor behavior during the execution of the same action. Far from representing a failure or noise in the system, this variability reflects the organism's ability to adapt to multiple internal and external demands while maintaining movement effectiveness (56,57). This view was anticipated by Russian neurophysiologist Nikolai Bernstein, who, in his pioneering studies on motor control, introduced the "degrees of freedom" problem and observed that no two movements are exactly alike, even when attempting to repeat the same action. He referred to this phenomenon as "repetition without repetition" (58), arguing that the nervous system does not execute fixed motor programs but rather adapts dynamically to each situation by reorganizing multiple components of the system. This self-organizing property of motor control enables the generation of diverse and efficient functional solutions, making variability an expression of the system's flexibility and health (59).

Various physiological and biomechanical mechanisms contribute to the presence of this motor variability. First, the redundancy of degrees of freedom in the musculoskeletal system allows the same motor goal to be achieved through multiple joint and muscular combinations, promoting exploration and adaptation to variable conditions (59). Various physiological and biomechanical mechanisms contribute to the presence of this motor variability. First, the redundancy of degrees of freedom in the musculoskeletal system allows the same motor goal to be achieved through multiple joint and muscular combinations, promoting exploration and adaptation to variable conditions (60). Finally, the musculoskeletal system does not act as a passive transmitter, but actively modulates the neural signal. The viscoelastic properties of the muscle-tendon complex filter high-frequency signals, altering the temporal and mechanical profile of the produced force. As a result, the final force output reflects not only the neural intent but also the mechanical characteristics of the contractile and connective tissues (61).

These mechanisms operate in an integrated manner, generating variability that is not random, but deterministic and structured—resulting from the dynamic interaction between multiple subsystems (56). From this perspective, motor variability presents nonlinear characteristics, as it arises from interdependent processes, sensitive to initial conditions, and capable of generating complex patterns that reflect the level of organization and flexibility of the motor system. Thus, analyzing how execution fluctuates provides insight into the underlying control mechanisms, the system's stability, and its capacity to adapt to different conditions. Therefore, variability adds valuable information, as it describes not only what is done (e.g., lifting a load or reaching a distance), but also how it is done, offering a deeper understanding of motor behavior and its internal organization.

1.3.1. How to Analyze Variability

To quantify and analyze levels of variability in human movement, two complementary approaches can be employed: linear measures and non-linear measures. The most traditional approach is based on linear metrics, which describe the magnitude of fluctuations in a signal relative to its mean. Among the most commonly used are standard deviation (SD), variance, and coefficient of variation (CV). These measures allow for capturing the absolute or relative magnitude of movement fluctuations across a time series (57,62). For example, in isometric force production tasks, such as maintaining a constant muscular contraction, the standard deviation indicates how much the exerted force fluctuates from the target value. The coefficient of variation, by relating SD to the mean, also facilitates comparisons between subjects or experimental conditions, even when force levels differ (63,64). These measures offer functionally relevant information about fine motor control and the interaction between the central nervous system and the musculoskeletal system. They are especially useful in clinical or aging populations, as they allow for the evaluation of force control at submaximal intensities (65).

However, this approach presents important limitations. On one hand, it assumes that variations are random, independent, and that the system follows stationary and linear dynamics—an assumption that contradicts the inherent complexity of biological systems (66,67). On the other hand, the use of averages—as occurs when analyzing normalized gait cycles—may mask the true temporal structure of the signal, removing crucial information about how patterns evolve over time (68). This can prevent the detection of underlying deterministic dynamics, which have been widely documented in physiological and movement signals and reflect an organized functioning of the neuromotor system. These signals often exhibit fractal and self-organizing properties, suggesting that the motor system operates with a high degree of complexity and adaptability (57). Therefore, although linear tools are valuable for quantifying the amount of variability, they alone do not capture the organization or quality of system behavior and should be complemented with non-linear methods (73).

Non-linear tools (NLT), derived from dynamical systems theory and complexity science, allow for the analysis of the temporal structure, stability, and self-organization of motor behavior (68). These techniques assume that variations are not merely noise, but may reflect deterministic and self-organizing patterns that are sensitive to initial conditions (56,67). Among the most commonly used tools are approximate entropy (ApEn) and sample entropy (SaEn), which quantify signal regularity; the Lyapunov exponent, which measures sensitivity to small perturbations; and detrended fluctuation analysis (DFA), useful for detecting long-range correlations (69). These techniques make it possible to evaluate how fluctuations evolve over time and to reveal the non-linear dynamics of the signal. Based on these methods, the theory of loss of complexity was proposed (67,70), according to which less functional systems (as seen in aging, fatigue, or certain pathologies) exhibit less "complex" variability, and therefore, are less adaptive. In contrast, a healthy motor system is characterized by an optimal level of complexity that allows it to be simultaneously stable, flexible, and adaptive—facilitating motor exploration, learning, and responses to perturbations (56,71).

Since movement variability emerges from the continuous interaction between the neuromuscular system, the task, and the environment, its analysis cannot be limited to a single dimension. It is therefore essential to combine linear and non-linear tools to obtain a more complete view of motor control. Linear methods offer the advantage of being simple to apply and requiring low computational cost, which makes them practical for routine analyses; however, they only quantify the magnitude of fluctuations and assume randomness and independence in the signal, so part of the "hidden" temporal information is lost. In contrast, NLT—although requiring more complex algorithms and higher computational demand—are more sensitive to the interactions among the different components of the organism, since biological systems follow non-linear, deterministic dynamics in which processes are neither random nor independent. Such dynamics can be detected through metrics such as entropy or DFA, which reveal alterations in the organization and complexity of motor control that remain undetected by linear indices.While the former allow for estimating the consistency or degree of fluctuation in performance, the latter reveal how that variability is temporally organized, providing key information on dynamic stability, control efficiency, and the functional state of the system. This integration is particularly relevant in areas such as motor learning (72), fatigue monitoring (73,74), aging (75) or in the detection of various pathologies and injuries (70,74,76), where small alterations in the structure of variability may anticipate significant functional changes. Ultimately, the combined use of both perspectives not only enhances the sensitivity and specificity of analyses but also strengthens the ability to make individualized, evidence-based decisions in both clinical and sports contexts.

1.3.2. Non-Linear Tools

For this thesis, entropy-based measures were used—specifically, sample entropy (SaEn) and fuzzy entropy (FuEn)—as well as detrended fluctuation analysis (DFA).

Entropy measures are used to quantify the degree of regularity or predictability of a time series. In practical terms, they indicate the probability that similar patterns of data (e.g., acceleration segments) will repeat over time. A highly regular signal, in which patterns are frequently repeated, will show low entropy values; by contrast, a more irregular or unpredictable signal will exhibit higher entropy values, which is associated with greater system complexity (77).

There are different variants for calculating entropy, among which approximate entropy, sample entropy, and fuzzy entropy are some of the most notable. All of them are based on the same algorithmic principle: they compare vectors of length *m* within the signal to determine how many of them are similar—that is, how many fall within a predefined tolerance *r*. They then analyze whether this similarity is maintained when one additional point is added to the vector. In this way, an estimate is obtained of the conditional probability that a pattern remains similar as it extends over time (78,79).

However, these variants differ in key aspects of their implementation. Approximate entropy (ApEn), the first developed measure, includes self-matches (i.e., comparisons of a pattern with itself), which introduces a bias toward regularity and may lead to unstable estimates, especially in short time series (78). To address this issue, Richman and Moorman (79) proposed sample entropy (SaEn), which excludes self-matches and improves the relative consistency of comparisons across conditions. Later, fuzzy entropy (FuEn) was developed, introducing a fuzzy membership function instead of a binary similarity window. This approach smooths the transition between similar and dissimilar patterns, making it more robust to noise, less sensitive to algorithm parameters, and more stable when working with short or physiological time series, such as those obtained from accelerometers (77). The formulas for calculating SaEn and FuEn are presented below.

Formula 1: Sample Entropy

$$\mathrm{SaEn}(m, r, \mathrm{N}) = -\ln \left[\mathrm{A}^{\mathrm{m}}(r) / \mathrm{B}^{\mathrm{m}}(r) \right]$$

Where:

- *m*: pattern length
- *r*: tolerance or similarity radius
- *N*: length of the time series
- $B^{m}(r)$: number of similar vector pairs of length *m*
- $A^{m}(r)$: number of similar vector pairs that remain similar after adding one point (length $m + 1$)

Formula 2: Fuzzy Entropy

$$\mathrm{D}_{\mathrm{ij}} = \exp \left[-\left(\mathrm{d}_{\mathrm{ij}} / r \right)^{\mathrm{n}} \right]$$

$$\mathrm{FuEn}(m, r, \mathrm{N}) = \ln \varphi^{\mathrm{m}}(r) - \ln \varphi^{\mathrm{m+1}}(\mathrm{r})$$

Where:

- d_{ij}: maximum distance between vectors X_i and X_j
- r: tolerance
- m: pattern length
- N: length of the time series
- n: shape parameter (commonly $n = 2$)
- $\varphi^m(r)$: average fuzzy similarity degree D_{ij} between vectors of length m

For its part, DFA offers a different perspective, as it does not evaluate the regularity of patterns but rather the presence of long-range correlations in the signal. The procedure consists of integrating the time series, dividing it into windows of different sizes, fitting a local regression line in each window (to remove the trend), and calculating the standard deviation of the residuals. If this average deviation follows a power-law relationship with respect to the window size, the signal is considered self-similar or fractal (80). The formula for DFA is shown below:

Formula 3: Detrended Fluctuation Analysis

$$F(n) = \sqrt{\left[(1 / N) \times \sum (y(k) - y_n(k))^2 \right]}$$

Where:

- $y(k)$: integrated signal
- $y_n(k)$: local trend within window n
- $F(n)$: average fluctuation at scale n

As Stergiou explains (69), his fractal property—also referred to as "self-similarity" or "scale-free"—implies that fluctuations in the motor system maintain a coherent organization across different temporal scales. In other words, the control patterns observed over short time intervals resemble those observed over longer intervals, which is characteristic of complex biological systems. This fractal organization is neither random nor rigidly periodic; rather, it reflects a structured form of variability that allows the motor system to dynamically adapt to internal and external perturbations.

The alpha exponent (α) obtained from DFA characterizes the signal's dynamics: a value close to 0.5 indicates the absence of correlation (white noise), values above 0.5 reflect persistence (i.e., a tendency that continues over time), and values below 0.5 indicate antipersistence (a tendency that tends to reverse) (80). According to Stergiou and collaborators, healthy motor systems exhibit an optimal degree of complexity, which translates into signals with intermediate fractal properties (for example, an α between 0.8 and 1.0). A loss of this complexity—whether due to excessive randomness or excessive rigidity—may indicate a reduction in the system's adaptive capacity, as occurs in situations of fatigue, aging, or pathology.

In this thesis, complexity refers to the temporal structure of variability in physiological and movement signals. It represents an intermediate state between excessive regularity and complete randomness, allowing biological systems to remain simultaneously stable, adaptive, and flexible. The loss of complexity occurs when the system deviates from this optimal intermediate state. Thus, complexity can decrease either through an increase in regularity and autocorrelation—leading to more rigid and predictable patterns—or through an excessive loss of regularity and reduced autocorrelation—leading to overly random and unstructured behavior (56). From a mathematical perspective, this phenomenon can be captured through entropy-based metrics and fractal analyses, which quantify the degree of regularity, predictability, and long-range correlations in time series.

From a functional standpoint, while entropy provides information about the system's regularity or predictability, DFA provides insight into the hierarchical organization and temporal dynamics of fluctuations. That is, both measures analyze the signal structure from complementary perspectives: entropy focuses on the probability of the occurrence of specific patterns, whereas DFA examines how those fluctuations are distributed and correlated across multiple time scales. This complementarity justifies their combined use in studies of motor control, as they capture different dimensions of nervous system behavior under functional or altered conditions.

1.3.3. Motor Variability as an Indicator of Fatigue

As mentioned earlier, from a practical perspective, coaches and strength and conditioning professionals can identify fatigue through subtle changes in movement quality. Even when external performance (e.g., the lifted load or number of repetitions) is maintained, signs such as loss of rhythm, increased stiffness, technical compensations, or less fluid and stable execution are often observed. In sport-specific movements, this may manifest as a more disorganized technique, alterations in trajectory or range of motion, or even asymmetries between sides of the body. These modifications reflect adaptive responses initiated by the motor system to sustain the task under fatigued conditions. Experimentally, it has been shown that fatigue causes changes in motor variability both at the kinematic level and in the organization of muscular synergies. In locomotor tasks, such as walking or running, fatigue has been found to increase joint angular variability, alter gait regularity, and reduce the dynamic stability of the locomotor pattern (75,81–83).

In the context of strength training, scientific literature has documented how fatigue alters the organization and execution of movement. At the kinematic level, several studies have shown that when an athlete performs tasks such as the squat under fatigue conditions, significant technical adjustments occur. Among the most common are increased trunk flexion, decreased movement depth, changes in the contribution of different muscle groups involved, as well as compensatory displacement of the center of mass (84–87). These changes—which can occur even when external performance is not compromised (e.g., the set is completed or the load is maintained)—indicate that the motor system reorganizes its strategy to sustain the task with lower mechanical efficiency. This reorganization may be reflected in more unstable movement patterns, less consistent repetitions, or altered trajectories, especially in individuals with less technical experience or under severe fatigue conditions..

In parallel, studies also show that fatigue considerably affects muscle activation during strength tasks. As the main muscles (agonists) lose their ability to generate force effectively, increased activity is observed in synergist or accessory muscle groups, which are recruited compensatory by the central nervous system (88,89). This redistribution reflects an alteration of the original muscular synergies and changes in intermuscular coordination patterns. For example, during squats performed with accumulated fatigue, variations have been observed in the activation timing and contribution magnitude of muscles such as the vastus lateralis, gluteus maximus, or spinal erectors, modifying the typical execution pattern (84,85,88–90).

These changes are not random but rather part of an adaptive strategy by the motor system to meet the task objective. However, they involve adjustments in movement patterns across repetitions, both in terms of kinematics and muscle activation, and therefore influence motor variability. This variability can be understood as a global marker that reflects both intramuscular changes and alterations in intermuscular coordinations. As such, it may serve as a functional indicator of the neuromuscular system's state, revealing the need to modify motor strategies in response to reduced available resources. In this regard, acceleration emerges as a particularly suitable variable to capture such reorganizations, since it not only offers the practical advantages of being inexpensive, portable, and easy to record, but also reflects fundamental biomechanical principles. Acceleration is directly related to the displacement of the center of mass and, through Newton's second law ($F = m \cdot a$), to the forces underlying movement. Thus, it provides information at both the kinematic and kinetic levels, making it a sensitive measure for detecting changes in motor control induced by fatigue. In this sense, the observation and analysis of these changes could serve as valuable indicators for coaches and researchers, allowing for the detection of fatigue signals before a drop in external performance is expressed, and contributing to the design of safer and more effective interventions in contexts such as high-performance sport, rehabilitation, or functional recovery.

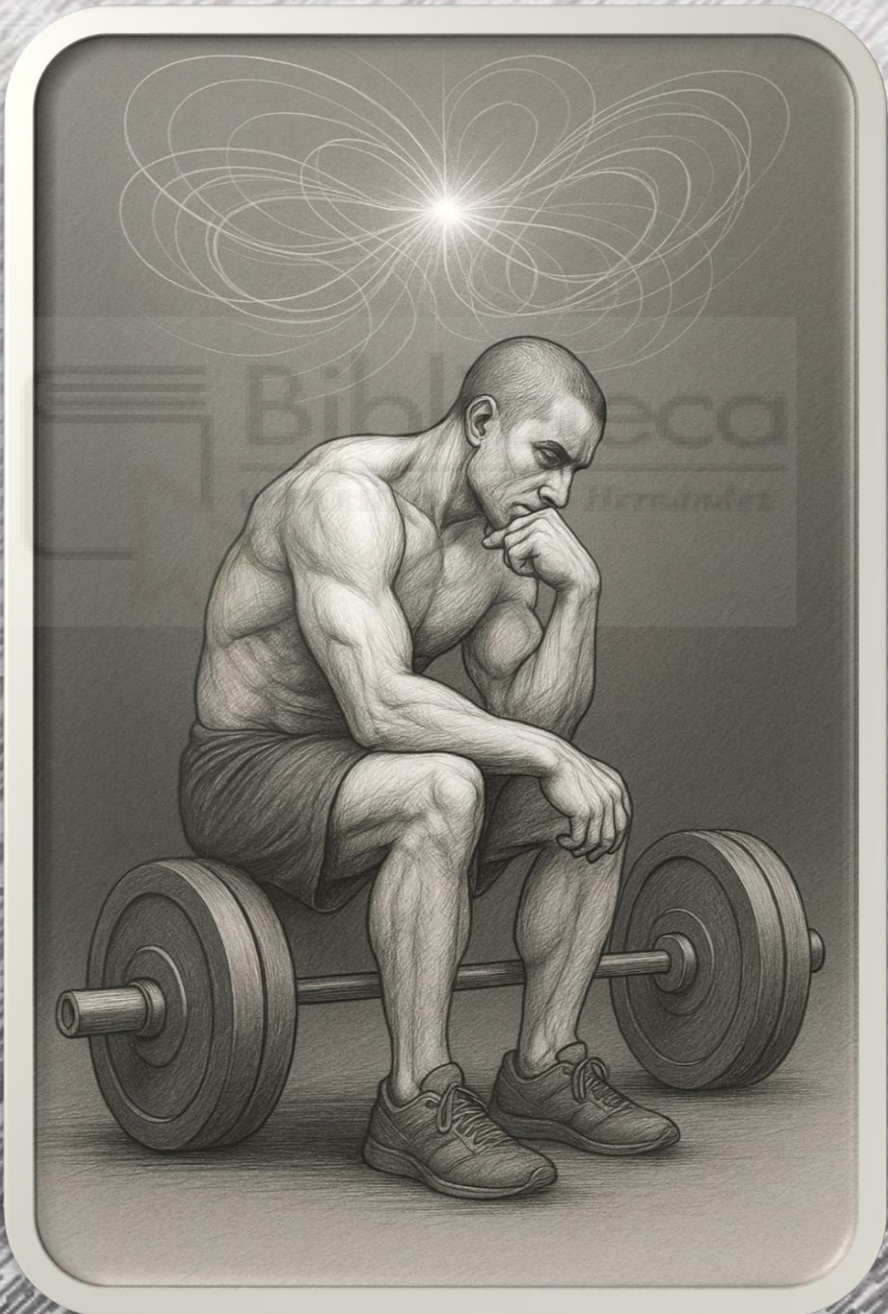
1.4. Research Question

The evidence presented suggests that fatigue induces specific and observable fluctuations in motor behavior, both at the kinematic level and in muscle activation patterns. These modifications are not always immediately reflected in external performance metrics, as the motor system tends to reorganize itself to maintain task execution. However, such changes are likely to be detected more sensitively through changes in motor variability.

Therefore, analyzing such variability could represent a promising avenue for identifying fatigue states. In this context, the use of Inertial Measurement Units (IMUs) offers an accessible, portable, and low-cost technological solution that allows for the recording of kinematic data in real training conditions (91,92). These sensors, increasingly used in sports settings, can capture fluctuations in repeated movement—such as during squat sets or dynamic tasks—and, through appropriate variability analyses, help detect alterations related to fatigue. Thus, the integration of motor variability measures obtained via IMUs could become a practical, automatable, and ecologically valid tool for non-invasive fatigue monitoring, contributing to more precise planning, more individualized workload management, and more effective prevention of overtraining and injury.

Determining whether motor variability analysis can truly serve as a useful tool for detecting fatigue states is the central aim of this thesis. This work seeks to answer fundamental questions regarding the utility of this type of analysis. While most previous studies on fatigue-related changes in motor variability have focused on isometric (static) tasks, this thesis applies the analysis to a dynamic movement. The squat was selected, as it is an exercise commonly used in both performance-oriented and health-focused training programs. Its dynamic and multi-joint nature provides a relevant and more ecological context for observing motor adaptations under fatigue. Additionally, a movement involving stability and postural control with moderate to high strength demands was included: the handstand. The ultimate goal is to provide coaches with a tool that complements existing information on the current state of their athletes or patients. To this end, this thesis will explore the most appropriate and accessible ways to analyze motor variability and will evaluate the reliability and sensitivity to fatigue of the proposed protocols.

2. Objectives and Hypotheses



2. Objectives and Hypotheses

Exercise-induced fatigue causes alterations in both performance and movement control. Traditionally, its monitoring has relied on performance indicators, physiological biomarkers, and/or subjective perception scales. However, in recent years, motor variability has gained prominence as a tool to detect less functional states of the organism, such as fatigue. This variability allows for the exploration of how such states modify motor control.

In order to establish a solid foundation for the potential use of motor variability as an indicator of fatigue—and to define appropriate methods for its application—this thesis was undertaken. It began with a systematic review of the scientific literature. This review aimed to assess the current state of knowledge regarding the use of NLT applied to motor variability analysis as an index of fatigue. It continued with a study that evaluatedthe reliability of variability analysis using IMUs in order to ensure the quality of data obtained for motor variability evaluation. Finally, it concluded with an analysis of the sensitivity of these measures to fatigue in two types of tasks: the squat and the handstand. Its ultimate purpose is to determine whether, through this accessible and user-friendly technology and variability analysis, it is possible to establish an additional fatigue indicator that can assist coaches and strength and conditioning professionals in optimizing strength training programs. Table 1 summarizes of the key points of each study included in this thesis.

2.1. General Objective

The general objective of this project is to determine whether variability in acceleration signals, analyzed through NLT, can be used as a valid indicator of the organism's fatigue state. It is hypothesized that fatigue states produce alterations in movement organization and force production, which are reflected in changes to the structure of motor variability. Identifying and validating these changes through accelerometry analysis would provide a functional, accessible, and objective marker to complement traditional methods of fatigue monitoring in the context of strength training.

2.2. Specific Objectives

Study 1 – Systematic review on the use of non-linear tools to monitor fatigue.

- To synthesize the existing scientific evidence on the relationship between fatigue and changes in the complexity of signals associated with motor control.
- To identify which NLT have been most frequently used to analyze force production and/or acceleration signals.

- To analyze methodological factors that influence the interpretation of these indicators: type of task (isometric vs. dynamic), intensity, duration, signal processing, among others.
- To determine whether a consistent pattern of complexity loss associated with fatigue exists across the analyzed motor tasks.

Study 2 – Assessing Motor Variability during Squat: The Reliability of Inertial Devices in Resistance Training.

- To evaluate intra-subject and inter-session consistency of linear (SD) and non-linear (entropy measures and DFA) indices applied to acceleration signals obtained with IMUs during squats at different intensities.
- To compare the reliability of these indicators across different sensor locations (barbell and lumbar region).
- To calculate the standard error of measurement (SEM).
- To analyze the agreement between the results obtained with IMUs and those recorded with force platforms.

Study 3 – Motor variability as an index of fatigue in dynamic actions: a perspective from the complexity loss theory.

- To analyze how fatigue induced by different strength training protocols (focused on power, hypertrophy, or maximum strength) affects the structure of motor variability during squat execution.

- To compare changes in variability indicators with a traditional fatigue indicator, such as loss of jump height.
- To observe post-exercise recovery profiles for each training modality in terms of both performance and motor complexity.

Study 4 – How does fatigue affect handstand balance? a non-linear approach to study fatigue influence in handstand performance.

- To determine whether fatigue affects postural control variability in handstand balance tasks, using variables derived from IMUs and force platforms.
- To assess the sensitivity of inertial sensors compared to force platforms for detecting qualitative changes in postural control following a fatigue protocol.

2.3. Hypotheses

Study 1 – The use of non-linear tools to analyze the variability of force production as an index of fatigue: A systematic review.

- **H1.1**: Most studies that apply NLT to analyze motor variability report a loss of complexity associated with the development of fatigue.
- **H1.2**: NLT are more sensitive than traditional linear methods in detecting fatigue-related changes, especially in isometric tasks.
- **H1.3**: Differences in study results can be explained by methodological factors such as task type, exercise intensity, the type of signal analyzed, and the signal processing procedures used.

Study 2 – Assessing Motor Variability during Squat: The Reliability of Inertial Devices in Resistance Training.

- **H2.1**: Non-linear measures applied to the analysis of motor variability analysis during squat execution are expected to prove to be a reliable measure.

- **H2.2**: Measurements obtained from force platforms, being considered a gold standard, will show higher consistency than those derived from accelerometers, in terms of result stability across sessions.

Study 3 – Motor variability as an index of fatigue in dynamic actions: a perspective from the complexity loss theory.

- **H3.1**: The three experimental training protocols will induce fatigue, which will be reflected in a reduction in jump height.
- **H3.2**: Fatigue is anticipated to lead to an increase in entropy and a decrease in DFA values in the acceleration signals.
- **H3.3**: Recovery time is expected to differ according to the type of training, both in the decrease of jump height and motor variability.

Study 4 – How does fatigue affect handstand balance? a non-linear approach to study fatigue influence in handstand performance.

- **H4.1** The experimental protocol will cause fatigue, which will be reflectedin both the area and the velocity of the center of pressure (COP) during handstand execution.
- **H4.2**: Under fatigued conditions, the COP signal is expected to show greater autocorrelated and lower irregular variability.

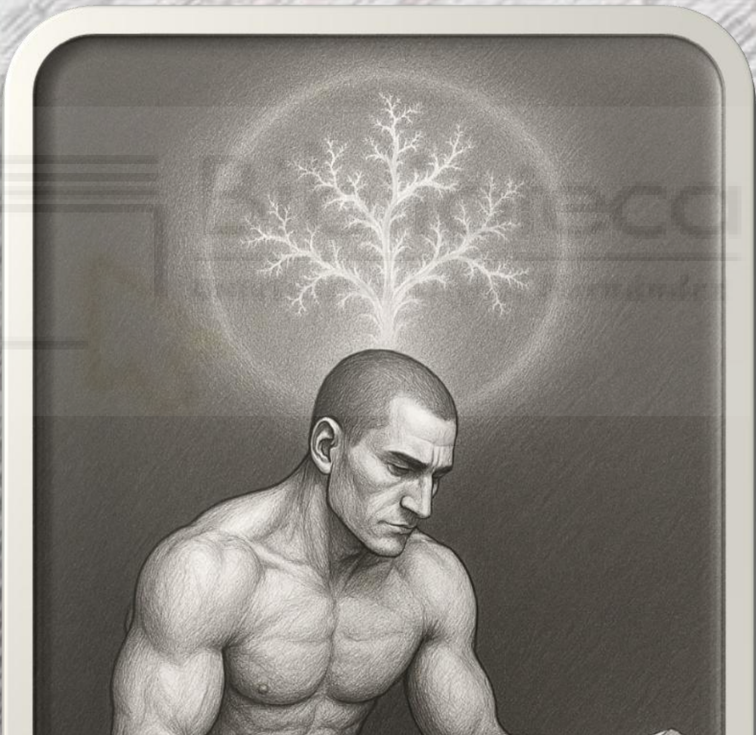
Table 1. Outline of the methodologies used in each of the Studies.

Methodological Outline

	Study 1: Systematic Review	**Study 2: Reliability of Measures**	**Study 3**	**Study 4**
General Objective	To review the current state of the art regarding the use of non-linear analysis for fatigue detection	To assess the reliability of the instruments and methodologies used	To examine the sensitivity of acceleration variability analysis to fatigue in high-force-demanding actions	To examine the sensitivity of acceleration variability analysis to fatigue in actions with moderate-to-high force demand and high postural control requirement
Design	Systematic review	Test-retest reliability	Cross-sectional	Cross-sectional
Sample	Published studies from databases (n = 25 articles)	66 participants (32 women, 34 men), physically active adults	35–38 participants (depending on the condition), adults with strength training experience	14 participants with experience in balance training or handstand work
Variables Analyzed	Non-linear tools, type of task, signal recording and processing	SD, DFA, FuEn, SaEn	SD, DFA, FuEn, CMJ	SD, DFA, FuEn
Equipment	Scientific databases (PubMed, Scopus, Web of Science, SPORTDiscus, ResearchGate, references)	IMUs and force platform	IMUs and contact platform	IMUs and force platform

3. Study 1

The Use of Non-linear Tools To Analyze the Variability of Force Production as an Index of Fatigue: A Systematic Review



3. Study 1

This section presents a summary of the study titled *"The use of non-linear tools to analyze the variability of force production as an index of fatigue"*, authored by Fernando García-Aguilar, Carla Caballero, Rafael Sabido, and Francisco J. Moreno, and published in the scientific journal *Frontiers in Physiology* in 2022. This work consists of a systematic review in which the use of NLT applied to the analysis of force variability as a potential indicator of fatigue was examined. The full article is available in the Appendix section for full consultation.

3.1. Contextualization of Study1

As discussed in the introduction of this thesis, fatigue induces modifications in movement execution that may be reflected in motor variability. While this variability has traditionally been analyzed using linear tools that describe the amount of fluctuation, non-linear methods allow for the study of the temporal organization of such variations, and in some cases, have shown greater sensitivity than linear tools (93). The literature suggests that fatigue is associated with a loss of complexity in signals related to force production, which may reflect a reduced adaptive capacity of the organism. This concept is grounded in the loss of complexity theory, which posits that less functional systems (e.g., aged, injured, or fatigued) exhibit more predictable and less flexible signals (67).

In recent years, several studies have applied NLT—such as entropy, DFA, or the Lyapunov exponent—to investigate force variability under fatigue conditions. Each of these tools assesses different aspects of the temporal structure of variability. Furthermore, various methodological considerations may influence the results, including sampling frequency, signal processing, the specific motor task analyzed, among others (69,94,95).

For these reasons, and as a preliminary step before conducting the experimental studies of this thesis, it was deemed essential to carry out a systematic review to understand how and for what purpose NLT have been applied in fatigue research. The aim of this review was to identify the main findings regarding the relationship between fatigue and complexity, to analyze methodological aspects that may influence results, and to establish recommendations for future studies. This study presents that review and serves as the starting point for the subsequent analyses included in this thesis.

3.2. Summary of the Methods of Study1

This study consisted of a systematic review conducted in accordance with PRISMA guidelines (96)The objective was to identify and synthesize studies that applied NLT to the analysis of variability in signals associated with force production under fatigue conditions.

Search Strategy

The literature search was conducted in the following databases: SPORTDiscus, Scopus, Web of Science, and PubMed. Articles published up to October 2022 were included. Various keyword combinations were tested to maximize the number of relevant articles. The final search string used was:

<fatigue AND (entropy OR Lyapunov OR detrended fluctuation analysis OR dfa OR hurst exponent OR fractal* OR recurrence quantification OR autocorrelation)>.

Reference management and duplicate removal were performed using Mendeley software. The following inclusion criteria were established:

- Original research involving human subjects.
- Analysis of the effect of fatigue during tasks focused on force production.
- Application of NLT to signals directly related to force production (force, torque, acceleration, kinematics).
- Published in English, with accessible title and abstract.

Study Selection Process

The selection process was carried out in three consecutive phases, following a standardized protocol to ensure transparency, reproducibility, and bias reduction.

In the **first phase**, an initial screening was conducted based on the titles retrieved. One researcher excluded studies clearly unrelated to the review objective (e.g., engineering topics, purely mathematical analyses, animal studies, or research on cognitive or cardiovascular fatigue without analysis of force production). In cases of doubt about a study's relevance, it was retained for later phases using a conservative criterion.

In the **second phase**, abstracts and titles of the preselected studies were independently reviewed by two experienced researchers, who rigorously applied the predefined inclusion and exclusion criteria. Disagreements were discussed, and if no consensus was reached, a third reviewer resolved the decision.

The **third phase** consisted of a full-text review of the articles that passed the previous stages. This ensured that each study met all inclusion criteria, especially the effective application of NLT to signals related to force production under fatigue conditions. The quality of reporting on fatigue protocols, signal acquisition, data processing, and results presentation was also assessed.

Additionally, a manual search was performed by reviewing the references of included articles to identify relevant studies not captured initially. The profiles of key authors (Google Scholar, ResearchGate) were also consulted to detect related works potentially omitted due to database or terminology limitations.

This rigorous and systematic process ensured that the studies included in the review were relevant, methodologically sound, and aligned with the research question. Figure 1 illustrates the flow diagram of the selection process.

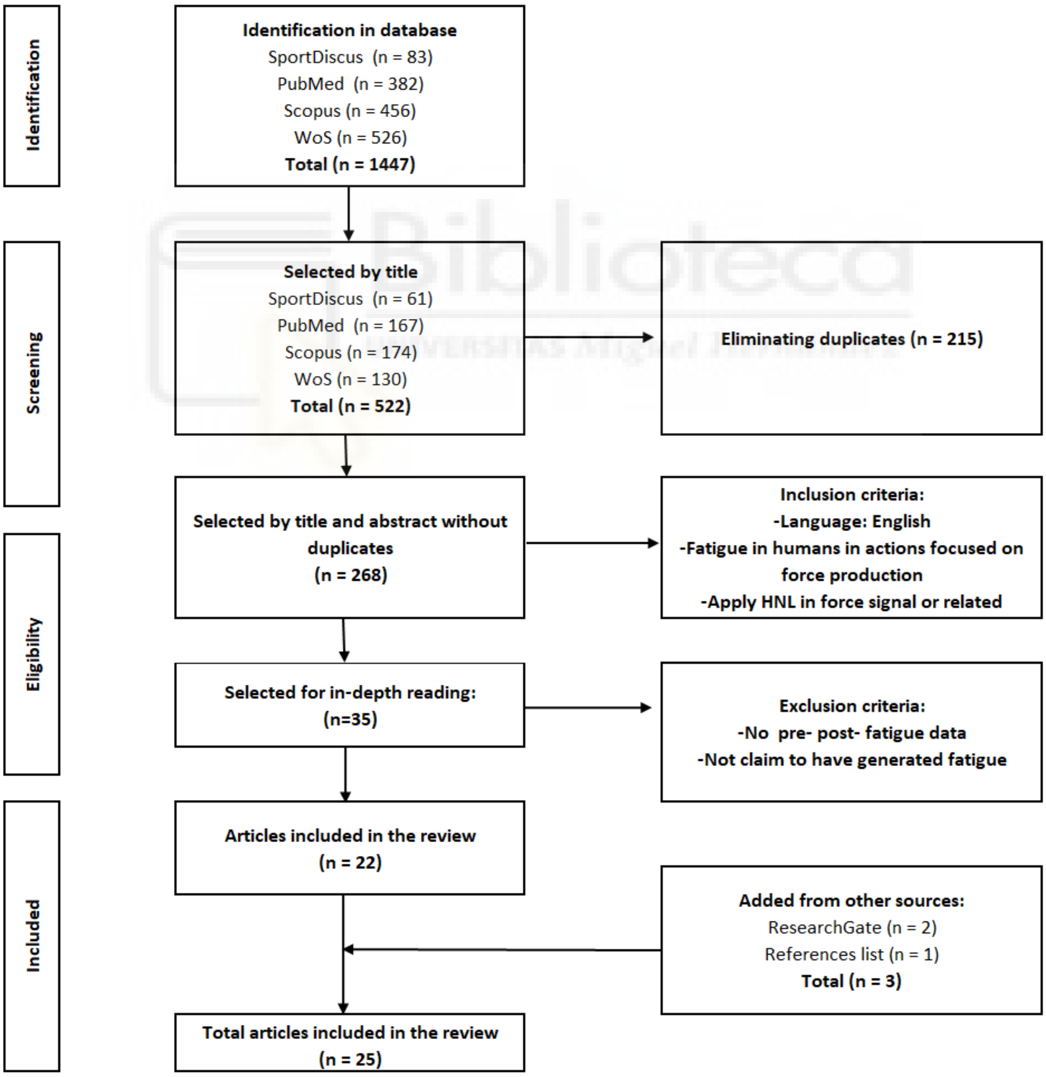


Figure 1. Flow diagram of the search strategy used in Study 1. Reproduced from: García-Aguilar F, Caballero C, Sabido R, Moreno FJ. The use of non-linear tools to analyze the variability of force production as an index of fatigue: A systematic review. Front Physiol. 2022;13:1074652. Licensed under CC BY 4.0.

Data Extraction

Data extraction was carried out systematically following a protocol previously agreed upon by the researchers. The extraction was performed by two reviewers: one conducted the primary collection, and the other verified its accuracy. In case of discrepancies, discussions were held until consensus was reached. The following variables were extracted from each study:

- **Sample characteristics**: number of participants, age, sex, level of experience or physical condition.
- **Fatigue protocol**: type of exercise used, duration, volume, relative intensity (expressed as a percentage of maximal voluntary contraction or equivalent), and whether it was performed to failure or with controlled time.
- **Type of contraction**: classified as isometric, dynamic (with or without joint displacement), eccentric, or combined.
- **Type of signal analyzed**: force, torque, acceleration, electromyography, or kinematic signals.
- **NLT used**: type of metric employed (sample entropy, fuzzy entropy, DFA, % determinism, Lyapunov exponent, etc.).
- **Sampling frequency**: expressed in hertz (Hz), and whether it was constant or variable.
- **Signal processing**: filtering, trimming, normalization, or segmentation procedures were described, along with the time length of the series analyzed.
- **Main results**: observed effects of fatigue on complexity measures, direction of changes (increase or decrease), and consistency across measures.

All this information was organized in Excel tables. Figure 2 shows an example of these tables and how the information was classified.

Authors	Sample	Protocol fatigue	HNL	Data acquisition and processing	Main results NLT
Bastida, Gómez y Pino (2017)	n =11 trained men	4 x 10 65% RM squat (dynamic)	ApEn	Acceleration data at 1000 Hz. There is no information about the data processing.	Decrement of complexity (decrease of ApEn) together with loss of average propulsive velocity
Bauer, et al. (2017)	n = 86 (42 men) n = 59 with low pain (30 men) 39.6 (±11.6) years n = 27 without low pain (12 men) 39.1 (±12.8) years	Pre-post-test: repeated trunk flexion and extension. Fatigue protocol: isometric trunk extensors to failure.	%DET + SampEn	Angular displacement and velocity at 200 Hz. Data were transformed into quaternions and filtered with low-pass Butterworth filter (6 Hz)	Participants without low back pain showed more complex behaviour (increase of SampEn and decrease of %DET) in angular velocity after fatigue.
Chatain C, Gruet M, Vallier JM, Ramdani S. (2020)	n = 11 Healthy active men 24.1 (± 6.6) years	Isometric knee extensor at 15% MVC to failure.	SampEn	Force sensor data at 2000 Hz were filtered with low-pass Butterworth filter (20 Hz) and down-sampled at 400 Hz. A Dickey-Fuller test and EMD were used.	Increase of complexity in the original signal (increase of SampEn), and decrease in complexity (decrease of SampEn) after eliminating non-stationarity
Chatain, C., Ramdani, S., Vallier, J. M., & Gruet, M. (2021).	n = 38 healthy young adults (19 men) 22.6 (± 2.9) years	Intermittent isometric contractions (8:4) of the knee extensors at 50% MVC until task failure.	RQA (DET)	Force sensor data at 2000 Hz were filtered with low-pass Butterworth filter (20 Hz) and down-sampled at 500 Hz. EMD was used.	Reduction of complexity (increase of DET). Men showed more complexity than women.
Cowley, Digwell y Gates (2014)	n= 20 healthy right-handed adults (11 men) 25 (±2.2) years	Pre-post-test: Sawing task (dynamic). Fatigue protocol: LIFT = shoulder flexor at 10%MVC at 0.5Hz for 3 min or failure.	DFA	Motion analysis system data at 120 Hz was resampled at 1,080 Hz and filtered with low-pass Butterworth filter (6 Hz).	Reduction of complexity (increase of DFA) for error in LIFT and speed in sawing. Men showed more complexity than women. Increment

Figure 2. Example of the Excel table used to collect and classify the information obtained during the search process in Study 1. Reproduced from: García-Aguilar F, Caballero C, Sabido R, Moreno FJ. The use of non-linear tools to analyze the variability of force production as an index of fatigue: A systematic review. Front Physiol. 2022;13:1074652. Licensed under CC BY 4.0.

Risk of Bias Assessment

To evaluate the methodological quality of the included studies and their potential risk of bias, two complementary tools were used. First, the *Quality Assessment Tool for Before-After (Pre-Post) Studies With No Control Group* (97), developed by the National Institutes of Health (NIH), was applied. This tool assesses aspects such as the clarity of objectives, description of the intervention, validity of the measures, dropout rates, and appropriateness of the statistical analysis. Each study was rated as "positive," "negative," or "not applicable/not reported" across 12 items, allowing for an overall judgment of its quality.

Second, the ROBIS (*Risk Of Bias In Systematic Reviews*) (98) framework was used to assess the potential risk of bias specific to the systematic review. This evaluation considered possible limitations in the search strategy, the study selection process, transparency in data extraction, and the analysis of results.

Overall, most of the included studies demonstrated adequate methodological quality and a low risk of bias. However, some recurring limitations were identified: in particular, several studies provided incomplete descriptions of signal processing procedures (e.g., failing to specify the type of filter used or the parameters applied in non-linear measures), and in some cases, small sample sizes were reported, which could affect the statistical power of the analyses and limit the generalizability of the findings. These aspects were taken into account when interpreting the overall results of the review.

3.3. Summary of the Results of Study 1

After the review and selection process, 25 studies were included in this systematic review. A detailed analysis of these works allowed the identification of both common trends and notable heterogeneity in the methodological approaches employed. Collectively, the reviewed studies provide an overview of the current state of NLT application to variability analysis during force production tasks under fatigue conditions. The extracted information was classified into four sections: (1) Type of action and intensity; (2) Type of signal and non-linear tool used; (3) Data acquisition and processing; (4) Effects of fatigue on motor variability.

Type of action, volume, and intensity

Of the 25 included studies, 20 used isometric contractions. Among these, 12 studies applied intermittent isometric contractions, 5 used sustained isometric contractions, one employed rhythmic isometric contraction, another combined intermittent isometric and eccentric contractions, and one used a quasi-isometric contraction. Regarding workload volume, most studies employed fatigue protocols either to failure or with a predefined time limit. As for intensity, 3 studies used a low relative intensity, below 30% MVC; 12 studies applied submaximal intensities between 30% and 80% MVC; and 6 studies used various combinations of intensities: low and submaximal, low and maximal, or submaximal and maximal.

On the other hand, 5 studies analyzed dynamic actions. In terms of volume, two of them used time-to-failure or time-limited protocols, while the remaining three used structured repetition formats: one applied 4 × 10 at 65% 1RM, another 5 × 20 at 30% MVC, and one did not clearly specify the volume. Regarding intensity, two studies used bodyweight as load, one applied 30% MVC, another used 65% 1RM, and one did not report intensity in relative terms. This distribution highlights a greater prevalence of studies analyzing variability in isometric tasks. Furthermore, the protocols were more homogeneous compared to the dynamic tasks, which showed greater variability in their design.

Type of signal and non-linear tool used

Regarding the type of signal analyzed, 17 of the 25 studies applied NLT to force or torque signals, while one study combined force and acceleration signals. The remaining 7 studies applied NLT to kinematic variables, including joint angles, distance, velocity, timing errors, acceleration, coupled joint motion (hip-knee), and mechanomyography. In terms of NLT used, entropy-based measures were the most common, appearing in 20 studies, including variants such as ApEn, SaEn, multiscale entropy, Shannon cross-entropy, and

FuEn. DFA was applied in 12 studies, while less common tools included recurrence quantification analysis (RQA) in three studies, the Lyapunov exponent in one study, and Lempel-Ziv complexity in one study.

Data acquisition and processing

Regarding signal acquisition and processing, most studies (19 out of 25) recorded data at 1,000 Hz or higher, while 5 studies used sampling frequencies below 200 Hz. One study combined high-frequency sampling for force signals with low-frequency sampling for acceleration. Four studies applied downsampling to the original signal, reducing the frequency to 50 Hz, 100 Hz, 400 Hz, or 500 Hz. Conversely, two studies applied upsampling, increasing the frequency to 1,080 Hz. As for filtering, 13 studies did not apply any filtering, while the others mainly used low-pass filters with cutoff points ranging from 6 Hz to 20 Hz. Only one study applied a high-pass filter with a threshold of 3 Hz to acceleration signals, and another used a Woltring quintic spline filter to smooth trajectories. Additionally, two studies implemented further processing procedures, such as the Dickey-Fuller test to detect non-stationarity and the use of Empirical Mode Decomposition (EMD)to obtain stationary signals.

Effects of fatigue on motor variability

In studies using isometric contractions, a consistent association was observed between fatigue and more predictable, autocorrelated signal patterns. Specifically, most of these studies reported a decrease in entropy measures and/or an increase in DFA values, indicating greater temporal regularity in the signal following fatigue. This pattern was consistent across different isometric formats, including intermittent, sustained, and quasi-isometric tasks. Moreover, one study showed that these metric changes only occurred at certain joint angles, suggesting a possible influence of joint position on the motor system's response.

In contrast, studies analyzing dynamic actions did not show a clear trend. Results were more variable and depended on factors such as protocol intensity, the metric used, or the signal processing method. Some studies reported decreases in entropy or increases in DFA after fatigue, mainly under high-intensity conditions. Others observed opposite responses, such as increased entropy measures, particularly when analyzing non-stationary original signals or using long time scales in multiscale entropy. This variability in responses during dynamic tasks suggests greater complexity in how the motor system reorganizes under fatigue when active movement and multiple degrees of freedom are involved.

3.4. Summary of the Discussion and Conclusions of Study 1

The results of this systematic review indicate that NLT are useful for detecting changes in motor variability during force-demanding tasks under fatigue, particularly in isometric exercises. In these contexts, most studies reported a decrease in entropy and an increase in autocorrelation (DFA), suggesting a reorganization of motor control toward more regular and less variable patterns. However, in dynamic tasks, the results were more inconsistent, likely due to the greater complexity of the movements, the heterogeneity of the experimental designs, and the diversity of signals analyzed. The following sections summarize the key findings and their implications.

Physiological mechanisms behind complexity loss

One of the main challenges in analyzing the effect of fatigue on motor variability is understanding what the observed changes in different signals reflect physiologically. Decreases in entropy or increases in DFA values not only indicate a change in signal structure but also point to a reorganization in neuromuscular system function. Therefore, it is essential to interpret these changes physiologically in order to provide functional and clinical meaning to the quantitative results obtained.
Several studies have suggested that force variability reflects the interaction between neuromuscular system components (66) and the control loops that regulate its output (75). Most of the works included in this review showed a decrease in entropy or an increase in DFA during short-duration and submaximal or maximal intensity tasks—conditions under which fatigue is usually attributed primarily to peripheral mechanisms (43). Some studies support this interpretation by comparing fatigued and non-fatigued limbs (99,100) and propose as possible causes of variability changes: the increase of metabolites (101–103), the reduction in the contractile capacity of motor units (103,104)(105), or muscle damage induced by eccentric contractions (105). It has also been suggested that metabolite accumulation could alter motor unit discharge (102), thereby affecting signal structure.

In parallel, it has been noted that central mechanisms also influence these changes, such as motor unit synchronization and discharge frequency. Several studies agree that changes in motor unit recruitment could explain the alterations observed in non-linear metrics (100–102,104,106–108), which aligns with research linking motor unit organization to force production fluctuations (109–112). Increased synchronization in response to reduced available force could reduce system degrees of freedom and generate a more predictable and autocorrelated signal. The influence of common input to motor units (113) and variations in discharge frequency—which may increase (106,108) or decrease (104,114) depending on the protocol—also affect results and may explain methodological heterogeneity.

Furthermore, tasks with high cognitive demand have been shown to intensify central fatigue effects, resulting in greater alterations in non-linear metrics (108,115,116). The fact that caffeine consumption—which affects the central nervous system—attenuates these changes (117) reinforces the hypothesis that central and peripheral mechanisms constantly interact. When peripheral fatigue reduces force production capacity, the central nervous system responds by increasing motor unit recruitment and synchronization, modulating motor control to sustain the task (101,104,118,119). Simultaneously, muscle afferents influence this response, protecting the system from further deterioration (43). In line with this integrated view, Lin et al. (106) proposed that alterations in multiscale entropy depend on the analyzed time scale: short scales would reflect central activation, while longer ones would capture peripheral noise. Thus, changes in signal structure could be interpreted as the result of a feedback loop between central and peripheral processes that reconfigure motor control and reduce system degrees of freedom, generating a more predictable and autocorrelated signal (73).

Intensity and Type of Contraction

Understanding how different methodological variables modulate the responses observed in non-linear metrics is essential for correctly interpreting the results of various studies. In this regard, the type of contraction, relative intensity, and nature of the task play a central role in the changes recorded in non-linear measures. Exercise intensity has been identified as a key factor: most studies using submaximal or maximal intensities reported a decrease in entropy or an increase in DFA after fatigue (103,104,114,120). In some cases, these effects also depended on joint angle, suggesting that effective intensity may be modulated by biomechanical factors such as lever arm length or force application point (121). In contrast, studies using low relative intensity did not show clear changes, possibly because the system was not sufficiently stressed to induce significant alterations in neuromuscular control (101,103,122). It has been proposed that changes in non-linear metrics only manifest when the so-called "critical torque" is exceeded—a functional threshold estimated between 20% and 25% of MVC—beyond which relevant physiological alterations in the neuromuscular system begin to occur (40,103,121). Below this threshold, the system can maintain performance without significantly compromising its adaptive capacity, which would explain the low sensitivity of NLT in these conditions.

Contraction type also seems to play a role. In isometric tasks, changes in metrics were consistent, showing decreases in entropy and increases in DFA. In the case of dynamic actions, the results were more variable. Only two studies showed decreases in entropy or RQA analysis (114,123), while others detected increases in entropy, decreases in DFA, or contradictory results—either increases or decreases in DFA depending on the analyzed variable (122–125). This disparity may be due to methodological heterogeneity, the influence of relative intensity, and especially the greater non-stationarity of dynamic signals, which complicates the precise application of certain NLT (69,95). Overall, these findings highlight the need to carefully consider task characteristics and fatigue protocol when interpreting changes in non-linear metrics. However, one of the most influential factors in these results is how signals are processed before analysis.

Therefore, the following section specifically addresses the role of signal processing as a key element in the application of NLT.

Influence of Signal Acquisition and Processing

Signal processing is a determining factor in the application and interpretation of NLT, as it can significantly influence the results obtained (69). One of the first aspects to consider is the sampling frequency. Although the studies included in this review did not directly analyze its effect, the results suggest that frequencies above 200 Hz are more suitable for capturing force production dynamics. In fact, most studies using high frequencies (83,100–108,114–117,120,121,123,126–128) observed a decrease in metrics such as entropy or an increase in DFA after fatigue, whereas studies with frequencies ≤200 Hz (122,124,125) showed more inconsistent or even contradictory results. This effect may be due to low sampling frequency distorting the signal shape and limiting detection of relevant fluctuations.

Filtering is another critical aspect. Although some authors advise against filtering to avoid altering signal structure (69,95), several studies employed low-pass filters with cut-off points between 6 Hz and 20 Hz. Results suggest that low cut-off frequencies (≤6 Hz) may offer lower consistency, possibly due to interference with voluntary and involuntary control components that operate at different frequency ranges (129,130). For example, frequencies below 4 Hz reflect voluntary control, while 8–12 Hz ranges are dominated by involuntary loops like physiological tremor. Some authors have proposed analyzing the signal at different bandwidths to explore the specific contributions of these systems.

Additionally, NLT are sensitive to signal stationarity. Two studies (127,128) applied EMD techniques to reduce non-stationarity. In one of them, it was observed that while the original signal showed an increase in entropy after fatigue, the processed signal showed a decrease, indicating that non-stationarity may obscure or distort the true effects of fatigue. This is especially relevant in dynamic tasks, where the signal tends to be less stable over time.

Taken together, these findings reinforce the need to establish clear methodological criteria for signal acquisition and processing, especially if NLT are to be applied robustly and reliably in contexts such as neuromuscular fatigue detection.

Conclusions

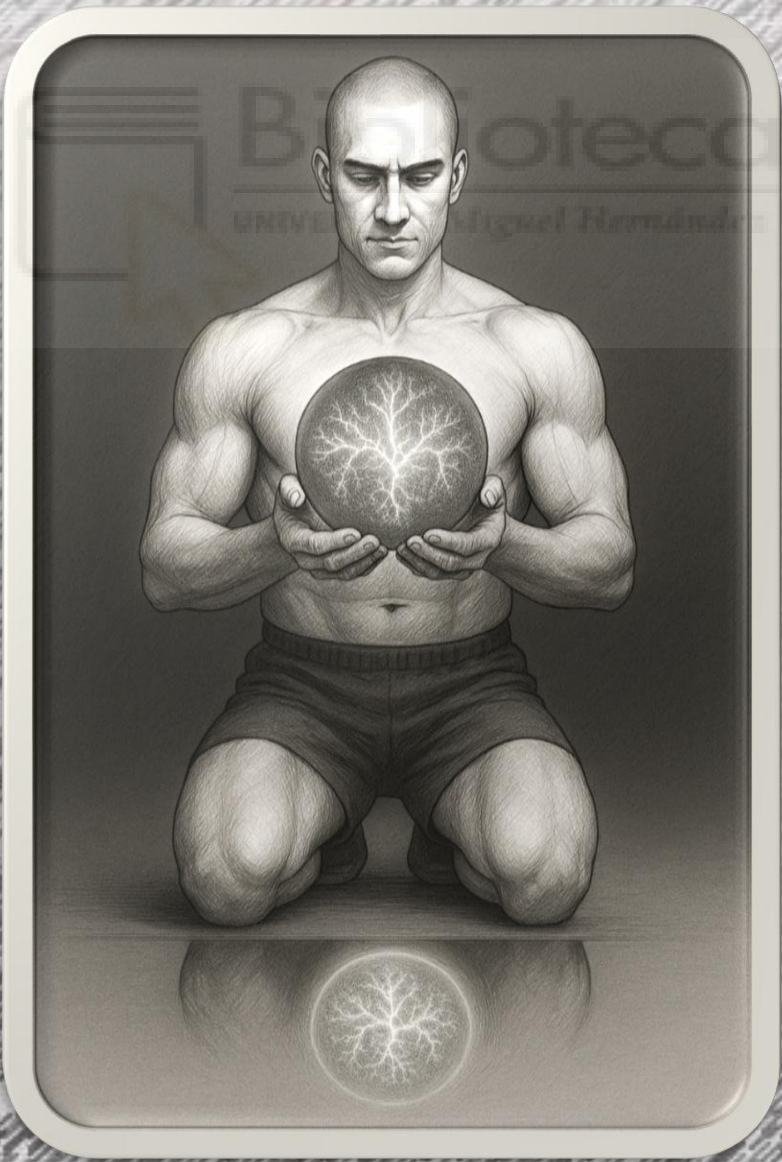
This systematic review has identified how NLT have been applied to the analysis of variability in force production signals under fatigue conditions. Most studies focused on isometric actions with submaximal or maximal intensities, applying metrics such as entropy and DFA to force or torque signals. In these contexts, it was consistently observed that fatigue is associated with more predictable and autocorrelated patterns in the signal, reflected in a decrease in entropy or an increase in DFA, especially when certain physiological thresholds such as the critical torque are exceeded. In contrast, studies involving dynamic actions showed more variable results, probably due to heterogeneity in experimental design, greater non-stationarity of the signals, and the sensitivity of the metrics used.

In addition to the type of task and its intensity, methodological factors such as sampling frequency, filtering, and the temporal stability of the signal were found to decisively influence the ability of NLT to detect fatigue-related changes. It is recommended, particularly in isometric tasks, to use sampling frequencies above 200 Hz, avoid excessive low-pass filtering below 6–8 Hz, and consider techniques such as EMD to address non-stationarity in dynamic signals.

Among the main limitations of this review are the heterogeneity of protocols, both in the tools employed and in the signal processing methods, as well as the scarcity of studies focused on dynamic actions. Additionally, certain individual variables such as the presence of pathologies or participant sex may also affect variability metrics (116,124,128,131).

This review highlights the need for future studies in two main directions. On one hand, to further investigate dynamic contractions, given their greater functional relevance in both sports and daily life contexts. On the other hand, to explore the applicability of these tools in fatigue monitoring during training, in order to optimize load and prevent overtraining or injury. Finally, it is considered essential to advance the understanding of the neural mechanisms involved in the observed changes, which could be achieved by incorporating complementary measures such as transcranial magnetic stimulation, enabling a more direct link between signal modifications and central nervous system activity.

4. Study 2: Assessing Motor Variability during Squat: The Reliability of Inertial Devices in Resistance Training



4. Study 2

This section presents a summary of the study *"Assessing Motor Variability during Squat: The Reliability of Inertial Devices in Resistance Training"*, written by Fernando García-Aguilar, Miguel López-Fernández, David Barbado, Francisco J. Moreno, and Rafael Sabido, and published in the scientific journal *Sensors* in 2024. This work consists of a cross-sectional study aimed at evaluating the reliability of variability analyses in acceleration signals during the squat exercise under a conditioning factor such as the load lifted. The full article is available in the Appendix section for full consultation.

4.1. Contextualization of Study 2

Study 1 revealed that although there is solid evidence in the scientific literature regarding the changes that fatigue induces in the structure of variability in force production during isometric actions, the evidence in dynamic actions is limited. Moreover, it should be noted that most of the reviewed studies on isometric actions were conducted in monoarticular movements. This limitation is relevant, as dynamic and multi-joint actions are most commonly used in training programs. Additionally, as noted in Study 1, the type of contraction appears to influence the values obtained for these metrics. A recent study (132) indicated that the number of degrees of freedom may affect the results. Thus, it is possible that both factors influence the outcomes of variability analyses.

Another critical aspect identified in Study 1 was that existing work on variability analysis using NLT in dynamic actions is scarce and methodologically heterogeneous. This inconsistency affects both the type of signal analyzed and the procedures for recording, preprocessing, and calculating the non-linear metrics. Given that the reliability of results depends largely on the quality and consistency of the measurement process, this lack of methodological uniformity may compromise data interpretation and limit its practical applicability.

As training professionals, when conducting assessments, we need tools and protocols to provide reliable measurement values. Otherwise, we cannot determine whether changes—or the lack thereof—are due to our intervention or to measurement errors or variations. As previously mentioned, IMUs are becoming increasingly relevant in the training world. In this regard, studies have evaluated their reliability in performance variables such as power, velocity, or displacement. However, it is still unknown whether variability measures—particularly those derived from NLT such as entropy or DFA—are reliable when obtained from these devices during dynamic tasks.

For all these reasons, this second study was designed with the objective of evaluating the reliability of different motor variability indicators, both linear and non-linear, from acceleration signals recorded with IMUs during the execution of squats. Additionally, different sensor placements were compared, and the agreement of results obtained with those from force platforms was analyzed, in order to determine whether these tools can be used consistently and validly in real training or rehabilitation settings. This step is key to advancing toward functional monitoring of fatigue based on motor variability.

4.2. Summary of the Method of Study 2

Participants

A total of 66 subjects (34 men and 32 women) with a minimum of one year of experience in strength training participated in this study. Descriptive data of the sample are presented in Table 2. All participants were healthy and free of injuries or illnesses that could alter the results, and they regularly performed squats in their training programs. Individuals who did not complete all sessions or whose data could not be properly recorded were excluded. Participants were instructed not to consume caffeine within the three hours prior to the measurements and to refrain from strength training during the 72 hours before testing. In addition, all sessions were scheduled at the same time of day to minimize experimental variability due to circadian cycles.

Table 2. Descriptive Data of the Participants in Study 2.

	Age (year)	Altura (cm)	Body Weight	RM (kg)	Ratio RM/BW
Men (n = 34)					
Mean	25.7	174.5	71.9	116.5	1.6
SD	4.4	7.4	13.6	23.2	0.3
Women (n = 32=					
Mean	25.1	161.0	60.4	76.5	1.3
SD	5.3	5.3	7.6	17.4	0.3

Procedure

The study was conducted over three sessions, each separated by at least 72 hours. During the first session, participants were familiarized with the warm-up protocol and their one-repetition maximum (1RM) in the squat was estimated using a linear encoder and specialized software (T-Force System, V. 3.70, Ergotech, Murcia, Spain). In sessions two and three, participants completed an experimental protocol consisting of two sets of four squat repetitions performed at their preferred speed. The first set was executed with a load equivalent to 30% of their 1RM, and the second set with 70% of their 1RM. Four minutes of rest were provided between sets.

Instrumentation and Data Acquisition

Force plates (Kistler, 9287BA) and two IMUs from the iSen system (STT Systems Inc.) were used. The IMUs were positioned on the lumbar region (near L5) and on the center of the bar used during the squat (see Figure 3). The lumbar placement was chosen based on previous studies (133–135) indicating that acceleration measurements at this location are representative of center-of-mass movements. The sensor on the bar was included to determine whether sensor location affects variability outcomes. The devices were synchronized using a trigger activated by a third IMU. All signals were recorded at 200 Hz. Figure 3 shows a schematic representation of the device setup and data acquisition configuration.

Figure 3. Recording setup from Study 2. The image on the left shows an overview including the IMUs and the force platform. The image on the right provides a closer view of the specific placement of the IMUs. Reproduced from: García-Aguilar F, López-Fernández M, Barbado D, Moreno FJ, Sabido R. Assessing motor variability during squat: The reliability of inertial devices in resistance training. Sensors. 2024;24(6):1951. doi:10.3390/s24061951. Licensed under CC BY 4.0.

Data Processing

Data analysis was performed using custom software developed in LabView (National Instruments, Austin, TX, USA). First, the vector magnitude of the acceleration signals (ACC), the forces recorded by the force platform (FM), and the center of pressure (COPM) were calculated from their respective vector components. Only the portion of the signal corresponding to the execution of the squat was selected for analysis.

The active phase of the exercise was identified using the FM signal, which detected the start of the first squat and the end of the last squat based on the force recorded by the platform. Specifically, the minimum force values observed during the first and last squat—corresponding to the deepest point of the eccentric phase—were used as cut-off points. This method enabled precise isolation of the effective execution period, removing any non-representative segments before or after the exercise bout.

Figure 4 shows the type of signals obtained from both the force platform and the IMUs, their correspondence with the participant's position during the squat, and the precise points at which the signals were segmented for analysis.

The signals were subsequently downsampled to 100 Hz and 50 Hz using a proportional selection method based on evenly spaced points (every other point for 100 Hz and every fourth point for 50 Hz). This strategy enabled the evaluation of the influence of sampling frequency on result stability, selecting frequencies that are commonly used by commercial accelerometers found in smartphones or wearables. This approach ensured the practical applicability of the findings to accessible technologies.

Once the signals were prepared, motor variability was analyzed using a dual approach. First, the amount of variability was calculated using the standard deviation (SD) of the acceleration magnitude or the center of pressure. Second, the structure of this variability was examined by applying three non-linear tools (NLT): FuEn, SaEn, and DFA. Entropy measures were used to evaluate the regularity or predictability of the signals, employing parameters $m = 2$, $r = 0.2 \times SD$, and $n = 2$, in line with the protocols of Chen et al. (136) and Yentes et al. (137). These tools were chosen for their robustness against changes in signal length and sensitivity to noise, with FuEn showing particular resistance to variations in the parameter r (138).

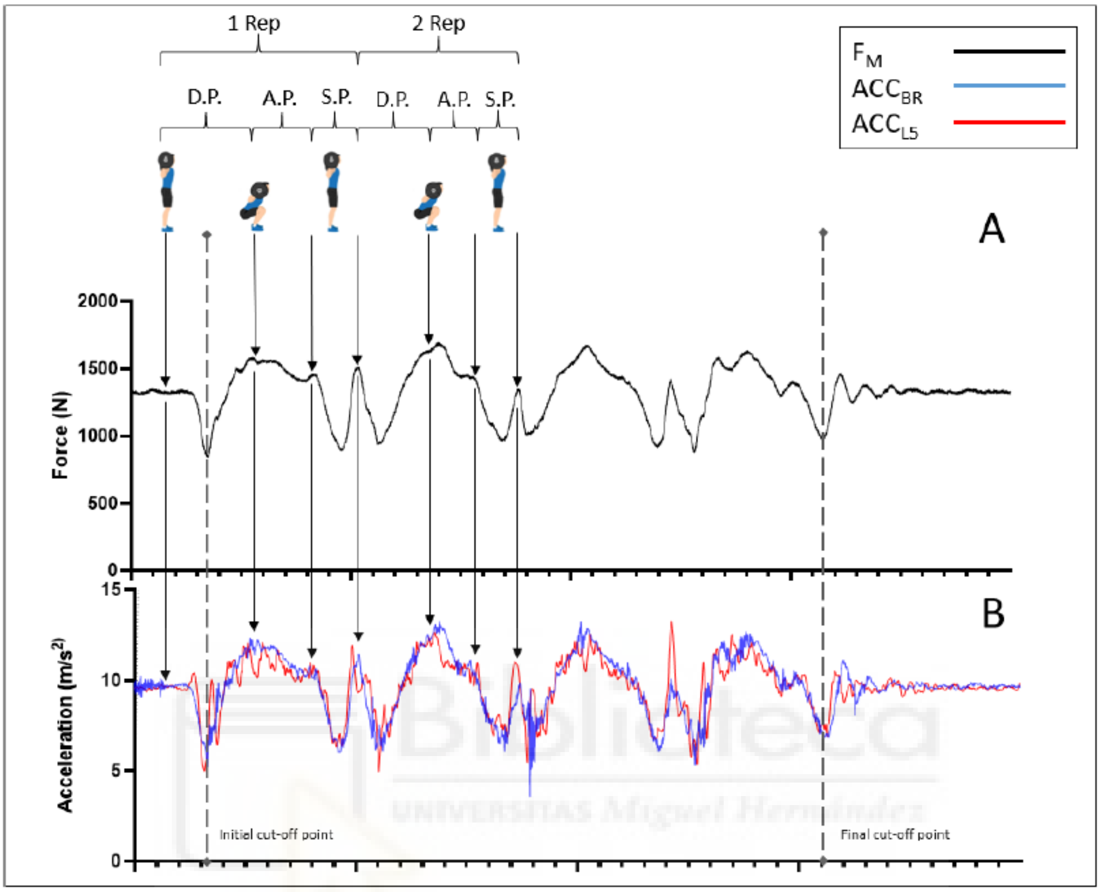


Figure 4. Representation of the different signals obtained in Study 2.The figure presents synchronized profiles of force and acceleration. The upper graph (A) shows the magnitude of force (FM, in Newtons), indicated by a solid black line. The lower graph (B) displays acceleration (in m/s²), with the blue line corresponding to the acceleration recorded at the bar (ACCBR), and the red line to the acceleration measured at the lumbar region (ACCL5). The dashed vertical lines indicate the start and end points used for data analysis. The different movement phases — descending phase (D.P.), stabilization phase (S.P.), and ascending phase (A.P.) — are marked with dotted arrows, which also illustrate the relationship between changes in force and the accelerations of both the bar and the lumbar area. At the top of the figure, icons depict the key positions during the squat cycle: standing position and the lowest point of the movement. Reproduced from: García-Aguilar F, López-Fernández M, Barbado D, Moreno FJ, Sabido R. Assessing motor variability during squat: The reliability of inertial devices in resistance training. Sensors. 2024;24(6):1951. doi:10.3390/s24061951. Licensed under CC BY 4.0.

For DFA, the analysis windows were adjusted based on the sampling frequency to maintain a constant temporal duration of one second. Accordingly, windows ranging from 8 to 200 data points were used at 200 Hz, from 4 to 100 data points at 100 Hz, and from 4 to 50 data points at 50 Hz, following the algorithm proposed by Peng et al. (80). All calculations related to variability metrics were implemented using custom Python code, allowing for reproducible processing tailored to the specific requirements of the study.

Statistical Analysis

Data normality was verified using the Kolmogorov–Smirnov test. Relative reliability was assessed using the intraclass correlation coefficient (ICC) (139), interpreted according to previously established criteria (140). Absolute reliability was calculated using the standard error of measurement (SEM) (141). Additionally, Pearson correlations were performed between data from the IMUs and the force platforms, and a two-way ANOVA (intensity × day) was conducted to assess the sensitivity of the metrics to load-induced changes. Bonferroni correction was applied for post hoc analysis.

4.3. Main Results of Study 2

Reliability analyses revealed that most indicators derived from acceleration signals demonstrated moderate to good consistency, particularly for IMUs and the force magnitude vector (FM), whereas results from the center of pressure magnitude (COPM) were consistently low across all metrics. In general, the relative reliability (ICC) for the sensor placed on the bar (ACCBR) ranged from 0.52 to 0.82, while the lumbar sensor (ACCL5) showed ICCs between 0.47 and 0.80. Metrics tended to improve slightly with increased load (70% 1RM vs. 30% 1RM), except for DFA in ACCL5, which did not follow this pattern.

Absolute reliability, assessed via the standard error of measurement (SEM), showed acceptable values at both sensor locations. For ACCBR, SEM values were: SD = 0.33–0.49 m/s^2; DFA = 0.10–0.13; FuEn = 0.05–0.07; SaEn = 0.05–0.10. For ACCL5: SD = 0.30–0.44 m/s^2; DFA = 0.11–0.15; FuEn = 0.07–0.12; SaEn = 0.05–0.14. SEM values remained stable across different sampling frequencies, indicating methodological robustness in the downsampling process.

As for the measures extracted from the force platform, FM yielded ICCs similar to those of the inertial sensors (0.52–0.85), whereas COPM consistently showed low reliability (ICC < 0.35) for all variables. SEM values associated with FM were: SD = 37.22–47.16; DFA = 0.10–0.14; FuEn = 0.02–0.05; SaEn = 0.03–0.07. For COPM, SEM values were higher: SD = 5.48–9.67; DFA = 0.15–0.16; FuEn = 0.06–0.12; SaEn = 0.07–0.12.

Pearson correlation analysis between variables revealed strong associations between accelerometers and FM for SD ($r = 0.94$–0.98) and DFA ($r = 0.74$–0.83), particularly under both load conditions. Entropy measures showed weaker to moderate correlations: for 30% 1RM, $r = 0.23$–0.39; for 70% 1RM, $r = 0.63$–0.79. Correlations between COPM and the other devices were generally low or nonsignificant.

The two-way ANOVA (intensity × day) revealed significant differences ($p < 0.05$) between load conditions for several variables. Overall, DFA displayed a consistent trend: higher intensity was associated with lower DFA values, both in FM and IMUs. However, response patterns for SD and entropy measures (FuEn and SaEn) varied across devices. For instance, while SD increased with load in FM and COPM, it decreased in accelerometers. Meanwhile, FuEn and SaEn decreased with load in FM and COPM but increased in the IMUs. No significant differences were observed between testing days, except for two isolated cases (FuEn in ACCL5 and SD in COPM).

Figures 5 and 6 present graphical representations of the ICC and SEM results, respectively. Collectively, these findings support the use of NLT applied to acceleration signals as a reliable strategy for quantifying motor variability during dynamic tasks. Reliability was highest in sensors placed in the lumbar region and under higher load conditions, and accelerometers showed good agreement with the force platform for key metrics such as SD and DFA. However, results also highlight the influence of device type and metric used, underscoring the need to standardize procedures for practical application.

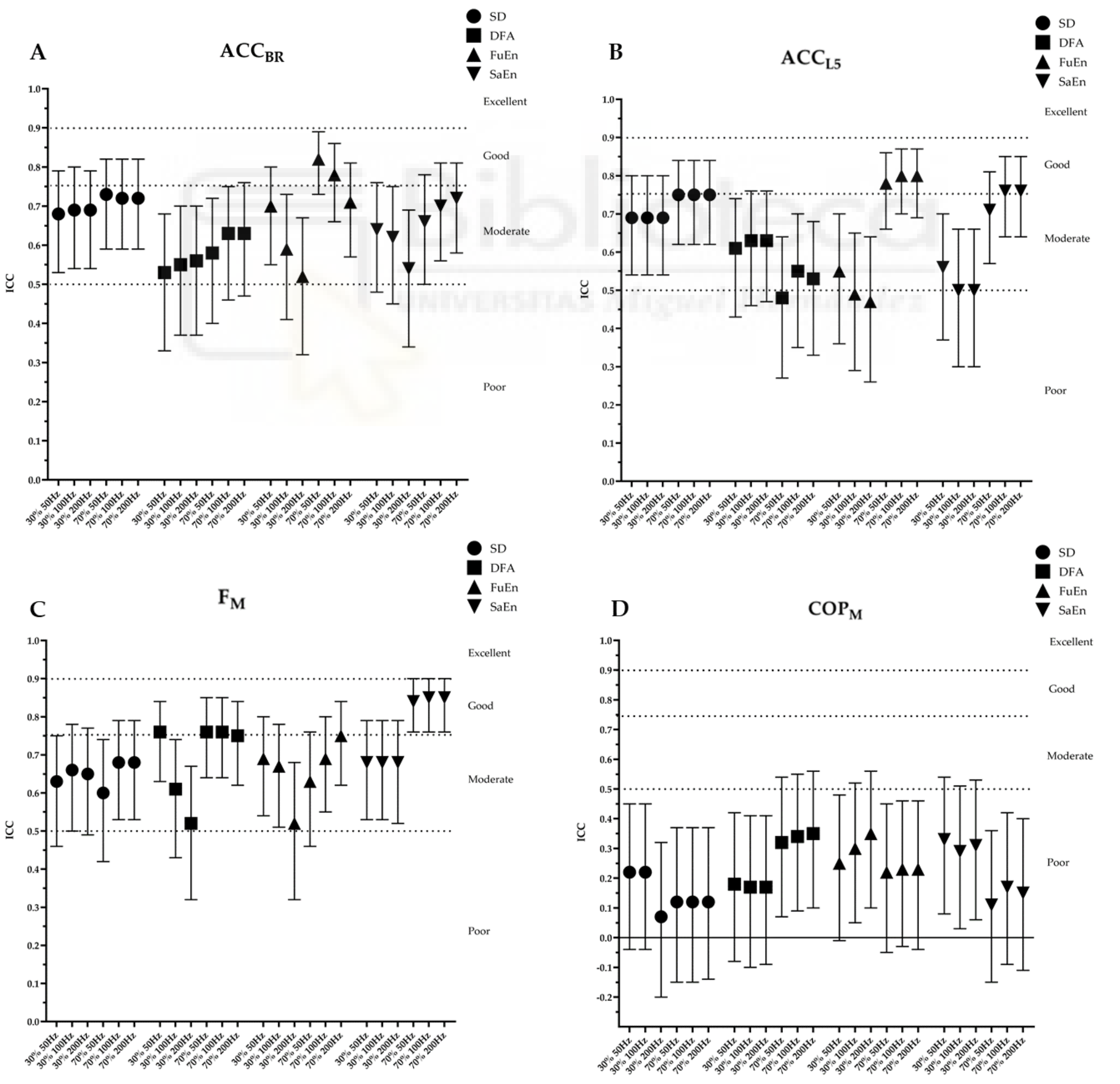


Figure 5. Graphical representation of the ICC results obtained in Study 2. Figure 5.A shows the ICC values for the IMU placed on the bar. Figure 5.B displays the ICC values for the IMU placed on the lumbar region.

Figure 5.C presents the ICC values for the force vector obtained from the force platform. Figure 5.D shows the ICC values for the COP vector obtained from the force platform. The graph displays the mean and the upper and lower limits of the 95% confidence interval. The dashed lines indicate the thresholds for each interpretation of the ICC values. Reproduced from: García-Aguilar F, López-Fernández M, Barbado D, Moreno FJ, Sabido R. Assessing motor variability during squat: The reliability of inertial devices in resistance training. Sensors. 2024;24(6):1951. doi:10.3390/s24061951. Licensed under CC BY 4.0.

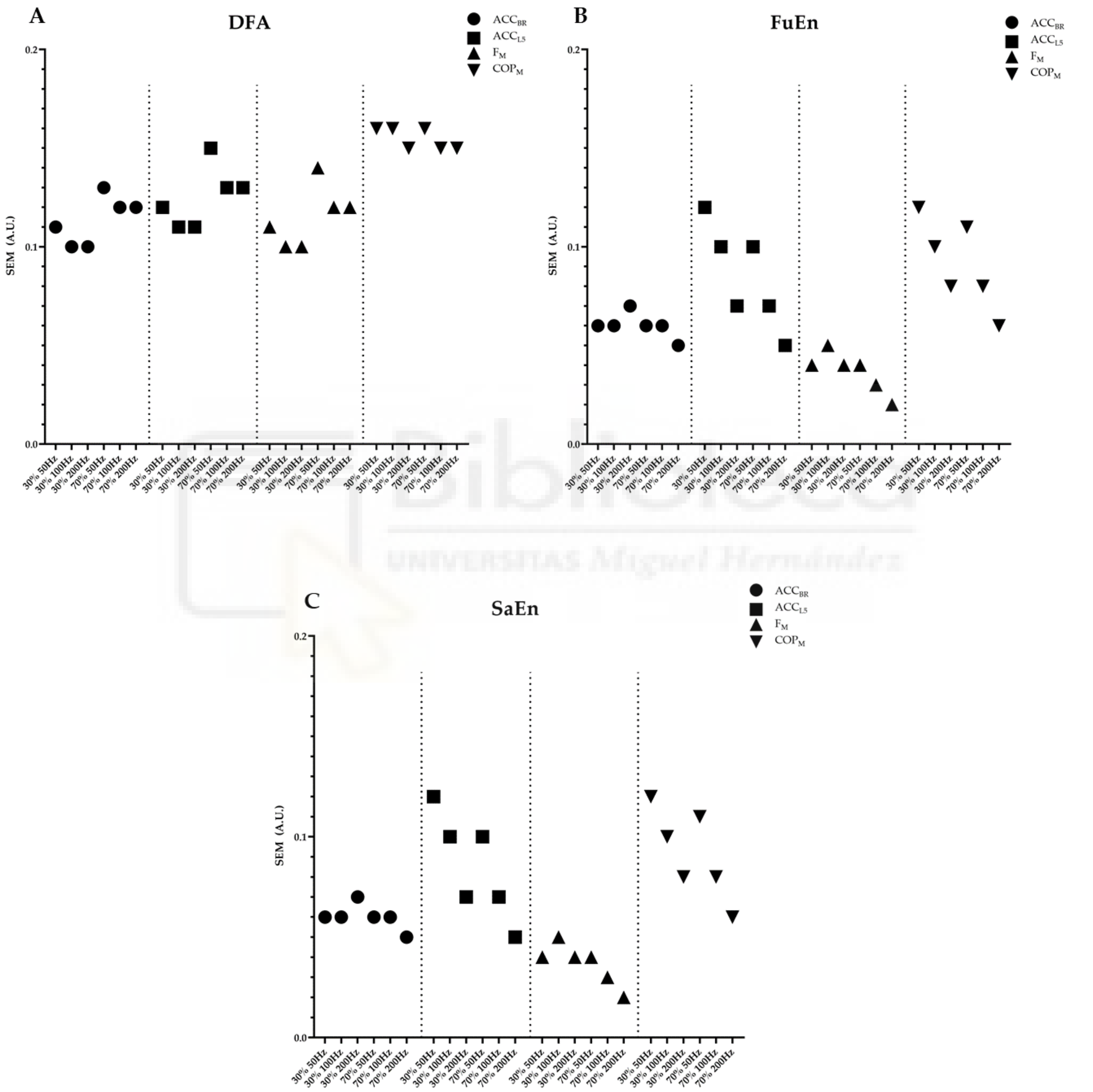


Figure 6. Graphical representation of the SEM results obtained in Study 2. (A) detrended fluctuation analysis; (B) fuzzy entropy; (C) sample entropy. The dashed lines group the results corresponding to the different devices. Note that the standard deviation of the SEM is not shown in the graphs because, due to the differences in measurement magnitudes between devices, they are not directly comparable. Reproduced from: García-Aguilar F, López-Fernández M, Barbado D, Moreno FJ, Sabido R. Assessing motor variability

during squat: The reliability of inertial devices in resistance training. Sensors. 2024;24(6):1951. doi:10.3390/s24061951.

4.4. Summary of the Discussion and Conclusions of Study 2

The aim of this study was to analyze whether motor variability measures obtained through inertial sensors during the execution of squats can provide reliable information about the effect of conditioning factors such as load on motor control. For this purpose, relative reliability was assessed using the intraclass correlation coefficient (ICC), and absolute reliability was evaluated through the standard error of measurement (SEM), considering both linear and non-linear metrics.

Regarding relative reliability, the results showed acceptable to good ICC values in all metrics obtained from the inertial sensors placed on the bar and in the lumbar region, with values ranging between 0.52 and 0.82. Force magnitude showed reliability values between 0.47 and 0.80. Although most variables also showed acceptable to good reliability, in some cases FuEn and DFA exhibited slightly lower than acceptable values ($0.41 < ICC < 0.49$). In contrast, the center of pressure did not reach acceptable values in any variable ($ICC < 0.50$), suggesting low consistency of this parameter in strength tasks. No previous studies have evaluated the relative reliability of motor control variability during strength tasks using non-linear metrics, thus these results represent a relevant contribution in this field. It is worth noting a general trend towards higher ICC values at greater loads (70% 1RM), especially in acceleration signals and force magnitude, which could be due to higher control demands allowing better discrimination among subjects.

Concerning absolute reliability, SEM values were reasonable and consistent with the magnitude of the variables. For linear measures (SD), SEM ranged from 0.30 to 0.49 m/s^2 in the IMUs, from 37.22 to 47.16 N in force magnitude, and from 5.48 to 9.67 mm in COPM. For non-linear metrics, the range was more homogeneous: FuEn between 0.05 and 0.12 arbitrary units (AU); SaEn between 0.05 and 0.14 AU; and DFA between 0.10 and 0.15 AU, depending on device and condition. Overall, all metrics showed SEM values smaller than the inter-subject standard deviation, indicating that measurement error was lower than interindividual variability, thus reinforcing their utility for detecting real changes caused by interventions or external conditions.

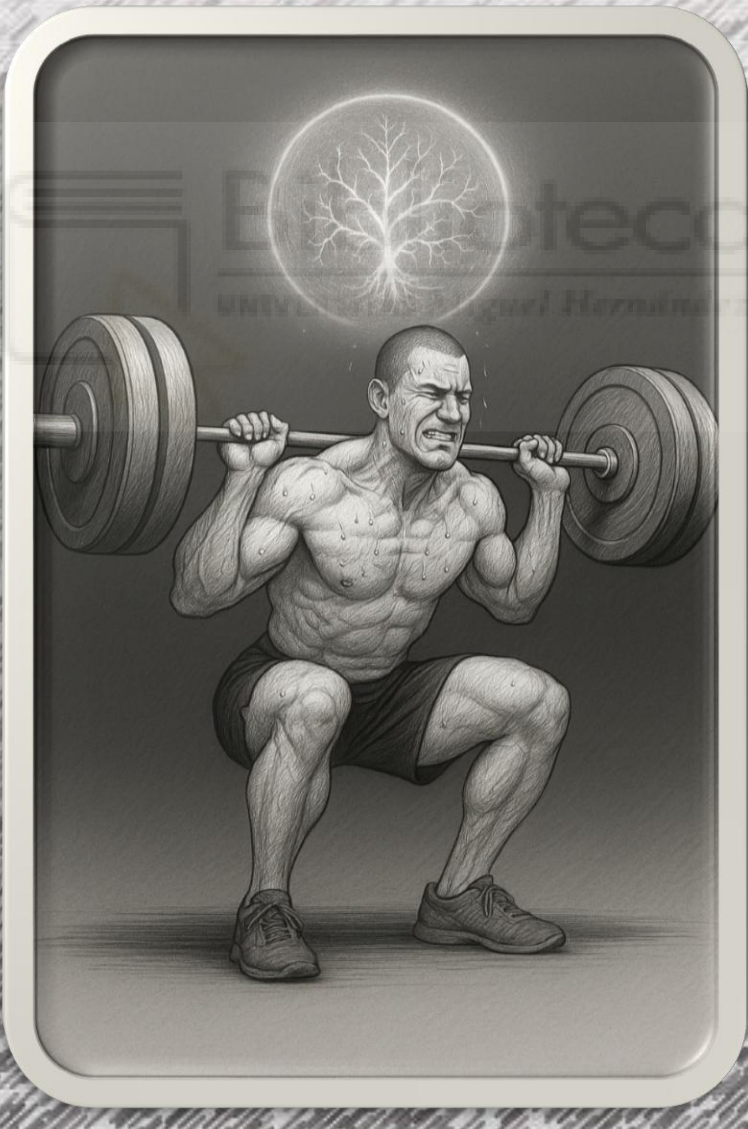
Analysis of the effect of sampling frequency on reliability revealed minimal differences (< 0.1 units in ICC), indicating that recording at frequencies between 50 and 200 Hz does not compromise measurement stability. Although changes in absolute values were observed (e.g., increase in SaEn and decrease in DFA with higher frequencies), overall trends remained and reliability was maintained in most cases. This suggests that different frequencies could be used interchangeably, provided consistency is maintained within the same analysis. Nonetheless, it may be of interest to identify which sampling frequency yields the highest reliability for each metric when developing measurement protocols.

Regarding convergent validity, correlation analyses showed strong associations between the two IMUs for SD and DFA, and also between FM and both IMUs for these same metrics. In contrast, entropy measures (FuEn and SaEn) exhibited weaker correlations, especially at 30% 1RM. COPM showed low or no correlations with the other variables. These results are consistent with previous research using force platforms or motion analysis systems as references, although they differ concerning the utility of COP in dynamic tasks such as squats. In this case, both IMUs and FM appear to capture the structure of movement variability more precisely in high mechanical demand actions.

Finally, ANOVA analyses showed significant differences between load conditions (30% vs. 70% 1RM) across all variables and devices, indicating that the protocols used are sensitive to changes in external demand. Moreover, the absence of differences between days in most metrics, and the consistency of trends when differences appeared, reinforce the validity of these tools for use in experimental designs or longitudinal monitoring applications.

In conclusion, this study demonstrated that motor variability analysis using inertial measurement units allows obtaining reliable data on the effect of conditioning factors such as load during strength exercises like the squat. These findings open a promising pathway for studying motor behavior in dynamic tasks using accessible, low-cost, and easily implementable equipment. Among the most relevant applied results is the limited influence of sampling frequency on metric reliability, as well as greater consistency of recordings under moderate loads (70% versus 30% 1RM). Particularly noteworthy is the practical utility of the employed protocols, which are easily transferable to real training and evaluation contexts. Finally, by confirming the reliability of these metrics, the methodological foundations are laid for the subsequent studies of this thesis, aimed at exploring their sensitivity to functional states such as fatigue.

5. Study 3: Motor Variability as an Index of Fatigue in Dynamic Actions: A Perspective from the Complexity Loss Theory



5. Study 3

This section presents a summary of the study titled *"Motor variability as an index of fatigue in dynamic actions: a perspective from the complexity loss theory"*, authored by Fernando García-Aguilar, Miguel López-Fernández, David Barbado, Francisco J. Moreno, and Rafael Sabido, currently under review in the scientific journal *Journal of Applied Physiology*. This study is a cross-sectional investigation aimed at assessing the sensitivity of variability analyses of acceleration signals during the squat exercise to a conditioning factor such as fatigue. The full article is available in the Appendix for complete consultation.

5.1. Contextualization of Study 3

As mentioned in the introduction of this thesis, strength training constitutes a fundamental pillar in any physical conditioning program, both in health and sports performance contexts. Within this type of training, different orientations—such as maximal strength, hypertrophy, or power—induce specific adaptations and generate varying levels of fatigue depending on the volume, intensity, and nature of the applied stimulus (142–144).

As addressed in previous studies of this thesis, motor variability emerges as a valid and reliable tool to detect the impact of certain conditioning factors, such as load. Specifically, the preceding study demonstrated that consistent variability metrics can be obtained from acceleration signals recorded via IMUs, representing an opportunity to monitor motor behavior in an accessible and applicable manner within real environments.

As evidenced in Study 1, there is strong support from isometric and single-joint tasks showing that fatigue induces changes leading to more predictable and autocorrelated patterns of force production. These effects appear to be mainly related to intramuscular coordination, understood as the regulation of motor unit recruitment and firing properties within a single muscle. In particular, fatigue has been associated with increased motor unit synchronization, which reduces the degrees of freedom available to the system and results in less complex outputs. Such evidence has been obtained predominantly in monoarticular tasks, where the role of a specific muscle group (e.g., the knee extensors) can be isolated, making it plausible that synchronization under fatigue translates into reduced complexity. However, an open question remains regarding dynamic and multi-joint tasks, where multiple muscles and joints must be coordinated simultaneously. In this broader context, intermuscular coordination—defined as the temporal and spatial organization of activity between different muscles—takes on fundamental importance, and its alteration due to fatigue may be directly related to changes in movement variability and, consequently, in the complexity of motor control. From both a practical and scientific point of view, the literature has documented a wide range of fatigue-related effects on motor control (see section 1.3.2.), ranging from modifications in activation patterns and the relative contribution of different muscle groups to kinematic alterations and postural compensations that allow performance to be maintained despite functional deterioration.Building upon this foundation, the present study aims to analyze whether motor variability metrics obtained through IMUs are sensitive to the acute effects of fatigue induced by different strength training modalities. For this purpose, an extensively accepted performance indicator in neuromuscular fatigue assessment—the loss of height in the countermovement jump (CMJ)—will be used as a comparison variable (58). This approach will allow evaluating whether NLT applied to acceleration signals can detect changes in movement execution derived from fatigue, thus providing a tool for load monitoring in strength programs.

5.2. Summary of the Method of Study 3

Participants

Forty-four individuals (18 women and 26 men) participated in this study. Descriptive data of the sample are shown in Table 3. All participants were healthy adults, free from injuries in the previous six months, and with prior experience in strength exercises, particularly the squat. They completed a health questionnaire to confirm eligibility and signed informed consent.

Table 3. Descriptive data of Study 3 participants

	Men = 26; Women = 18			
	Age (years)	Height (cm)	Body Weight(kg)	RM (kg)
Mean	29.6	169.4	72.8	99.6
SD	9.0	9.1	11.6	34.8

Procedure

The study was conducted over four weeks. Figure 7 presents a schematic timeline of the study. During the first week, two initial sessions were carried out: one for familiarization with the testing protocols and another for estimating the 1RM in the squat and hip thrust exercises, using a linear transducer (T-Force System, v3.70). In the following three weeks, each participant completed one training session per week, corresponding to a different strength modality: hypertrophy (HS), maximal strength (MS), and power (PS). Each training week included five assessment points: before training (pre), immediately after (post), and at 24-, 48-, and 72-hours post-training. Figure 7 illustrates the structure of each session. At each assessment point, participants performed three CMJs and a test consisting of 10 squat repetitions at 70% of 1RM. The CMJ test provided jump height data to evaluate whether the training protocols induced a reduction. During the 10-repetition squat test, acceleration signals were recorded to analyze motor variability.

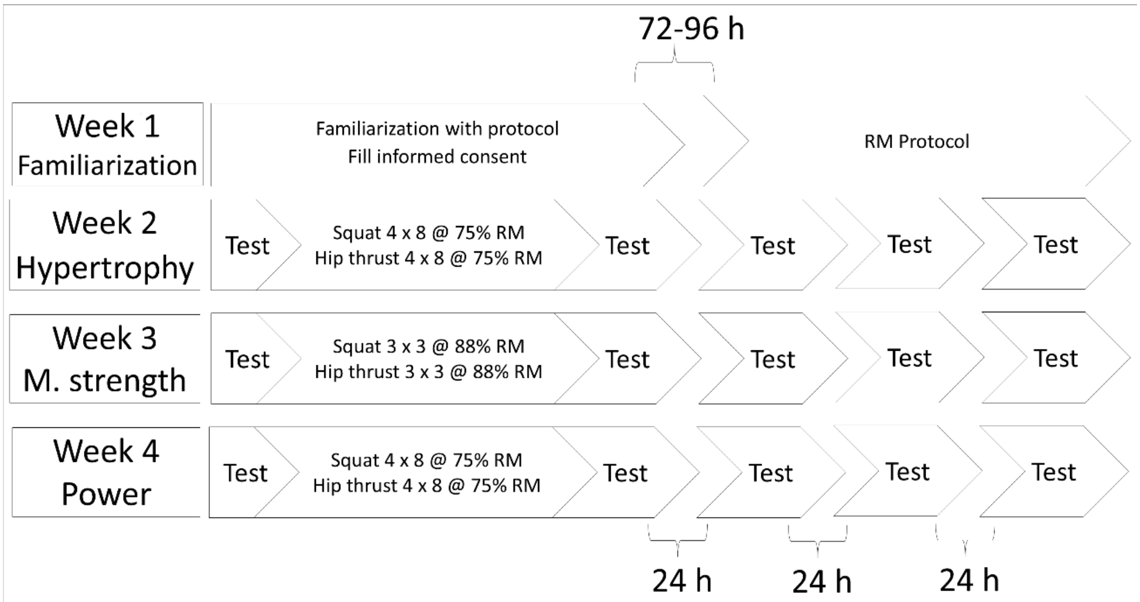


Figure 7. Diagram of the timeline used in Study 3. Elaborated by the author (unpublished data).

The training sessions were structured according to the objective of each modality. During the power week, jump squats and explosive hip thrusts were performed at 30% of 1RM (3 sets of 6 repetitions, with 180 seconds rest). In the hypertrophy week, participants completed 4 sets of 8 repetitions at 75% of 1RM with a 90-second rest. During the maximal strength week, 3 sets of 3 repetitions at 88% of 1RM were performed with 180 seconds rest. All sessions were conducted at the same time of day to avoid circadian rhythm effects.

The CMJ was performed on a ChronoJump platform (Boscosystem, Barcelona, Spain), with hands placed on the hips and controlled triple extension. Three valid attempts were completed, and the average of the three attempts was used for subsequent analyses, as this has been shown to be a more stable and representative value (58). During the squat test, participants executed 10 repetitions at 70% of 1RM at a preferred velocity, using femoral height parallel to the floor recorded during familiarization as a reference. Prior to this, two approach sets at 30% and 50% of 1RM were performed.

Data Recording and Analysis

During the squat test, the data recording and processing protocol employed in Study 2 was replicated. Acceleration was recorded at the lumbar region (L5) via an IMU (iSen, STT Systems Inc., San Sebastián, Spain) placed on the back at the level of the iliac crests. The signal was recorded at a sampling frequency of 200 Hz and subsequently downsampled to 100 Hz after spectral analysis confirmed that 99.9% of the signal's energy was concentrated below this threshold. The acceleration magnitude (AccL5) was obtained by combining the three Cartesian axis components.

Once the signal was segmented using the same criteria applied in Study 2, three variability metrics were analyzed: SD, as an indicator of variability magnitude, and two NLT, FuEn and DFA, as indicators of motor pattern complexity. These metrics were selected due to their demonstrated superior reliability values in Study 2. Likewise, identical parameters were used: for FuEn, $m = 2$, $r = 0.2 \times SD$, and $n = 2$; for DFA, windows were adjusted to a duration of one second, with sizes ranging from 4 to 100 points.

Statistical Analysis

Data analysis was conducted using SPSS v25. Normality was verified by the Shapiro–Wilk test. Although some variables did not meet this assumption, ANOVA was considered sufficiently robust given the sample size ($n > 30$) (145,146). A repeated measures ANOVA with five time points (pre, post, 24h, 48h, 72h) was applied in each of the three training weeks, considering CMJ, SD, FuEn, and DFA as dependent variables. The Greenhouse–Geisser correction was applied when sphericity was violated, and effect size was reported using partial eta squared (η^2p), interpreted as small (≈0.01), moderate (≈0.06), or large (≥0.14). Data are presented as mean ± standard deviation (147)(145,146)(147).

5.3. Main Results of Study 3

A total of 38 participants completed all assessments during the power session (PS) week, 35 during the hypertrophy session (HS) week, and 41 during the maximal strength session (MS) week. Participants who missed any of the assessment sessions were excluded from the corresponding statistical analysis. The acceleration signals recorded during the squat repetitions ranged from 928 to 2,959 data points in length. Figure 8 presents the graphs with the main results.

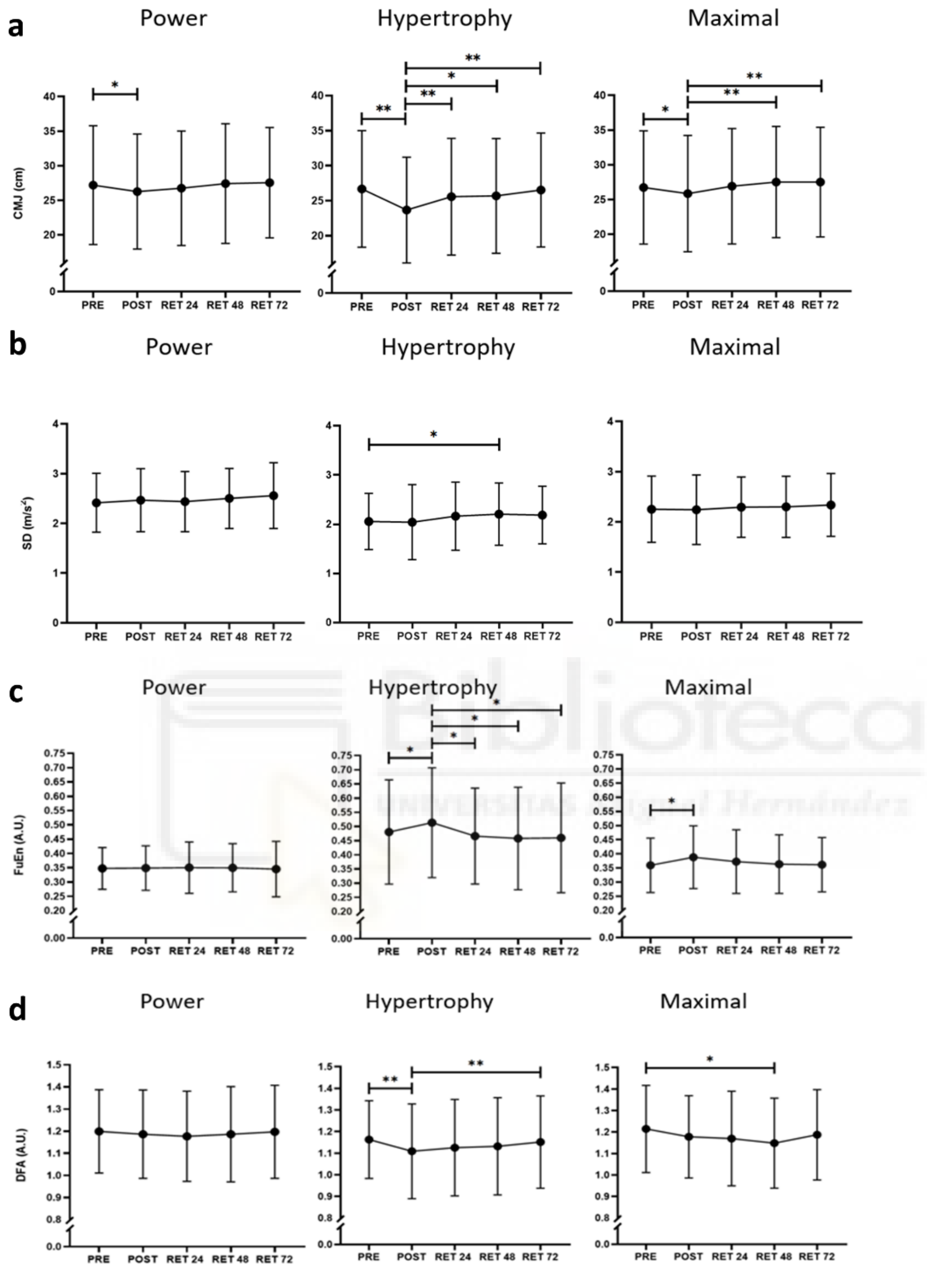


Figure 8. Results of the different variables analyzed in the Study3. (A) height in the countermovement jump; (B) standard deviation of acceleration; (C) diffuse entropy; (D) analysis of fluctuations without trend. * indicates significant differences at $p < 0.05$; ** indicates highly significant differences at $p < 0.01$.. Elaborated by the author (unpublished data).

Regarding CMJ performance, no significant main effects of time were observed during the power session week. However, a significant decrease was detected between the pre-test and the immediate post-test ($p < 0.05$), indicating a transient drop in performance. In the hypertrophy and maximal strength weeks, significant main effects were found, with a clear reduction in jump height immediately following the session ($p < 0.01$). During HS, jump height returned to baseline values at 24 hours, whereas in MS, recovery was more gradual; no significant differences were observed between the 24-hour retest and the post-test, while differences relative to the post-test emerged starting at 48 hours.

Concerning motor variability metrics, the magnitude of variability (SD of AccL5) showed no significant effects of time in any of the three weeks, suggesting this metric was not sensitive to fatigue-induced changes.

In contrast, variability structure measures (FuEn and DFA) reflected significant changes during the hypertrophy and maximal strength weeks. No relevant modifications were observed in the PS following the fatigue protocol. In HS, FuEn significantly increased and DFA decreased immediately after training. FuEn returned to baseline values at 24 hours, while DFA remained altered up to 72 hours. A similar pattern was observed in MS: FuEn increased between pre- and post-tests, although no significant differences were found at subsequent recovery points; DFA showed a decreasing trend, with significant differences only between pre-test and the 48-hour measurement.

Together, these results suggest that while SD is unaffected by acute fatigue induced by strength training, non-linear measures such as FuEn and DFA are sensitive to these changes, particularly in higher load or volume sessions like hypertrophy and maximal strength. This reinforces the value of NLT for monitoring the functional state of the motor system in response to fatigue.

5.4. Summary of the Discussion and Conclusions of Study3

The aim of this study was to analyze the acute and short-term effects of fatigue induced by different strength training modalities (power, hypertrophy, and maximal strength) on motor variability, using linear and non-linear measures derived from acceleration signals. Consistent with previous studies, it was explored whether these metrics were sensitive to fatigue effects and if their temporal evolution reflected distinct recovery profiles depending on the type of applied stimulus.

Regarding the performance measure, CMJ, results showed a significant reduction in jump height between pre- and post-tests in all three training modalities, indicating an immediate fatigue effect. However, during the power session, this effect was mild and transient, without a significant sustained impact over time. This lower fatigue induced by the PS aligns with previous studies that have reported no significant effects following similar protocols (148–152), or even observed performance increases (144). In cases where fatigue was observed, recovery typically occurred within 24 hours (153–155).

In the hypertrophy and maximal strength sessions, the fatigue impact was more pronounced. In hypertrophy, jump height loss was greater (approximately −3 cm), with complete recovery at 24 hours, consistent with prior studies (144,148), although others have reported recovery times up to 72 hours (55,152,154–157). In maximal strength, although the loss was smaller (−1 cm), recovery was slower, with differences persisting until 48 hours, as also reported elsewhere (144,149,153,158). Overall, these findings are consistent with existing literature and demonstrate that fatigue and recovery profiles differ according to the stimulus type.

Regarding motor variability analysis, movement magnitude (measured by SD) was not sensitive to fatigue effects in any training modality. Conversely, non-linear measures were sensitive to fatigue generated during HS and MS sessions, but not during PS, likely due to the low fatigue induced by the latter, as indicated by CMJ height loss results. This behavior suggests that non-linear metrics capture aspects of motor behavior not detected by linear measures. Although observed changes were statistically significant with large effect sizes, caution is advised in interpretation, as change magnitudes were smaller than the SEM reported in Study 2.

Specifically, in HS, fatigue caused an increase in FuEn and a decrease in DFA, with FuEn recovering fully at 24 hours while DFA remained altered up to 72 hours. A similar pattern was observed in MS: FuEn increased post-training, though no significant differences were observed at subsequent recovery points; DFA showed partial recovery at 72 hours. These findings coincide with CMJ results, where HS showed a faster recovery profile than MS. However, variability metrics reveal that fatigue effects may persist beyond what performance indicators suggest. This is relevant because CMJ reflects motor performance, which can be maintained via compensatory mechanisms even when fatigue signs are present (44). For example, during a squat, fatigue can alter the relative contribution of involved muscle groups (159), producing changes in motor patterns that sustain execution. Thus, FuEn and DFA may be capturing such motor strategy modifications. Concretely, fatigue appears to induce more unpredictable behavior (higher FuEn) and less autocorrelation (lower DFA), which could reflect exploration of alternative motor solutions to maintain movement execution (72,82,160).

Since FuEn and DFA measure different complexity aspects—predictability and autocorrelation, respectively—it is reasonable their response and recovery profiles differ. These observations support the combined use of both metrics to obtain a more comprehensive view of fatigue's functional impact.

From a theoretical perspective, findings can be interpreted via the complexity loss theory (67,70), which posits that in non-optimal states—such as fatigue, illness, or aging—there is a reduction in complexity across various physiological signals (67,70,74,161–164). In isometric tasks, this loss has been associated with increased regularity and autocorrelation, as observed in Study 1 and reported by Pethick and Tallent (73). However, in dynamic actions, results are more heterogeneous: some studies report increased regularity (114), recurrence (123), or autocorrelation (125), while others find increased irregularity (124) or decreased autocorrelation (122,125). As proposed by Stergiou et al. (56), both overly predictable and overly noisy behaviors may represent complexity loss, understood as reduced adaptive capacity.

As seen in Study 1, most physiological explanations of this loss derive from monoarticular isometric tasks, linked to increased motor unit synchronization and reduced strategy availability (73). However, as Cortes et al. (81) note, this framework cannot be directly applied to multisegmental dynamic tasks such as the squat, involving multiple joints and complex coordination patterns. In such actions, fatigue may induce neuromuscular “noise” that, when projected over longer temporal scales, manifests as greater unpredictability and diminished temporal structure in movement. Additionally, compensatory strategies against fatigue—such as kinematic alterations in the hip or knee (84–87,90), changes in muscle activation (87), or reorganization in intermuscular networks (88,89)—may contribute to modifying the global motor pattern structure.

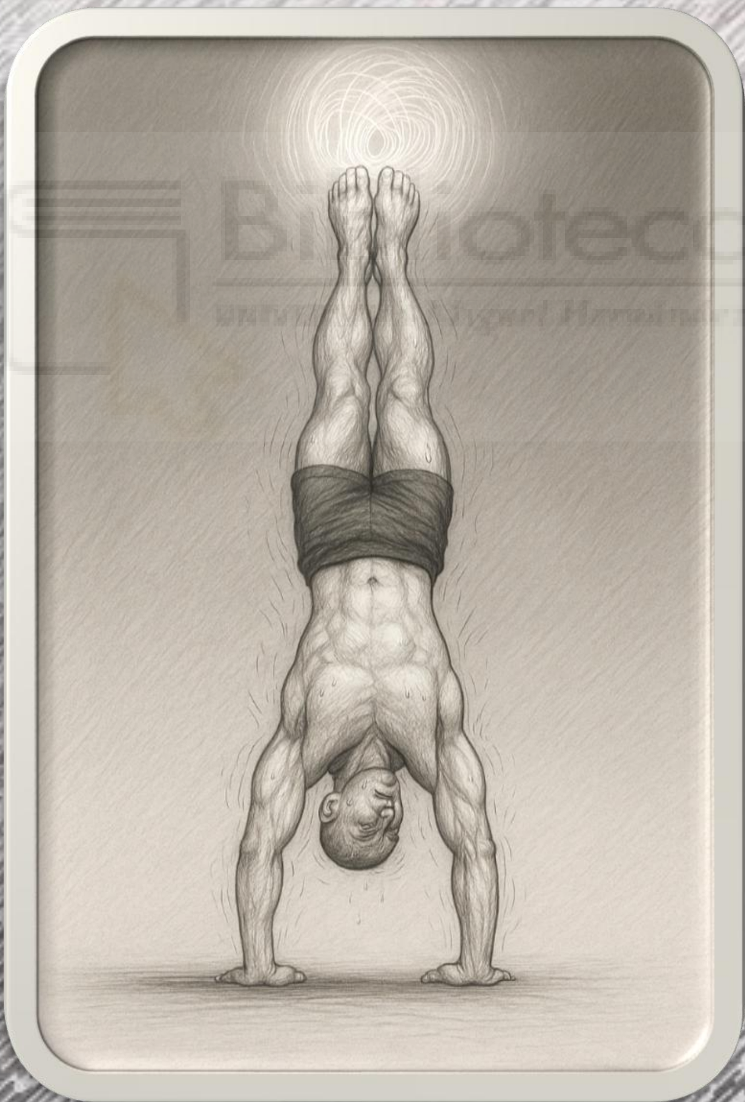
Thus, increased irregularity (higher FuEn) and decreased autocorrelation (lower DFA) could reflect how the organism distributes control across temporal scales to adapt to fatigue. Recent studies (165) have shown that increased load during the squat elevates both FuEn and DFA, suggesting that this type of disorganization strategy occurs not only in fatigue but also in response to higher demands. In sum, less autocorrelated movements may indicate a greater number of adjustments (72), supporting the notion that in more demanding situations, the motor system requires more adaptations to maintain execution.

Although this theoretical framework requires further development, it offers a plausible explanation for divergent patterns observed in non-linear measures under fatigue in dynamic versus isometric tasks.

The results of this third study advance the line initiated in previous works, consolidating the usefulness of motor variability analysis as a tool to monitor functional states such as fatigue. Here, findings suggest that acceleration variability analysis through non-linear measures is sensitive to fatigue-induced changes. In particular, FuEn and DFA were sensitive to fatigue effects after hypertrophy and maximal strength sessions, showing a tendency towards more unpredictable and noisy behavior. These measures also appear more sensitive than linear metrics such as standard deviation when detecting changes in motor variability in such actions.

These alterations reflect a motor system reorganization, manifesting as changes in fluctuation behavior in the lumbosacral region. This may be interpreted as a temporary loss shifting towards more random and noisy behavior. In contrast, after the power-oriented session, fatigue levels were lower and no variability changes were observed, underscoring the stimulus-dependent nature of these effects. Although not the primary objective, results suggest complexity loss may manifest differently in dynamic versus isometric tasks, and that such loss does not necessarily imply reduced variability but rather an alteration of its internal organization. Collectively, these findings support the use of non-linear metrics derived from acceleration signals as a valuable complement to traditional performance indicators such as the countermovement jump, consolidating the thesis proposition of using variability as a sensitive fatigue marker in functional contexts.

6. Study 4: How Does Fatigue Affect Handstand Balance? A Non-Linear Approach to Study Fatigue Influence in Handstand Performance



6. Study 4

This section presents a summary of the study *"How does fatigue affect handstand balance? A non-linear approach to study fatigue influence in handstand performance"*, published by Rafael Sabido, Fernando García-Aguilar, Carla Caballero, and Francisco J. Moreno in the scientific journal *of NeuroEngineering and Rehabilitation* in 2024. This work consists of a cross-sectional study aimed at assessing the sensitivity of variability analyses of acceleration signals during a task with high motor control demands—the handstand—under the conditioning factor of fatigue. The full article is available in the Appendix for complete consultation

6.1. Contextualization of Study 4

Throughout this thesis, the utility of motor variability analysis as a tool to detect the functional state of the organism—especially those induced by fatigue—has been explored. Previous studies focused on tasks where force production was the primary requirement to perform the task, such as the squat. Although postural control, primarily at the trunk level, is fundamental in such tasks, the demands for fine postural control are relatively low. However, human motor control also manifests in tasks where precision, balance, and multisegmental coordination are critical. Therefore, given the large number of publications by our group on these topics (72,166–172), this fourth study proposes to extend the focus to an action that combines moderate to high force demands with elevated postural and motor control requirements: the handstand. Compared to conventional balance or strength tasks, the handstand offers a unique opportunity to examine how fatigue affects motor control under conditions of high instability, inverted posture, and elevated coordination demands, thereby complementing the insights gained from traditional movements such as the squat.

The handstand is defined as the action of maintaining the body in an inverted vertical position, with the hands as the sole support point (173). It is a key skill in acrobatic and gymnastic disciplines (174), and its correct execution requires precise body alignment—straight back and legs—to maintain the center of mass (COM) within the support area generated by the hands (175,176). To achieve this stability, the subject performs constant adjustments through small pressure changes in the hands and coordinated limb actions, demanding high precision in controlling multiple degrees of freedom (173). This task involves complex neuromuscular and biomechanical control processes (176) and has mainly been studied from the analysis of individual or segmental structures such as the hip, shoulder, or wrist joints (177). However, global variables such as the center of pressure (COP), widely used in bipedal balance tasks, have received less attention in handstand studies.

Various factors influence motor control during inverted balance, including experience level (175,176), visual availability (178), athlete clothing (179), and surface characteristics (180). Among these, upper limb strength is considered a key variable, as these limbs perform an uncommon antigravity function in human locomotion (174) and require high muscular activation to sustain the posture (181), making them more vulnerable to fatigue. Fatigue is a relevant conditioning factor in acrobatic sports since it affects biomechanical performance, perception, load tolerance, and increases injury risk during training or competition (182,183). Despite this, no previous studies have directly analyzed fatigue's influence on handstand performance, representing an important gap in the literature.

In recent years, extensive research has examined the relationship between fatigue and motor control, both in health contexts (184,185) and sports performance (52). Specifically, fatigue's effect on postural control in bipedal stance has been documented, showing increases in COP variables such as area and velocity (186–189). Furthermore, variability analysis via NLT such as entropy and DFA (93,95,190,191) has been incorporated; these metrics explore motor pattern regularity and autocorrelation during balance tasks (167,192), relating them to the necessary adjustments for task execution (72). NLT have demonstrated sensitivity to fatigue in various tasks, as observed in Study 1. Additionally, NLT application through devices like IMUs has been proposed as a valuable alternative to more costly and less accessible technologies, such as force platforms or isokinetic dynamometry (74,93,191).

Given that this thesis centers on variability analysis as a functional indicator, and considering that many fatigue-induced alterations manifest through postural control, a study involving a task with high demand in this domain combined with moderate to high force requirements was incorporated. Thus, the present study adopts an exploratory approach to analyze how fatigue affects motor control during inverted balance, comparing linear and non-linear metrics extracted from COP via IMUs. It is expected that COP area and velocity will increase with fatigue, while non-linear metrics will reflect decreased irregularity (lower entropy) and increased autocorrelation (higher DFA), indicating a loss of complexity during fatigued execution (174).

6.2. Summary of the Study method 4

Participants

Fourteen male athletes participated in this study. Their descriptive data are presented in Table 4. Inclusion criteria required participants to be able to maintain the handstand position for at least 40 seconds. None of the participants exhibited neuromuscular dysfunction or relevant injury history at the time of measurement.

Table 4. Descriptive data of the Study 4 participants.

	Men = 14		
	Age (years)	Height (cm)	Body Weight(kg)
Mean	25.8	174.0	69.7
SD	5.8	0.1	8.8

Procedure

The tests were conducted in a laboratory room specially prepared to eliminate visual or auditory stimuli that could interfere with postural control. Participants wore gymnastics attire and performed the task barefoot. Balance evaluation in the inverted position was performed using a force platform (Kistler 9287BA, Switzerland) and four IMUs (STT Systems, Spain) placed on the forearm and upper arm of the dominant limb, as well as on the C7 and L5 vertebrae. Figure 9 shows an example of the equipment used and its placement.

Figure 9. Image of the equipment used for data collection in Study 4. Reproduced from: Sabido R, García-Aguilar F, Caballero C, Moreno FJ. How does fatigue affect handstand balance? A non-linear approach to study fatigue influence in handstand performance. J Neuroeng Rehabil. 2024;21:171. doi:10.1186/s12984-024-01442-6. Licensed under CC BY-NC-ND 4.0.

After a general and specific 15-minute warm-up, including ten handstand attempts for familiarization, participants performed two 30-second trials separated by a fatigue protocol. This protocol consisted of two sets of 15 push-ups at a preferred speed, with one minute of rest between sets. The second trial was conducted three minutes after completing the fatigue protocol. Measurement began once participants reached a stable vertical position; at this moment, a trigger was activated on the force platform to synchronize it with the IMUs. Participants were instructed to maintain the position "as stable as possible," using only wrist control strategies and avoiding compensations in other joints (193). Figure 10 presents a schematic of the session procedure.

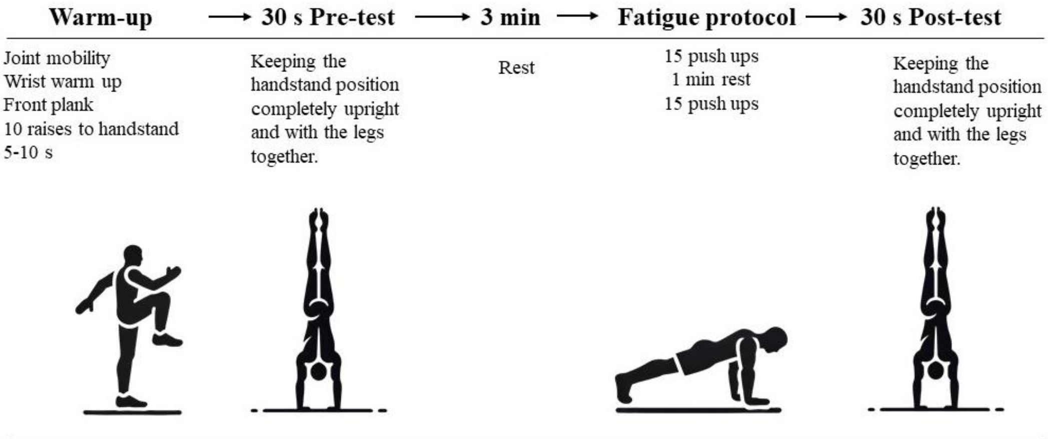


Figure 10. Representation of the protocol development in Study 4. . Reproduced from: Sabido R, García-Aguilar F, Caballero C, Moreno FJ. How does fatigue affect handstand balance? A non-linear approach to study fatigue influence in handstand performance. J Neuroeng Rehabil. 2024;21:171. doi:10.1186/s12984-024-01442-6. Licensed under CC BY-NC-ND 4.0.

Data Recording and Analysis

Signals were recorded at a frequency of 100 Hz both on the force platform (Kistler 9287BA, Switzerland) and the four IMUs (STT Systems, Spain). To avoid artifacts derived from task initiation and termination, the first and last 5 seconds of each trial were discarded (194), thus analyzing a central segment of 20 seconds (1000 data points). Subsequently, signals were downsampled to 50 Hz. This change in sampling frequency was made because many studies involving similar tasks utilize frequencies lower than 100 Hz (167,195,196). No filtering was applied in order to preserve the dynamic characteristics necessary for non-linear analyses (201).

From the force platform, three variables related to postural performance were analyzed: COP area, the bivariate variable error (BVE), defined as the mean error relative to each participant's individual centroid, and the mean velocity magnitude of the COP (MVM) (197). From the IMUs, resultant acceleration was obtained, and SD was calculated as an indicator of variability magnitude. To evaluate the variability structure of signals from both the force platform and the IMUs, FuEn and DFA were employed, following previously validated methodologies (80,136,198).

Statistical Analysis

Normality of the data was verified using the Kolmogorov–Smirnov test. To compare pre- and post-fatigue values, a repeated measures t-test was utilized. Given the exploratory nature of the study and the number of variables, a Bonferroni adjustment was applied grouping by device, setting the significance threshold at $p < 0.007$. Effect size was calculated using Cohen's d, with values ≥ 0.80 considered large, ≥ 0.50 moderate, and ≥ 0.20 small (199). All analyses were conducted using SPSS software (v.22, SPSS Inc., Chicago, IL).

6.3. Main Results of Study 4

Prior to analyzing the effect of the fatigue protocol, an exploratory analysis was performed to verify whether observed changes were directly attributable to the protocol and not due to prolonged maintenance of the inverted position. To this end, the first and last 10 seconds of each trial (pre and post) were compared using paired t-tests. No significant differences were found between temporal segments within each condition, supporting that effects observed following the protocol are attributable to induced fatigue rather than progressive exhaustion during the task.

The main reported results for linear and non-linear measures are shown in Tables 5 and 6, respectively. Traditional variables used in postural control, BVE and MVM, showed no significant changes due to the fatigue protocol. Regarding linear variables, comparative analysis between pre- and post-fatigue conditions showed a significant increase in mediolateral COP displacement (Y-axis) recorded by the force platform, with a large effect size. Other variables, such as SD of the IMU located at L5, COP displacement in the Y-axis, and COP magnitude, did not reach the established significance threshold ($p < 0.007$), although they exhibited consistent trends with $p < 0.05$ and moderate to large effect sizes, suggesting possible fatigue influence.

Concerning non-linear metrics, significant differences were observed only in the DFA of the mediolateral axis (PLA Y) of the force platform, with a large effect size. Although other variables did not surpass the established significance threshold, they exceeded the typical $p < 0.05$ value, with considerable effect sizes identified in the DFA of the vertical axis and the DFA of force magnitude, as well as in the FuEn recorded by the sacral IMU. The remaining non-linear variables showed no significant changes or relevant trends, with low or moderate effect sizes.

Table 5. Comparison between pre- and post-fatigue protocol of linear measurements.

Variable	Pre Mean ± SD	Post Mean ± SD	p	t	d
BVE	13.68 ± 14.85	14.85 ± 2.57	0.19	-1.38	-0.37
MVM	151.79 ± 154.27	154.27 ± 23.66	0.78	-0.28	-0.07
SD IMU FA	0.40 ± 0.20	0.42 ± 0.17	0.43	-0.82	-0.22
SD IMU AR	0.41 ± 0.18	0.40 ± 0.13	0.64	0.49	0.13
SD IMU C7	0.28 ± 0.12	0.29 ± 0.13	0.46	-0.77	-0.21
SD IMU L5	0.36 ± 0.15	0.41 ± 0.17	0.04*	-2.14	-0.57
SD PLA X	7.43 ± 1.98	7.69 ± 1.54	0.34	-0.99	-0.26

SD PLA Y	4.24 ± 0.69	4.79 ± 0.82	<0.01**	-3.16	-0.84
SD PLA Z	17.38 ± 3.36	18.32 ± 3.10	0.22	-1.30	-0.35
SD PLA AX	14.08 ± 2.81	14.80 ± 2.24	0.37	-0.93	-0.25
SD PLA AY	6.44 ± 1.66	7.76 ± 2.32	0.03*	-2.37	-0.63
SD PLA MF	17.38 ± 3.36	18.31 ± 3.10	0.22	-1.29	-0.34
SD PLA MC	11.81 ± 3.72	13.39 ± 2.18	0.04*	-2.13	-0.57

Note. The values presented in Table 5 depict the comparison between pre- and post-fatigue protocol of linear measurements. Mean values and standard deviations (SD) are reported for each variable. The statistical analysis results include the p-value (p) and the outcomes of paired Student's t-test (t)s. The effect size measure (d) is utilized to assess the magnitude of the observed differences. **p < 0.01 indicates a highly significant difference, and *p < 0.05 indicates a significant difference. BVE: Bivariate variable error; MVM: Mean velocity magnitude; SD: Standard deviation; IMU: Inertial measurement unit; PLA: force platform; FA: Forearm; AR: Arm; C7: Seventh cervical vertebra; L5: Fifth lumbar vertebra; X: Antero-posterior axis of force platform; Y: Medium-lateral axis of force platform; Z: Vertical axis of force platform; AX: Antero-posterior axis of center of pressure; AY: Medio-lateral axis of center of pressure; MF: Modulus of force axis; MC: Modulus of center of pressure.

Table 6. Comparison between pre- and post-fatigue protocol of non-linear measurements.

Variable	Pre Mean ± SD	Post Mean ± SD	p	t	d
DFA IMU FA	0.21 ± 0.14	0.20 ± 0.09	0.78	0.29	0.08
DFA IMU AR	0.33 ± 0.14	0.31 ± 0.10	0.59	0.56	0.15
DFA IMU C7	0.40 ± 0.07	0.42 ± 0.16	0.66	-0.45	-0.12
DFA IMU L5	0.18 ± 0.12	0.18 ± 0.07	0.99	0.01	0.00
DFA PLA X	0.91 ± 0.09	0.9 ± 0.08	0.92	0.10	0.00
DFA PLA Y	0.92 ± 0.17	1.06 ± 0.16	<0.01**	-3.46	-0.92
DFA PLA Z	0.32 ± 0.13	0.49 ± 0.22	0.02*	-2.81	-0.75
DFA PLA AX	1.25 ± 0.10	1.24 ± 0.11	0.53	0.64	0.17
DFA PLA AY	1.38 ± 0.15	1.38 ± 0.11	0.99	-0.01	0.00
DFA PLA MF	0.32 ± 0.13	0.49 ± 0.22	0.02*	-2.81	-0.75
DFA PLA MC	1.27 ± 0.10	1.24 ± 0.11	0.05	2.17	0.58
FuEn IMU FA	0.29 ± 0.16	0.30 ± 0.14	0.44	-0.79	-0.21
FuEn IMU AR	0.29 ± 0.12	0.29 ± 0.09	0.78	0.29	0.08
FuEn IMU C7	0.19 ± 0.08	0.20 ± 0.08	0.20	-1.35	-0.36
FuEn IMU L5	0.23 ± 0.10	0.27 ± 0.12	0.01*	-2.96	-0.79
FuEn PLA X	1.40 ± 0.15	1.41 ± 0.14	0.74	-0.34	-0.09
FuEn PLA Y	1.45 ± 0.15	1.40 ± 0.20	0.37	0.94	0.25
FuEn PLA Z	2.01 ± 0.22	2.00 ± 0.25	0.74	0.34	0.09
FuEn PLA AX	0.56 ± 0.15	0.54 ± 0.12	0.63	0.50	0.13
FuEn PLA AY	0.54 ± 0.15	0.54 ± 0.11	0.86	0.18	0.05
FuEn PLA MF	2.01 ± 0.22	2.00 ± 0.25	0.74	0.33	0.09
FuEn PLA MC	0.62 ± 0.14	0.59 ± 0.12	0.49	0.71	0.19

Note. The values presented in Table 6 depict the comparison between the pre- and post-fatigue protocol of non-linear measurements. Mean values and standard deviations (SD) are reported for each variable. The statistical analysis results include the p-value (p) and the outcomes of paired Student's t-tests (t). The effect size measure (d) is utilized to assess the magnitude of the observed differences. **p < 0.01 indicates a highly significant difference, and *p < 0.05 indicates a significant difference. DFA: Detrended fluctuation analysis; FuEn: Fuzzy entropy; IMU: Inertial measurement unit; PLA: force platform; FA: Forearm; AR: Arm; C7: Seventh cervical vertebra; L5: Fifth lumbar vertebra; X: Antero-posterior axis of force platform; Y: Medium-lateral axis of force platform; Z: Vertical axis of force platform; AX: Antero-posterior axis of center of pressure; AY: Medio-lateral axis of center of pressure; MF: Modulus of force axis; MC: Modulus of center of pressure.

6.4. Summary of the Discussion and Conclusions of Study 4

The aim of this study was to analyze how fatigue influences motor variability during an inverted balance task, using linear and non-linear measures extracted from force platform and accelerometry signals. Unlike previous studies in this thesis, which focused on dynamic strength tasks, this work centered on an action that, while presenting moderate force demands, requires a high degree of postural control and fine motor coordination. This paradigm shift is relevant because the type of task profoundly conditions the motor control strategies employed and, consequently, how fatigue manifests in system behavior (193).

To the best of our knowledge, this is the first study to examine fatigue's impact on postural performance during inverted balance. Previous studies had analyzed other conditioning factors on the handstand, such as surface type, vision, or performer experience, showing effects on force production and COP displacement (178,200–202). Our findings partially coincide with these works: following the fatigue protocol, a significant increase was observed in the amount of COP variability in the mediolateral axis (PLA Y), as well as clear trends in other variables such as variability magnitude of COP module and Y-axis, and the sacral IMU. This increase in variability magnitude may indicate greater COP displacement, reflecting increased difficulty in maintaining stability after the fatigue protocol.

Regarding NLT, a significant increase was found in the DFA of the force platform's Y-axis, with relevant trends in DFA of the vertical axis and force magnitude, as well as in FuEn recorded by the L5 IMU. These results suggest that fatigue affects not only the amount of postural movement but also its internal organization, consistent with previous studies documenting complexity loss following fatigue in bipedal balance and cognitive or muscular tasks (177,203–205).

We interpret the results as indicating that force production against the platform became more consistent, whereas global movement—represented by COP magnitude and sacral IMU—required more adjustments to maintain balance post-fatigue, reflected in more unpredictable behavior (lower FuEn) and reduced autocorrelation (lower DFA).

It is important to emphasize that interpretation of variability structure changes must be contextualized according to task type. In isometric or sustained force tasks, increased motor synchronization and "freezing" of degrees of freedom have been observed, reflected in lower entropy and higher autocorrelation (103,206), possibly influenced by greater synchronization and reduced alternation between motor units, as seen in Study 1 and suggested by Pethick and Tallent (73). In contrast, in tasks requiring continuous postural adjustments—such as the handstand—fatigue may induce control reorganization leading to increased irregularity (higher FuEn) and decreased autocorrelation (lower DFA), as proposed by Donker et al. (207) and Vuillerme et al. (208). Our data support this view of motor variability structure interpretation: while force values obtained from the force platform showed increased DFA (indicative of lower complexity), COP and accelerometry revealed trends toward lower DFA and higher entropy respectively after fatigue.

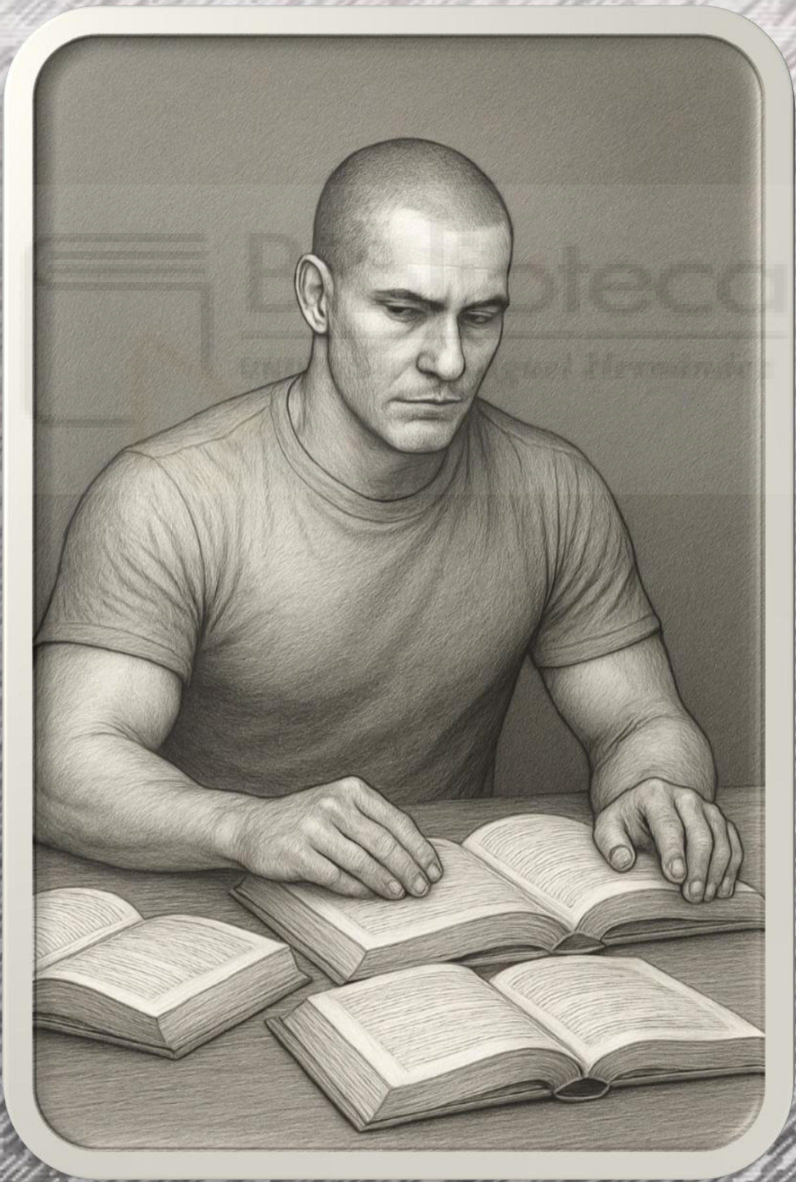
These results reinforce the idea that measures extracted from different sources (platforms vs. IMUs) may be complementary rather than redundant (209,210). Acceleration recorded at L5, close to the center of mass, appears better at capturing hip compensatory strategies, especially when postural sway increases, as typically occurs under fatigue conditions (193). Nonetheless, in our study, force platform variables showed superior sensitivity in detecting fatigue effects on postural organization, contrasting with previous studies suggesting the opposite (160). This may be because complexity analysis from force more directly reflects the outcome of global motor adjustments required to maintain the COM within the support area.

Finally, these results should be interpreted within the broader context of this thesis, which proposes motor variability analysis as a valid and sensitive tool to monitor the functional state of the motor system. However, the findings of this study reinforce a key idea already presented in earlier chapters: the analyzed task type profoundly conditions how fatigue effects manifest on motor control. Evaluating a task centered on force production—such as the squat—is not equivalent to assessing an action like the handstand, where fine adjustments, complex postural control, and high attentional demand predominate. Similarly, analyzing isometric versus dynamic tasks is not equivalent.

These findings suggest that accelerometers can be useful tools to monitor inverted balance tasks under fatigue, particularly from a quantitative perspective. However, if the goal is to detect qualitative changes in motor control organization, such as complexity loss, the use of force platforms appears more appropriate. Overall, the results of this study open new research avenues and emphasize the need to adapt variability analysis to the particularities of each task.

Given the exploratory nature of the study, it is important to note that further research is required to identify which variables are most useful and consistent in detecting fatigue effects during inverted balance tasks. Future studies should validate these findings in larger samples and different contexts to assess their applicability and generalizability.

7. General Discussión



7. General Discussion

Once the results of the various studies comprising this thesis have been presented and analyzed, this chapter delves into the use of motor variability as a potential indicator of fatigue state. From an integrative perspective, the findings are addressed transversely to assess the extent to which changes in movement structure—quantified through linear and non-linear tools applied to acceleration signals—reflect the functionality of the motor system under acute fatigue conditions. Additionally, the practical implementation possibilities of these analyses in applied contexts are discussed, along with their main methodological and conceptual limitations. This comprehensive overview advances understanding of the value of motor variability as a sensitive and complementary metric for monitoring fatigue during strength training.

7.1. Why Use Non-Linear Measures

One of the main challenges in fatigue monitoring is that, in many cases, the changes caused by fatigue in the organism are not immediately reflected in classical performance measures. It is possible for a task to be successfully completed—such as lifting a given load or maintaining a posture—because the motor system has internally reorganized to meet the demands of the task. Therefore, analyzing how the movement is executed can provide complementary information to that obtained by simply assessing task completion. In this sense, if we assess not only *what* is achieved (i.e., whether the task is completed), but also *how* it is achieved (i.e., the control strategy employed), we gain a more comprehensive understanding of the organism's functional state—specifically, whether it is showing signs of accumulating excessive fatigue.. In this context, motor variability analysis offers a complementary avenue to identify subtle modifications in neuromuscular system behavior.

The relevance of NLT lies in their demonstrated greater sensitivity than traditional measures in certain contexts for detecting alterations related to fatigue or less functional organism states. For example, recent studies have shown that, for the same task, linear measures may remain stable while entropy or autocorrelation indices exhibit significant changes, revealing modifications in movement organization that would otherwise go unnoticed (67,93). This greater sensitivity may be explained by these metrics capturing the system's ability to adapt to perturbations through multiple degrees of freedom, a key aspect in understanding complex motor behavior. Therefore, rather than being mutually exclusive, linear and non-linear measures should be understood as complementary tools. Their combined analysis allows for a more complete and accurate view of the system's functional state, which is especially useful in contexts where changes are subtle or maximal testing is not feasible. In summary, incorporating temporal structure analysis of variability represents a relevant methodological advance for better interpreting how movement is regulated under fatigue conditions.

7.2. How to Apply Non-Linear Measures

As previously mentioned, the use of NLT to analyze motor variability offers great potential for better understanding the temporal organization of movement, but it requires special attention to methodological aspects related to data recording and processing. Unlike traditional linear metrics, which generally provide a more straightforward and stable application, NLT—such as entropy or DFA—are highly sensitive to how the time series are constructed and processed (211,212). Ignoring these aspects can lead to erroneous interpretations or even inconsistent results. Therefore, before applying any non-linear metric, it is essential to know what type of time series is being analyzed, what characteristics the signal has, and under what conditions it was recorded.

A time series is a sequence of measurements taken in an ordered manner over time. In human movement, these series allow observation of how motor behavior evolves over multiple repetitions or during prolonged actions, thus capturing the system's underlying dynamics (69). This temporal sequencing is not a mere technical detail; it is what makes the series contain information about how the system generates and regulates movement. Unlike linear methods, which assume independence among observations, human movement time series present strong dependence between adjacent points. This dependence—its regularity, degree of correlation, or predictability—is precisely what NLT attempt to capture. In this regard, it is crucial to distinguish between discrete series (sampled at fixed intervals) and continuous series (recorded continuously).

Alongside this temporal classification, it is also essential to understand exactly what is being analyzed. As highlighted in this thesis, applying a non-linear tool to a sustained isometric force signal is not equivalent to applying it to an acceleration signal during a dynamic, multi-joint task. On the one hand, the type of task conditions aspects such as the duration, the presence of phases or the number of cycles of the same action being analyzed. On the other hand, the type of signal conditions aspects such as stationarity or signal noise. This causes the intrinsic nature of the signal to change, and must therefore be taken into account. For example, an electromyography signal tends to be noisier than an acceleration signal.. Similarly, cyclic tasks like running allow for a sufficient number of repeated cycles of the same action for analysis, whereas discrete tasks such as squats or jumps require brief, standardized windows, which may limit series length and affect algorithm robustness (69). For example, somemethods, suach as SaEn and DFA, require at least 200–500 stable data points to provide reliable results, which can be difficult to achieve in very short or explosive actions (95).

In this context, signal recording and processing play a central role in the validity and reliability of non-linear analysis. Variables such as sampling frequency, potential downsampling, series length, and filtering must be carefully defined according to task type and recorded signal.

According to Raffalt et al. (94), in isometric force signals, it is advisable to use sampling frequencies between 100 and 250 Hz, as this range adequately captures relevant dynamics without introducing excessive noise. Other authors have used even higher frequencies, reporting sensitivity in fatigue detection (103,127,128). In contrast, for postural control tasks—especially those analyzing center of pressure—lower frequencies around 20 Hz are typically recommended, since relevant changes occur at much slower speeds (166,196).

In our case, focused on analyzing acceleration signals during dynamic tasks, we have observed that sampling frequencies between 50 and 200 Hz yield reliable information, with good reliability properties in measures such as fuzzy entropy and DFA. Specifically, using a sampling frequency of 100 Hz, we were able to detect fatigue-induced sensitive changes in the temporal structure of acceleration during squats, reinforcing the validity of this parameter in dynamic and applied contexts. As Raffalt et al. (94) emphasize, it is crucial to identify the frequency range where the majority of significant signal behavior is concentrated. Setting a sampling frequency far above or below this range can alter the signal's informational content, affecting complexity estimation or introducing artificial noise. This consideration is especially important in non-linear analysis, where preserving the signal's true temporal content is essential for calculated metrics to reflect the genuine behavior of the motor system.

Signal processing prior to non-linear analysis is a critical aspect that can significantly influence results. Stergiou (69) recommends avoiding filtering and smoothing of movement time series when the goal is to study their temporal structure, as these procedures may alter the very dynamic patterns intended to be preserved. From this perspective, he proposes working with the raw, as-recorded signal, arguing that any transformation could distort the temporal dependence between adjacent observations, which is the foundation of non-linear analysis. Nevertheless, some studies have employed filtering preprocessing techniques (106,108,115,116,122,123,125,127,128). These decisions may be justifiable in certain contexts, but it is essential to know what type of processing is applied, for what purpose, and how it may alter the signal's dynamic properties.

In the particular case of non-stationary signals—a common characteristic in dynamic actions like squats or balance tasks—Stergiou (69) warns that this condition may complicate the application of many non-linear techniques, which assume some statistical stability over time. To address this, methods such as the Dickey-Fuller test (213,214) for non-stationarity detection and techniques like EMD (215) have been proposed, decomposing the signal into more stable components without assuming linearity or applying predefined frequency filters. In the case of the acceleration signals—both those obtained during the squat and those recorded during the handstand—the Dickey-Fuller test indicated stationary behavior. Therefore, the signals were considered stationary and did not require preprocessing to address non-stationarity. It is worth noting that other studies (127,128) analyzing force signals have reported a high proportion of non-stationary cases. In such instances, techniques like EMD were applied to ensure the interpretability of the results. Therefore, analyzing signal stationarity is advisable, and if non-stationarity is found, additional techniques like segmentation or EMD may be required to obtain interpretable results. In any case, given the recent application of these methods in training or rehabilitation contexts, it is recommended to continue exploring different signal processing strategies. What is essential is to maintain a rigorous approach: every methodological decision must be justified based on the analytical objective and accompanied by reflection on how it may affect the validity and interpretability of obtained non-linear metrics.

In summary, to apply NLT rigorously and meaningfully, it is essential to jointly consider: (1) Regarding the nature of the time series, it has to be specified whether it is continuous or discrete, ensure sufficient duration (e.g., ≥200–500 data), and assess stationarity using tests like Dickey-Fuller; (2) We propose to avoid equating dynamic acceleration data with static isometric force signals due to their distinc nature; (3) identify the frequency band where relevant motor information is concentrated (we propose 50–200 Hz for dynamic acceleration signals); and (4) ensure transparent recording and processing decisions in the reports, justifying the use of filters or downsampling when studying temporal structure, prefering raw signals. Only by integrating these factors can one ensure that obtained metrics truly reflect the motor system's dynamics and not methodological artifacts.

7.3. Reliability of Non-Linear Measures in Acceleration Signals

The reliability of the measures we use is a key factor for their practical application in monitoring motor control and the functional state of the organism. Regardless of how advanced or sensitive a metric may be, it loses practical value if it does not consistently yield stable results across repeated measurements. In this context, the current body of evidence remains limited and inconsistent, with most studies focusing on postural tasks or actions involving low functional demands. This highlights the need to assess the reliability of these measures in more dynamic and ecologically valid conditions to ensure their usefulness in real-world applications.. In Study 2, the reliability of indicators such as SaEn, FuEn, and DFA applied to acceleration signals during high-force demand movements like the squat was evaluated for the first time. Results showed moderate to good reliability levels for both tools, with relatively low standard errors, supporting their potential utility for movement analysis in dynamic actions. These data suggest that, at least under well-controlled conditions, non-linear indicators can provide consistent information about the temporal organization of the motor system.

These findings align with previous research in the postural control domain, where various non-linear metrics have demonstrated acceptable reliability. Roerdink et al. (192) analyzed approximate entropy and DFA applied to COP time series, observing moderate between-session reliability. Donker et al. (207) also reported consistent values for entropy of postural signals under different balance conditions. More recently, Lee and Newell (214) studied DFA reliability in static and dynamic bipedal tasks, finding values comparable to Study 2, especially in conditions with lower postural variability. Collectively, these studies suggest that although NLT exhibit some sensitivity to task type and signal processing, their reliability can be considered acceptable provided appropriate methodological criteria are met.

However, beyond the postural domain, studies analyzing the reliability of these metrics in force production tasks or strength training exercises are practically nonexistent. In ongoing work currently under review, we have found good to excellent reliability ($0.10 < ICC < 0.80$) for SaEn applied to isometric force signals, reinforcing the feasibility of these metrics in contexts with higher neuromuscular demand. Nevertheless, aside from this study, no known research has systematically evaluated NLT reliability in dynamic contractions, multi-joint exercises, or explosive tasks, where signals may present greater complexity and variability.

This scarcity of research represents an important limitation for widespread implementation of these tools in training and functional evaluation. Further validation of non-linear metrics under varying conditions, populations, and task types—especially in force production or dynamic exercise contexts—is necessary. However, although the evidence remains preliminary, results from our studies suggest these tools can offer adequate reliability in dynamic signals and force actions, reinforcing their potential as a valid methodology. Still, continued evidence accumulation is essential to precisely establish conditions under which these metrics can be confidently used as stable and reliable motor behavior indicators.

7.4. Effect of Fatigue on Motor Variability

Exercise-induced fatigue generates alterations in the motor system's capacity to produce force and regulate movement, manifesting as changes in motor variability. Generally, various studies have shown that fatigue can induce both increases and decreases in motor behavior complexity, depending on task type and measurement conditions. This variability in responses has motivated theoretical frameworks such as the Loss of Complexity Theory, which proposes that under non-optimal conditions—such as fatigue, illness, or aging—physiological systems tend to exhibit reduced complexity, reflecting diminished adaptive capacity (56,70).

In isometric tasks, evidence is more consistent: multiple studies have shown that as fatigue accumulates, the magnitude of force fluctuations increases and complexity decreases, i.e., signals become more regular and autocorrelated. This pattern has been linked to increased motor unit synchronization, reflecting greater common synaptic input and a reduction in the repertoire of available motor strategies (74,104). This phenomenon is especially evident when contractions exceed the "critical torque," where peripheral fatigue processes develop more rapidly and significant increases in signal regularity are observed, evaluated through measures such as entropy and DFA (83,104).

In contrast, fatigue effects on motor variability in dynamic tasks have yielded inconsistent results. While some studies report reduced movement complexity—reflected in increased regularity (114,123,125)—others observe the opposite effect, with increased randomness and unpredictability following fatigue (122,124,125). According to the original Loss of Complexity Theory (67,70), complexity is not reduced solely when the system becomes more regular but also when behavior becomes excessively erratic or disorganized. Thus, both overly rigid and overly noisy patterns represent functional complexity loss (56). Within this framework, fatigue does not necessarily produce a universal decrease in irregularity or autocorrelation but induces a system dynamic reorganization that compromises adaptability.

A possible explanation for the differences in results is that distinct components of motor control operate at different temporal scales, depending on the nature of the task. In isometric tasks, where there is no joint displacement or significant muscle demand variation, signal fluctuations are dominated by high-frequency, short-duration processes mainly linked to local neuromuscular dynamics. In these contexts, fatigue tends to increase motor unit synchronization, resulting in decreased entropy and increased DFA, i.e., a more regular and predictable signal (62,73). However, as Cortes et al. (81) cautioned, this explanation may not apply to more complex dynamic tasks involving multiple joints, degrees of freedom, and constantly changing coordination patterns.

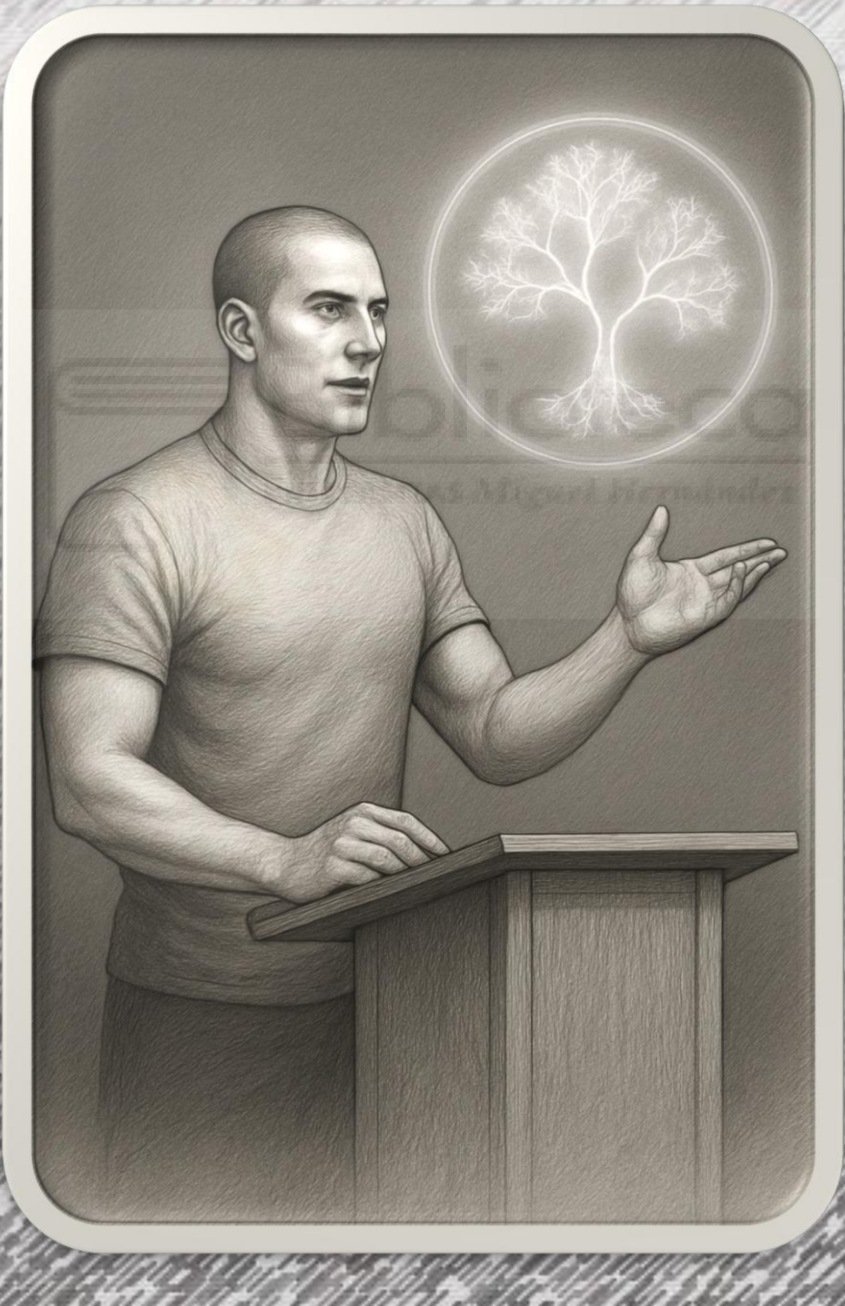
In dynamic tasks, signal oscillations are strongly determined by low-frequency processes (i.e., long temporal scales) linked to global movement adjustment. When fatigue sets in, neuromuscular-level changes—such as increased "noise" from motor unit activation—project onto these longer scales, disrupting global movement control. This may manifest as increased irregularity and decreased autocorrelation. Moreover, compensatory strategies emerging to maintain performance—such as joint kinematic adjustments (84,85), effort redistribution among muscle groups (90,159), activation pattern modifications (87), or intermuscular network reorganization (88,89)—add variability to the system, contributing to loss of functional structure and organization.

Thus, increases in entropy and decreases in DFA observed under fatigue in dynamic tasks may not represent adaptive gains but rather the system's need to perform more adjustments to successfully complete the task (162,165). Indeed, recent studies have shown that even increasing load in tasks like the squat, without inducing explicit fatigue, results in increased complexity (165), suggesting this response could also be linked to environmental demands. Overall, this theoretical framework provides a plausible basis for interpreting divergent patterns observed in non-linear metrics under fatigue, especially when comparing controlled isometric tasks to complex dynamic tasks.

Additionally, as reported by López-Fernández et al. (165), this irregular response is not exclusive to fatigue but may also appear under high motor demand or effort conditions, such as increasing squat load. In that study, load increases were associated with entropy and DFA increases, suggesting a greater number of adjustments to maintain performance. This supports the idea that in dynamic tasks, the motor system's response to fatigue is not necessarily a classical complexity loss but a temporal reorganization reflecting the system's efforts to maintain functionality.

Together, these findings show that fatigue effects on motor variability critically depend on task nature. While in isometric tasks shifts toward more regular signals appear to reflect reduced adaptability, in dynamic tasks opposite responses—such as increased irregularity—may occur, also representing a form of functional disorganization. Therefore, it is essential to analyze each motor context specifically to correctly interpret complexity changes under fatigue.

Conclusions



Conclusions

The results obtained in this thesis support the use of motor variability as a valuable indicator of fatigue, with practical applications in the field of sports performance, the clinical setting, and general health. It has been shown that non-linear tools, such as entropy and detrended fluctuation analysis, are capable of detecting subtle alterations in movement organization that often go unnoticed by traditional metrics focused solely on external performance. These changes, interpreted within the theoretical framework of complexity loss, reflect variations in the adaptability and functional state of the neuromuscular system under fatigue conditions.

Importantly, the findings of this thesis confirm that these tools can be applied with reasonable reliability, provided that certain methodological criteria are met. The effects of fatigue on variability are not uniform, but depend on the type of task, the type of signal analyzed, and the timing of data collection. This contextual dependency does not invalidate the utility of the metrics, but rather underscores the need to apply them in an informed and task-specific manner.

One of the most notable practical contributions is that non-linear tools allow for the detection of fatigue states without the need for maximal efforts. This feature is especially advantageous in high-performance contexts, where monitoring fatigue without generating additional load is essential, as well as in clinical populations, older adults, or individuals undergoing rehabilitation, where applying high intensities may be contraindicated. In this regard, the analysis of motor variability using inertial measurement units and non-linear tools represents a non-invasive, automatable, and easily integrable strategy within functional training and evaluation routines.

Moreover, the use of non-linear tools not only complements classical variability metrics, but in some contexts may be more sensitive. While traditional metrics inform about the amount of variability, non-linear approaches allow for understanding its temporal structure and regularity, thus offering a deeper insight into how the system adapts under fatigue. This added informational richness is key to identifying early compensatory mechanisms and anticipating possible functional deterioration before it becomes evident in external performance.

In summary, although broader research and methodological standardization are still needed, the results of this thesis reinforce the potential of motor variability—and particularly its non-linear analysis—as a functional marker of fatigue state. This line of work lays the foundation for its application in individualized training load monitoring and opens new avenues for research and practice in both sports science and movement health and rehabilitation.

Likewise, the results obtained make it possible to identify a series of practical applications that may be highly useful in sports, clinical, or general health contexts. Firstly, it has been demonstrated that motor variability can act as a sensitive indicator of fatigue state, providing information on how the motor system organizes under conditions of overload or functional reduction. This approach goes beyond traditional measures focused exclusively on external performance and allows for the detection of subtle changes in movement control before observable declines in performance appear.

Secondly, it has been shown that the use of non-linear tools complements—and in some cases surpasses—traditional measures of variability. While the latter inform about the quantity of variability, non-linear tools offer a deeper understanding of its temporal organization and regularity, making it possible to identify alterations in system complexity that are not always reflected in classical indicators. Thus, incorporating non-linear analyses, such as entropy or detrended fluctuation analysis, into training monitoring provides a richer and more comprehensive view of the functional state of the athlete or patient.

A particularly relevant aspect is that these tools allow for fatigue detection without requiring maximal efforts, which represents a key advantage in many application contexts. In high-performance settings, this enables load monitoring without interfering with recovery processes or inducing additional fatigue. In clinical populations, older adults, or individuals undergoing rehabilitation, this feature is even more valuable, as it avoids exposure to high loads that could compromise safety or hinder progress. In this sense, motor variability analysis using inertial measurement units and non-linear metrics offers a non-invasive, automatable, and easily integrable solution into training and evaluation routines.

Taken together, the findings of this thesis reinforce the value of motor variability as a functional monitoring tool, suggest potential improvements in the individualization of workload, and open new avenues for fatigue monitoring in both sports and clinical or rehabilitation environments.

Future Directions

The findings of this doctoral thesis open new research avenues to further explore the applicability of motor variability analysis as a tool for fatigue monitoring. In this regard, the next steps should be directed toward three main areas:

1. **Reproducibility across different contexts.** It is necessary to verify that the changes in complexity observed in this thesis are consistently reproduced in other exercises and populations. So far, each of the analyzed tasks has been evaluated in a single study, which makes it essential to confirm that the loss of complexity

associated with fatigue represents a consistent pattern across different movements, levels of expertise, and subject groups.

2. **Physiological basis of complexity loss.** To better understand what variability truly reflects, it is important to analyze what happens at the neuromuscular level when fatigue induces a loss of complexity. Future studies should therefore integrate physiological signals, such as electromyography, with variability analysis. This approach would allow the observed changes in the structure of the signal to be directly related to processes of muscle activation and coordination.

3. **Longitudinal intervention studies.** Finally, it is crucial to assess whether using variability as a fatigue indicator and as a criterion for daily training prescription can optimize adaptation processes. Longitudinal studies, with a minimum duration of 12 weeks, are needed to compare the effects of traditional periodization with a "day-to-day" periodization based on variability. Such designs will help determine whether this approach provides improvements in terms of effectiveness (achieved outcomes) or efficiency (relationship between outcomes and resources used).

Conclusiones

Los resultados obtenidos en esta tesis respaldan el uso de la variabilidad motora como un indicador valioso de la fatiga, con aplicaciones prácticas en el ámbito del rendimiento deportivo, el entorno clínico y la salud en general. Se ha demostrado que herramientas no lineales, como la entropía y el análisis de fluctuaciones sin tendencia, son capaces de detectar alteraciones sutiles en la organización del movimiento que a menudo pasan desapercibidas para las métricas tradicionales centradas en el rendimiento externo. Estos cambios, interpretados dentro del marco teórico de la pérdida de complejidad, reflejan variaciones en la capacidad de adaptación y en el estado funcional del sistema neuromuscular bajo condiciones de fatiga.

De forma relevante, los hallazgos de esta tesis confirman que estas herramientas pueden aplicarse con una fiabilidad razonable, siempre que se respeten ciertos criterios metodológicos. Los efectos de la fatiga sobre la variabilidad no son uniformes, sino que dependen del tipo de tarea, del tipo de señal analizada y del momento en que se realiza el registro. Esta dependencia contextual no invalida la utilidad de las métricas, sino que subraya la necesidad de aplicarlas de forma informada y específica según el tipo de tarea.

Una de las contribuciones prácticas más destacadas es que las herramientas no lineales permiten detectar estados de fatiga sin necesidad de esfuerzos máximos. Esta característica resulta especialmente ventajosa en contextos de alto rendimiento, donde es fundamental monitorizar la fatiga sin generar una carga adicional, así como en poblaciones clínicas, personas mayores o individuos en proceso de rehabilitación, donde aplicar altas intensidades puede estar contraindicado. En este sentido, el análisis de la variabilidad motora mediante unidades de medición inercial y herramientas no lineales representa una estrategia no invasiva, automatizable y fácilmente integrable en rutinas de entrenamiento y evaluación funcional.

Además, el uso de herramientas no lineales no solo complementa a las métricas clásicas de variabilidad, sino que en algunos contextos pueden ser más sensibles. Mientras que las métricas tradicionales informan sobre la cantidad de variabilidad, los enfoques no lineales permiten comprender su estructura temporal y regularidad, ofreciendo así una visión más profunda de cómo se adapta el sistema ante la fatiga. Esta mayor riqueza informativa es clave para identificar mecanismos compensatorios tempranos y anticipar un posible deterioro funcional antes de que se manifieste en el rendimiento externo.

En resumen, aunque aún se requiere una investigación más amplia y una estandarización metodológica, los resultados de esta tesis refuerzan el potencial de la variabilidad motora—y en particular de su análisis no lineal—como marcador funcional del estado de fatiga. Esta línea de trabajo sienta las bases para su aplicación en la individualización de la carga de entrenamiento y abre nuevas vías de investigación y práctica tanto en la ciencia del deporte como en la rehabilitación y la salud del movimiento.

Asimismo, los resultados obtenidos permiten identificar una serie de aplicaciones prácticas que pueden resultar altamente útiles en contextos deportivos, clínicos o de salud general. En primer lugar, se ha demostrado que la variabilidad motora puede actuar como un indicador sensible del estado de fatiga, proporcionando información sobre cómo se organiza el sistema motor ante condiciones de sobrecarga o reducción funcional. Este enfoque va más allá de las medidas tradicionales centradas únicamente en el rendimiento externo y permite detectar cambios sutiles en el control del movimiento antes de que se manifiesten caídas observables en el desempeño.

En segundo lugar, se ha comprobado que el uso de herramientas no lineales complementa—y en algunos casos supera—a las medidas tradicionales de variabilidad. Mientras estas últimas informan sobre la cantidad de variabilidad, las herramientas no lineales ofrecen una visión más profunda de su organización temporal y regularidad, permitiendo identificar alteraciones en la complejidad del sistema que no siempre se reflejan en los indicadores clásicos. Así, la incorporación de análisis no lineales como la entropía o el análisis de fluctuaciones sin tendecia en la monitorización del entrenamiento proporciona una perspectiva más rica y completa del estado funcional del deportista o del paciente.

Un aspecto particularmente relevante es que estas herramientas permiten detectar la fatiga sin exigir esfuerzos máximos, lo que representa una ventaja clave en muchos contextos de aplicación. En entornos de alto rendimiento, esto permite monitorizar la carga sin interferir con los procesos de recuperación ni inducir fatiga adicional. En poblaciones clínicas, personas mayores o en rehabilitación, esta característica es aún más valiosa, ya que evita la exposición a cargas elevadas que podrían comprometer la seguridad o el progreso. En este sentido, el análisis de la variabilidad motora mediante IMUs y métricas no lineales ofrece una solución no invasiva, automatizable y fácilmente integrable en rutinas de entrenamiento y evaluación.

En conjunto, los hallazgos de esta tesis refuerzan el valor de la variabilidad motora como herramienta de monitorización funcional, apuntan a mejoras potenciales en la individualización de la carga de trabajo y abren nuevas vías para la monitorización de la fatiga tanto en entornos deportivos como clínicos o de rehabilitación.

Perspectivas futuras

Los resultados obtenidos en esta tesis doctoral abren nuevas líneas de investigación que permitirán profundizar en la aplicabilidad del análisis de la variabilidad motora como herramienta de monitorización de la fatiga. En este sentido, los próximos pasos deberían orientarse hacia tres direcciones principales:

1. **Reproducibilidad en diferentes contextos**. Es necesario comprobar que los cambios en la complejidad observados en esta tesis se repiten en otros ejercicios y poblaciones. Hasta el momento, cada una de las tareas analizadas se ha evaluado en un único estudio, por lo que resulta fundamental confirmar que la pérdida de complejidad asociada a la fatiga se mantiene como un patrón consistente en distintos movimientos, niveles de práctica y grupos de sujetos.
2. **Bases fisiológicas de la pérdida de complejidad**. Para comprender con mayor profundidad qué refleja la variabilidad, es preciso analizar qué ocurre a nivel neuromuscular cuando la fatiga induce una pérdida de complejidad. En esta línea, futuros trabajos deberían integrar el registro de señales fisiológicas, como la electromiografía, con el análisis de la variabilidad, lo que permitiría relacionar los cambios en la estructura de la señal con procesos de activación y coordinación muscular.
3. **Estudios longitudinales de intervención**. Finalmente, resulta imprescindible valorar si el uso de la variabilidad como indicador de fatiga y como criterio para la prescripción diaria del entrenamiento puede optimizar los procesos de adaptación. Para ello se requieren estudios de carácter longitudinal, con una duración mínima de 12 semanas, que comparen los efectos de una periodización tradicional frente a una periodización "day-to-day" basada en la variabilidad. Este tipo de diseños permitirá determinar si esta herramienta aporta mejoras en términos de eficacia (resultados alcanzados) o eficiencia (relación entre resultados y recursos empleados).

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Appendix

Appendix 1: The use of non-linear tools to analyze the variability of force production as an index of fatigue: A systematic review

Study 1: García-Aguilar F, Caballero C, Sabido R, Moreno FJ. The use of non-linear tools to analyze the variability of force production as an index of fatigue: A systematic review. Front Physiol. 2022 Dec 14;13:1074652. doi: 10.3389/fphys.2022.1074652. PMID: 36618513; PMCID: PMC9813695.

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The use of non-linear tools to analyze the variability of force production as an index of fatigue: A systematic review

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Background: Fatigue is a process that results in a decreased ability to produce force, and which could eventually affect performance and increase the risk of injury. Force variability analysis has been proposed to describe the level of fatigue with the purpose of detecting the development of fatigue. Variability is credited to play a functional and adaptive role through which the components of a system self-organize to solve a motor problem. Non-linear tools have been applied to analyze the variability of physiological signals, revealing that the structure of motor fluctuations provides relevant information about the functional role of variability. It has been suggested that the presence of lower complexity in the variability structure could reveal a less functional and adaptive state (e.g., ageing or illness). In the last years, an increased number of studies have applied these techniques to force variability analysis in relation to fatigue.

Objective: To provide an overview of the current knowledge on the use of non-linear tools on force variability as a fatigue index.

Methods: Following PRISMA guidelines, a systematic search of SPORTDiscus, Scopus, Web of Science and PubMed was carried out. Studies included were: a) original studies that analyzed the effect of fatigue on humans during an action focused on force production; b) published studies with their title and abstract in English; c) studies that applied non-linear tools on a signal directly related to force production.

Results: Twenty-five studies were included in this review. The relationship between fatigue and the complexity of force variability, the type of action and relative intensity, the nature of the signal and the non-linear tools used, and the methods of data acquisition and processing were identified.

Conclusion: The articles reviewed suggest that fatigue leads to a decrease in complexity mostly in isometric contractions, but this is not as clear in dynamic contractions. This fatigue-induced loss of complexity seems to be a result of changes in the nervous system at the central level, albeit triggered by peripheral mechanisms. It should be noted that non-linear tools are affected by the relative intensity of contraction, non-stationarity, and the acquisition and treatment of the signal.

KEYWORDS

force control, strength, non-linear, complexity, neuromuscular fatigue

Introduction

Fatigue can be defined as a multifactorial process resulting in a decrease or failure to produce force by a muscle or muscle group (Gandevia, 2001; Enoka and Duchateau, 2008; Carroll et al., 2017). This decrease in force production affects the ability to perform a motor task (Taylor and Gandevia, 2008; Ament and Verkerke, 2009; Boyas and Guével, 2011; Carroll et al., 2017), reducing contractile function and muscle activation (Enoka and Duchateau, 2016), and it is related to an increase in the risk of injury (Almonroeder et al., 2020). The onset of fatigue is an intricate process that affects the organism in different ways depending on factors which may be either intrinsic (e.g., age, sex, body composition) or extrinsic (e.g., features of the task, environmental conditions) (Enoka and Duchateau, 2008). These factors impact on the development of fatigue (central or peripheral) and how it reveals itself (Place and Millet, 2020), and, thus, on how we can detect fatigue in the organism.

Classical measures of fatigue, such as maximal voluntary contraction force (MVC) or energy output, may be an index of fatigue, but they do not provide information on the intensity of fatigue (Enoka and Duchateau, 2016), i.e., they do not allow us to quantify the fatigue state of the organism. In addition, different methods are recommended depending on both the task and the predominant source of fatigue (Zwarts et al., 2008; Place and Millet, 2020). Among the methods used to examine the level of fatigue in humans, the variability in force production has been proposed in several studies (Slifkin and Newell, 2000; Contessa et al., 2009; Cortes et al., 2014). Motor variability is considered to be the variations or fluctuations that occur in motor behavior during the repetitive execution of an action (Stergiou, 2004). The production of muscle force involves multiple interacting elements (e.g., motor neurons, myofibrils, tendon units) (Badillo, 2002), which vary along different time scales (e.g., nerve impulses vary over smaller time scales than joint movement variations). Therefore, it can be assumed that these variations represent how the different components self-organize to adapt to the environment and to the task to be performed. Fatigue can be regarded as a determinant affecting how these elements interact, modifying the neuromuscular system's response during a task. Some studies have analyzed the variability of force production in different contexts (Slifkin and Newell, 2000; Vaillancourt and Newell, 2003; Missenard et al., 2008; Contessa et al., 2009; Singh et al., 2010; Cashaback and Cluff, 2015) identified an increase in variability as relative intensity increased, either due to the effect of age or due to the development of fatigue. In these studies, variability has traditionally been analyzed with measures of dispersion such as standard deviation (Harbourne and Stergiou, 2009) or coefficient of variation (Christou and Carlton, 2001). These measures provide an insight into the magnitude or the amount of variability, and they assume that the variations that occur are random and independent of each other (Caballero et al., 2014).

Nevertheless, these measures of dispersion may not be sensitive to the nature of nested fluctuation patterns of the interdependent elements involved in muscle contraction (Holden, 2005). The multiple time scale of change of the elements implied in motor behavior are often hidden when linear data reduction techniques are applied (Newell et al., 2001). Therefore, as summary statistics would not be neatly applicable to address the complexity of a heterogeneous variable process, measuring the fluctuation changes over time is necessary. The temporal evolution of these fluctuations is known as the structure or dynamics of variability (Caballero et al., 2014). The so-called Non-Linear Tools (NLTs) have been applied to different physiological signals and human movement to analyze the structure of variability (Stergiou, 2004, 2016).

NLTs are mathematical methods that aim to capture variations in how a driving behavior emerges over time. Temporal organization of fluctuations is quantified by the degree to which values emerge in a structured manner across a range of time scales, and its underlying complexity (Harbourne and Stergiou, 2009). Some authors have defined complexity as chaotic temporal variations in a biological system (Yentes et al., 2013) and its structure can be studied through NLTs. Previous studies have linked the loss of complexity to a decrease in the adaptive capacity of the organism, which has led to "the theory of complexity loss" (Goldberger, Peng, et al., 2002), reported in studies on ageing and pathology (Lipsitz and Goldberger, 1992; Slifkin and Newell, 1999; Goldberger, Peng, et al., 2002), and recently extended to studies on fatigue (Beretta-Piccoli et al., 2015). If we understand fatigue as a state in which the organism is in a non-optimal situation we can expect a loss of complexity in the different signals related to force production. Some NLTs are, for example, entropy measures, which estimate the predictability of a signal, i.e., the probability that a data sequence pattern repeats itself in a time series (Pincus, 1991; Richman and Moorman, 2000; Costa et al., 2005). Other NLTs have also been used to study the predictability of a time series, such as the percentage of Determinism (%DET) (Bauer et al., 2017) or the Lyapunov Exponent (LyE), which measures the extent to which the data series represents a similar pattern along time (Wolf et al., 1985).

Additionally, attention must be paid to the tools that analyze the autocorrelation of a time series to understand the complexity of the physiological signals, such as the Detrended Fluctuation Analysis (DFA) (Peng et al., 1995). These tools quantify complexity in different ways, so a decrease in entropy measures [such as approximate entropy (ApEn), sample entropy (SampEn) or fuzzy entropy (FuzzyEn)], in LyE or %DET would reflect a loss of complexity, and an increase in their values would indicate an increase in complexity. Conversely, increasing values of DFA, CrossDet or Cross Shannon Entropy indicate a loss of complexity, and decreasing values indicate an increase in complexity. This NLT has proven to be useful in detecting the flexibility and adaptability of the organism in different scenarios, such as at a physiological level (Goldberger et al., 2002; Goldberger, Peng, et al., 2002; Decker et al., 2011), in postural control (Peng et al., 2009), in injuries detection (Stergiou et al., 2006; Bauer et al., 2017) or learning processes (Barbado et al., 2017). Thus, more complex behaviors have been associated with the individual's more adaptable and healthy condition. In contrast, more periodic or random behaviors may be associated with a less adaptable or less healthy condition (Stergiou et al., 2006), due to pathology, injury or other factors limiting the organism's functionality.

Different studies have applied NLTs to analyze fluctuations in force production (Slifkin and Newell, 1999, 2000; Forrest et al., 2014) and electromyography (Farina et al., 2002; González-Izal et al., 2012; Beretta-Piccoli et al., 2015) and kinematic variables (Mann et al., 2015) in fatigue conditions. Given the additional information provided by the NLTs, and that, in some cases, they seem more sensitive than linear measurements (Cavanaugh et al., 2005), applying these methods to force signals for fatigue detection is of interest. In the past few years, there has been an increase in the number of studies that have applied these techniques to force variability concerning fatigue analysis (Missenard et al., 2008; Singh et al., 2010; Cashaback and Cluff, 2015). Therefore, considering the increasing interest in this topic, this review aimed to summarize the findings of studies that analyzed the variability in force production during a muscle fatigue protocol in humans using NLTs. Furthermore, factors such as relative intensity, type of muscle action, recording frequency, and signal processing will also be analyzed to understand their impact on results.

Methods

General procedure

This revision was based on the criteria of the PRISMA guidelines (Page et al., 2021). The search, inclusion and exclusion criteria were decided by consensus of all researchers. The search process was carried out in different phases. First, the research question and the search criteria were defined (Supplementary Appendix S1) based on the PICO (participants, interventions, comparisons, outcomes) recommendations (Whiting et al., 2016). Then, the search string was defined, for which different exploratory searches with different keywords were performed. To confirm which combination endorsed the lowest risk of bias, we consulted with experts in systematic reviews, using non-linear tools and in-strength training. Following this, one of the investigators (FGA) performed one first screening to discard titles that were not related to the topic (e.g., articles from the field of engineering). If there was any doubt about a paper, it was added for review at a later stage. In the selection phase by title and abstract, it was necessary to have the consensus of two researchers (FGA and FM) to be included. In the event of a discrepancy a third researcher (RS) was consulted. Once the different articles had been reviewed in depth, it was discussed and decided by consensus of the group whether they could be added to the review.

Data search and sources

The search was conducted in the following databases: Web of Science (WoS), PubMed, Scopus, and SPORTDiscus (EBSCO). The following search string was used: fatigue AND (entropy OR Lyapunov OR "detrended fluctuation analysis" OR dfa OR "hurst exponent" OR fractal* OR "recurrence quantification" OR autocorrelation). Articles published up to October 2022 were included for this review. The reference manager Mendeley was used to collect and manage the references found, as well as the excel software to manage the results obtained.

Selection process

The criteria for inclusion in the review were set to answer the target question, which was defined on the basis of the PICO items. Thus, the following inclusion criteria were used: a) published studies with their title and abstract in English, b) original studies that analyzed the effect of fatigue on humans during an action focused on force production, c) studies that applied NLTs on a signal directly related to force production (force signal or kinematic variables).

The findings from each database and the selection process are shown in Figure 1. In addition, the number of articles that were included after reading the title and abstract of each database are also shown in this same figure. Once the duplicates had been eliminated, two reviewers (FGA and FM) agreed on the articles to be included, and when there was any doubt, a third reviewer (RS) was consulted. Additional searches were performed based on the list of references, articles and reviews included, and on the ResearchGate profiles of authors, finding three additional studies that satisfied the inclusion criteria.

Extraction dates

Data extraction was carried out using a protocol agreed by the authors. The following data were extracted from the selected articles: 1) number of participants; 2) characteristics of the participants; 3) type of fatigue protocol; 3) muscle group targeted by the protocol; 4) intensity and volume of the fatigue protocol; 5) pre- and post-test performed; 6) instruments used for data recording; 7) frequency used for data recording; 8) data processing; 9) NLT used; 10) main results; 11) observations, if relevant.

Data extraction was performed by two reviewers. One performed the main extraction (FGA), and the other

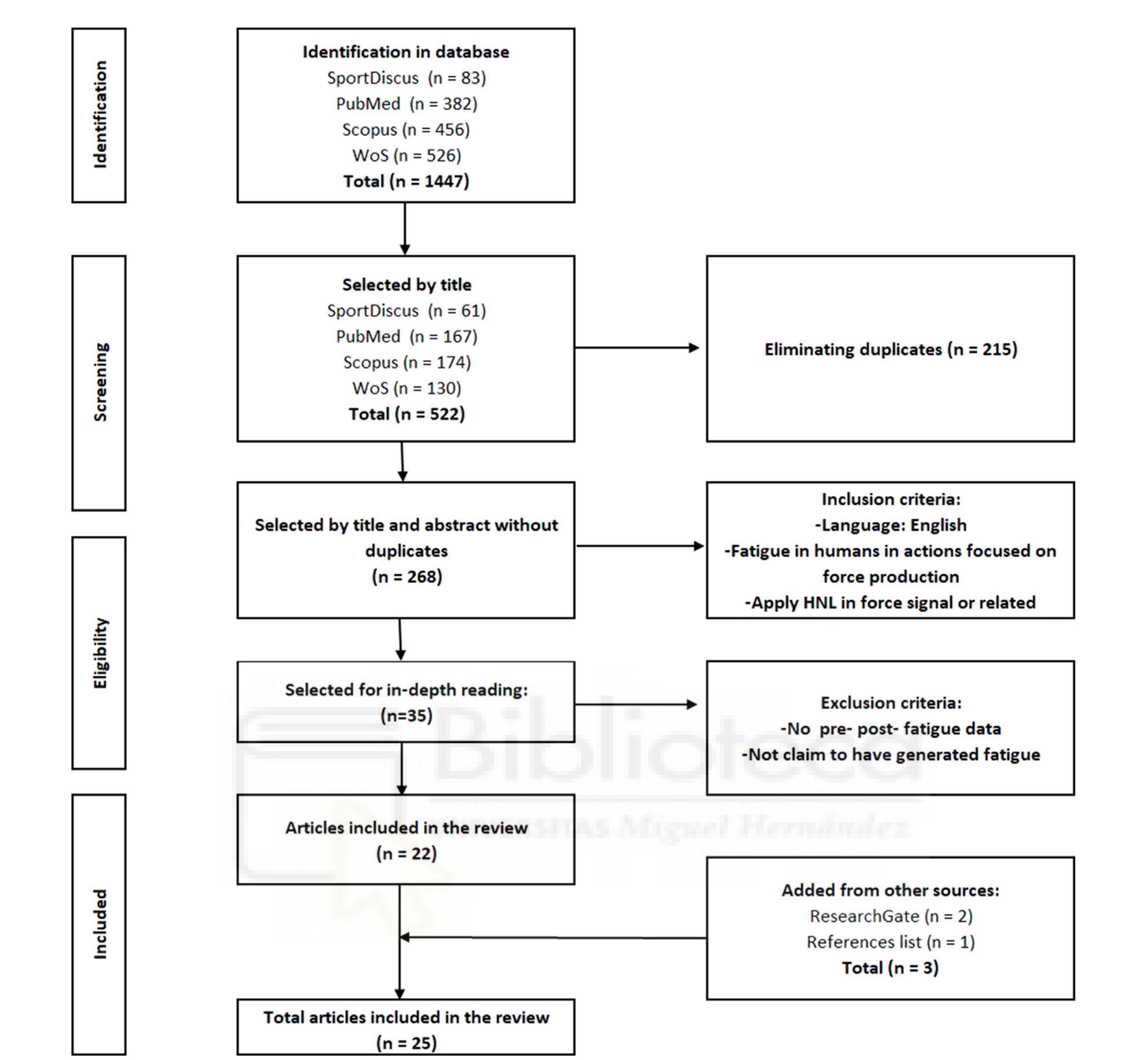

FIGURE 1
Flowchart of the search strategy.

confirmed it (CC). The data led to the following sections: 1) main results; 2) physiological explanations for changes in the structure of variability; 3) protocol factors affecting changes in the structure of variability (intensity, volume, type of action, etc.); 4) instrument or data processing factors affecting changes in the structure of variability; 5) other relevant aspects.

Risk of bias assessment

To analyze the risk of bias of each of the included articles, the Quality Assessment Tool for Before-After (Pre-Post) Studies With No Control Group scale developed by the National Institutes of Health (NIH), was used, which has been recommended for pre-post interventions without a control group (Ma et al., 2020). In addition, ROBIS recommendations (Whiting et al., 2016) were followed to analyze the risk of review bias.

Results

As a result of the search process, 35 studies were selected from the 268 reviewed and thoroughly read. After analysis according to the above criteria, 22 articles were selected and included in the review. The remaining 12 articles were not included for one of the following reasons: 1) they did not report pre and post fatigue data; 2) they did not claim to have generated fatigue with their protocol. Adding those found from other sources (ResearchGate and references), a total of 25 papers were included in this review.

In terms of risk of bias, most studies had a high NIH score (8 positive, 3 not applicable or not reported, and 1 negative), which is interpreted as high quality. Two studies stand out as potentially slightly biased, namely Bastida-Castillo et al. (2017), as it does not report the data processing completely, and Vázquez et al. (2016), as the sample size seems to be too small. As for the ROSBIS guidelines, the limitations of a narrative review have been found. Supplementary Appendix S2 and S3 reports the results of both assessments.

Twenty-five studies (Gates and Dingwell, 2008; Cowley et al., 2014; Lin et al., 2014; Pethick et al., 2015; Pethick et al., 2016; Vázquez et al., 2016; Bastida-Castillo et al., 2017; Bauer et al., 2017; Pethick et al., 2018a; Pethick et al., 2018b; Cruz-Montecinos et al., 2018; Pethick et al., 2019a; Pethick et al., 2019b; Pethick et al., 2019c; Jiang et al., 2019; Chatain et al., 2020; Guzmán-González et al., 2020; Hollman et al., 2020; Pethick et al., 2020; Tyagi et al., 2020; Zhu et al., 2020; Chatain et al., 2021; Pethick et al., 2021c; Pethick et al., 2021c; Oliveira et al., 2022), which were published between 2008 and 2022, were selected for this review. Table 1 shows the characteristics of the studies, including the sample, the protocol used to cause fatigue, the NLT used, the data acquisition and processing, and the main results.

Type of action and intensity

Isometric contractions were carried out in most of these studies (20 out of 25). The participants of 12 studies performed intermittent isometric contractions (Pethick et al., 2015; Pethick et al., 2016; Pethick et al., 2018a; Pethick et al., 2018b; Pethick et al., 2019b; Chatain et al., 2020; Pethick et al., 2020; Tyagi et al., 2020; Zhu et al., 2020; Pethick et al., 2021b; Chatain et al., 2021; Pethick et al., 2021c), in five studies sustained isometric contractions were applied (Cruz-Montecinos et al., 2018; Pethick et al., 2019a; Jiang et al., 2019; Guzmán-González et al., 2020; Oliveira et al., 2022), one study conducted rhythmic isometric contraction (Lin et al., 2014), another study combined intermittent isometric and eccentric contractions (Pethick et al., 2019c), and one study performed a quasi-isometric contraction (Vázquez et al., 2016). The remaining five studies analyzed dynamic contractions (Gates and Dingwell, 2008; Cowley et al., 2014; Bastida-Castillo et al., 2017; Bauer et al., 2017; Hollman et al., 2020) in different movements.

Regarding the volume applied during fatigue protocol, twenty-three studies applied a protocol of fatigue until failure or time limit (Gates and Dingwell, 2008; Cowley et al., 2014; Lin et al., 2014; Pethick et al., 2015; Pethick et al., 2016; Vázquez et al., 2016; Bauer et al., 2017; Pethick et al., 2018a; Pethick et al., 2018b; Cruz-Montecinos et al., 2018; Pethick et al., 2019a; Pethick et al., 2019b; Pethick et al., 2019c; Jiang et al., 2019; Chatain et al., 2020; Guzmán-González et al., 2020; Hollman et al., 2020; Pethick et al., 2020; Tyagi et al., 2020; Zhu et al., 2020; Chatain et al., 2021; Pethick et al., 2021c; Pethick et al., 2021c). In these twenty-three studies, three of them applied a low relative intensity, less than 30% of maximum contraction (Gates and Dingwell, 2008; Cowley et al., 2014; Chatain et al., 2020). Twelve studies applied a sub-maximal relative intensity between 30% and 80% of maximum (Vázquez et al., 2016; Pethick et al., 2018a; Pethick et al., 2018b; Cruz-Montecinos et al., 2018; Pethick et al., 2019c; Jiang et al., 2019; Guzmán-González et al., 2020; Tyagi et al., 2020; Zhu et al., 2020; Pethick et al., 2021b; Chatain et al., 2021; Pethick et al., 2021c). Two different types of relative intensity were analyzed in six studies: low and sub-maximal (Pethick et al., 2016; Pethick et al., 2019b; Pethick et al., 2020), low and maximum (Pethick et al., 2019a) and sub-maximal and maximum (Lin et al., 2014; Pethick et al., 2015). And two studies used body weight (Bauer et al., 2017; Hollman et al., 2020).

The other hand, two studies used different volumes to induce fatigue. Bastida-Castillo, Gómez-Carmona and Pino (2017) conducted a 4 × 10 at 65% of Repetition Maximum (RM). And Oliveira et al. (2022) carry out 5 × 20 at 30% of MVC.

Type of signal and non-linear tools used

NLTs (see Table 1) were applied in force signal or torque for 17 studies (Lin et al., 2014; Pethick et al., 2015; Pethick et al., 2016; Pethick et al., 2018a; Pethick et al., 2018b; Cruz-Montecinos et al., 2018; Pethick et al., 2019a; Pethick et al., 2019b; Pethick et al., 2019c; Chatain et al., 2020; Guzmán-González et al., 2020; Pethick et al., 2020; Tyagi et al., 2020; Chatain et al., 2021; Pethick et al., 2021c; Pethick et al., 2021c; Oliveira et al., 2022). In one study (Zhu et al., 2020) the signal force was combinate with acceleration force. The other seven studies implemented NLTs in kinematic variables, such as joint angle (Vázquez et al., 2016), distance, speed and timing error (Gates and Dingwell, 2008; Cowley et al., 2014), the coupled hip and knee (Hollman et al., 2020), acceleration signals (Bastida-Castillo et al., 2017; Bauer et al., 2017) and mechanomyography (Jiang et al., 2019). The most common NLT used was entropy measurements, assessed by ApEn (Pethick et al., 2015; Pethick et al., 2016; Bastida-Castillo et al., 2017; Pethick et al., 2018a; Pethick et al., 2018b; Pethick et al., 2019a; Pethick et al., 2019b; Pethick et al., 2019c; Pethick et al., 2020; Tyagi et al., 2020; Zhu et al., 2020; Pethick et al., 2021b; Pethick et al., 2021c), SampEn (Pethick et al., 2015; Bauer et al., 2017; Cruz-Montecinos et al., 2018; Chatain et al., 2020;

TABLE 1 General characteristics of the studies.

Authors	Sample	Protocol fatigue	NLT	Data acquisition and processing	Main results NLT
Bastida-Castillo et al. (2017)	*n* = 11 trained men	4 × 10 65% RM squat (dynamic)	ApEn	Acceleration data at 1,000 Hz. There is no information about the data processing	Decrement of complexity (decrease of ApEn) together with loss of average propulsive velocity
Bauer et al. (2017)	*n* = 86 (42 men) *n* = 59 with low pain (30 men) 39.6 ± 11.6 years *n* = 27 without low pain (12 men) 39.1 ± 12.8 years	Pre-post-test: repeated trunk flexion and extension. Fatigue protocol: isometric trunk extensors to failure	%DET + SampEn	Angular displacement and velocity at 200 Hz. Data were transformed into quaternions and filtered with low-pass Butterworth filter (6 Hz)	Participants without low back pain showed more complex behavior (increase of SampEn and decrease of %DET) in angular velocity after fatigue
Chatain et al. (2020)	*n* = 11 Healthy active men 24.1 ± 6.6 years	Isometric knee extensor, blocks of 80s at 15% MVC to failure	SampEn	Force sensor data at 2000 Hz were filtered with low-pass Butterworth filter (20 Hz) and down-sampled at 400 Hz. A Dickey-Fuller test and EMD were used	Increase of complexity in the original signal (increase of SampEn), and decrease in complexity (decrease of SampEn) after eliminating non-stationarity
Chatainet al. (2021)	*n* = 38 healthy young adults (19 men) 22.6 ± 2.9 years	Intermittent isometric contractions (8:4s) of the knee extensors at 50% MVC until task failure	RQA (DET)	Force sensor data at 2000 Hz were filtered with low-pass Butterworth filter (20 Hz) and down-sampled at 500 Hz. EMD was used	Reduction of complexity (increase of DET). Men showed more complexity than women
Cowley, Digwell and Gates (2014)	*n* = 20 healthy right-handed adults (11 men) 25 ± 2.2 years	Pre-post-test: Sawing task (dynamic). Fatigue protocol: LIFT at 10%MVC at 0.5 Hz for 3 min or failure. SAW at 25% MVC for 4 min or failure	DFA	Motion analysis system data at 120 Hz was resampled at 1,080 Hz and filtered with low-pass Butterworth filter (6 Hz)	Reduction of complexity (increase of DFA) for error in LIFT and speed in SAW. Men showed more complexity than women. Increment of complexity (decrease of DFA) for speed in LIFT
Cruz-Montecinos, et al. (2018)	*n* = 15 healthy men, age between 18 and 25, right-handed, 21 ± 1 years	Isometric elbow flexor 50% MVC until failure	SampEn	Load cell data at 1000 Hz were filter with low-pass Butterworth filter (12 Hz)	Reduction of complexity (decrease of SampEn)
Gates and Dingwell (2008)	*n* = 14 healthy right-handed (9 men) 27 ± 2.7 years	Sawing task (dynamic) to 15% of this maximum pushing/pulling force until failure	DFA	Motion analysis system data at 60 Hz were resampled at 1,080 Hz and filtered with low-pass Butterworth filter (6 Hz)	Increase of complexity in the original signal (decrease of DFA) in speed and timing error
Guzmán-Gónzalez et al. (2020)	*n* = 12 healthy men right-handed dominance, with sedentary lifestyle 20 ± 2 years	Isometric handgrip flexor 50% MVC until failure	SampEn	Force signal data at 1,500 Hz were filtered with low-pass Butterworth filter (12 Hz)	Reduction of complexity (decrease SampEn)
Hollman, et al. (2020)	*n* = 40 healthy adults (14 men) 23.85 ± 1.7 years	Pre-post-test: 20 step-down task with their preferred stance limb. Fatigue of the hip extensors protocol: isometric trunk extensors to failure. Fatigue sham control group: push-ups until failure	cRQA + cShaEn	Motion analysis system data at 100 Hz were smoothed with a Woltring quintic spline filter (20 mm mean square error)	Reduction of complexity (decrease of cross determinism and mean line) in fatigue hip extensor group

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TABLE 1 (*Continued*) General characteristics of the studies.

Authors	Sample	Protocol fatigue	NLT	Data acquisition and processing	Main results NLT
Jiang, et al. (2019)	*n* = 10 healthy men 24 ± 2 years	Isometric contraction of the upper trapezius at 50% MVC until failure	LZC + FEN + LyE	Acceleration data at 1,000 Hz. There is no information about the data processing	Reduction of complexity (decrease of SampEn) in the three conditions (control, self-regulated dual task and regulated dual task)
Lin, Kuo and Hwang (2014)	*n* = 16 healthy men right-handed dominance and between 20 and 24 years	Isometric power gripping in a rhythmic manner at 50–100% MVC until failure	MSE (SampEn)	Digital force gauge data at 1,000 Hz were down-sampled to 100 Hz and filtered with low-pass Butterworth filter (6 Hz)	Increase of complexity (increase of SampEn). In MSE, increase of complexity in high time scale (increase MSE) and reduction of complexity (decrease in low scale time) in low time scale
Oliveira et al. (2022)	*n* = 10 healthy young adults (8 men) 24.9 ± 5.4 years	Pre-post-test: isometric contraction from ankle plantar flexors at 30% MVC for 90s. Fatigue protocol: 5 × 20 unilateral calf raises, 1-min rest between sets	SampEn	Isokinetic dynamometer data at 1,000 Hz. The last 30s were down-sampled to 50 Hz, and analyzed	Reduction of complexity (decrease of SampEn)
Pethick et al. (2020)	*n* = 10 healthy participants (6 men) 25.9 ± 6.7 years	Intermittent isometric (6s: 4s) knee extension at 40% MVC until failure, in ischemic preconditioning and sham treatment groups	ApEn + DFA	Isokinetic dynamometer data at 1,000 Hz. Analyzed the most stable 5s	Reduction of complexity (decrease of ApEn and increase DFA) in both conditions, but with ischemic preconditioning the reduction of complexity was attenuated
Pethick et al. (2015)	*n* = 11 healthy participants (10 men) 25 ± 5.6 years	Intermittent isometric (6s: 4s) knee extension at 40% and maximal MVC until failure	ApEn + SampEn + DFA	Isokinetic dynamometer data at 1,000 Hz. Analyzed the most stable 5s	Reduction of complexity (decrease of ApEn and SampEn and increase DFA) in both conditions, but with submaximal intensity the reduction of complexity was attenuated
Pethick et al. (2016)	*n* = 9 healthy participants (5 men) 25.3 ± 5.8 years	Intermittent isometric (6s: 4s) four trails above CT (approx. 25–35% MVC) and two trials at 50% and 90% of CT	ApEn + DFA	Isokinetic dynamometer data at 1,000 Hz. Analyzed the most stable 5s	Reduction of complexity (decrease of ApEn and increase DFA) in trials above TC but no significant differences below TC
Pethick et al. (2018a)	*n* = 11 healthy participants (7 men) 26.1 ± 6 years	Intermittent isometric (6s: 4s) knee extension at 40% MVC until failure with and without caffeine	ApEn + DFA	Isokinetic dynamometer data at 1,000 Hz. Analyzed the most stable 5s	Reduction of complexity (decrease of ApEn and increase DFA) in both conditions, but with caffeine the reduction of complexity was attenuated
Pethick et al. (2018b)	*n* = 9 healthy participants (5 men) 23.9 ± 5.7 years	Intermittent isometric (6s: 4s) knee extension at 40% MVC until failure with different fatigue conditions ipsilateral, contralateral, ipsilateral with occlusions and contralateral occlusion trials	ApEn + DFA	Isokinetic dynamometer data at 1,000 Hz. Analyzed the most stable 5s	Reduction of complexity (decrease of ApEn and increase DFA) in all conditions, except occlusion ipsi-lateral in which initial complexity was lower

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TABLE 1 (*Continued*) General characteristics of the studies.

Authors	Sample	Protocol fatigue	NLT	Data acquisition and processing	Main results NLT
Pethick et al. (2019a)	n = 9 healthy participants (7 men) 24.6 ± 5.5 years	Isometric knee extension at 20% and maximal MVC until failure	ApEn + DFA	Isokinetic dynamometer data at 1,000 Hz. Each of the experimental trials was divided into 10 s intervals, using the most stable 5 s	Reduction of complexity (decrease of ApEn and increase DFA) in maximal, but in submaximal only decrease of ApEn
Pethick et al. (2019b)	n = 13 healthy participants (10 men) 27.6 ± 6.4 years	Intermittent isometric (6s: 4s) knee extension at 20% and 40% MVC until failure	ApEn + DFA	Isokinetic dynamometer data at 1,000 Hz. Analyzed the most stable 5s	Reduction of complexity (decrease of ApEn and increase DFA) in maximal intensity but non-significant at 20% MV
Pethick et al. (2020)	n = 12 healthy participants (7 men) 24.7 ± 4.8 years	Intermittent isometric (6s: 4s) three trails above CT (approx. 25–35% MVC) and four trials at ± 1 and 2 ES of CT	ApEn + DFA	Isokinetic dynamometer data at 1,000 Hz. Analyzed the most stable 5s	Reduction of complexity (decrease of ApEn and increase DFA) at 40% MVC but no significant differences at 20% MVC
Pethick et al. (2021b)	n = 11 healthy participants (9 men) 26.3 ± 6 years	Intermittent isometric contractions (6s: 4s) knee extension at 50% MVC, in different knee angles: 30°, 60° and 90° until failure or for 30 min	ApEn + DFA	Isokinetic dynamometer data at 1,000 Hz. Analyzed the most stable 5s	Reduction of complexity (decrease of ApEn and increase DFA) in 90° and 60° angle but no in 30°
Pethick et al. (2019c)	n = 10 healthy participants (8 men) 24.8 ± 6.2 years	Intermittent isometric (6s: 4s) knee extension at 50% MVC until failure and eccentric contraction until than MVC >40%	ApEn + DFA	Isokinetic dynamometer data at 1,000 Hz. Analyzed the most stable 5s	Reduction of complexity (decrease of ApEn and increase DFA) in both conditions, but in eccentric recovery it was slower
Tyagi, et al. (2020)	n = 42 adults 20 with T1D (9 men) and 22 control (10 men) 22.7 ± 4.5 years	Intermittent isometric (15s: 15s) handgrip at 30% MVC until inability of maintaining contractions or voluntary fatigue	ApEn	Data from the intermediate 10s of the hand-held dynamometer at 1,000 Hz were filtered with a Butterworth low-pass filter (15 Hz)	Reduction of complexity (decrease of ApEn)
Vazquez et al. (2016)	n = 7 caucasian men 22.34 ± 3.5 years	Quasi-isometric elbow flexion of 90° at 80% 1RM until failure	DFA	Electro goniometer data at 50 Hz. Amplitude resolution was 0.1° for each extremity do not report to inform about the processing of data	Reduction of complexity (increase DFA)
Zhu et al. (2020)	22 healthy (10 men) and 20 with type 1 diabetes (9 men)	Intermittent isometric (15s: 15s) handgrip at 30% MVC until exhaustion	ApEn	Data from the intermediate 10s of the hand-held dynamometer at 1,000 Hz were filtered with a Butterworth low-pass filter (15 Hz) and of the accelerometer at 45 Hz were filtered with a Butterworth high-pass filter (3 Hz)	Reduction of complexity (decrease of ApEn) in both instrumentals and both groups

Note. RM, repetition maximum; MVC, maximum voluntary contraction; CT, critical torque; SAW, sawing task; LIFT, shoulder flexor; ES, standard error; ApEn, Approximate Entropy; SampEn, Sample Entropy; FEN, fuzzy entropy; MSE, multi scale entropy; cShaEn, cross Shannon Entropy; LZC, Lempel-Ziv complexity; LyE = Lyapunov Exponent; RQA, recurrence quantification analyses; cRQA, cross Recurrence Quantification Analyses; DET, determinism; DFA, detrended fluctuation analysis; EMD, empirical mode decomposition.

Guzmán-González et al., 2020; Oliveira et al., 2022), Multi Scale Entropy (MSE) (Lin et al., 2014), Cross Shannon Entropy (Hollman et al., 2020) and FuzzyEn (Jiang et al., 2019). DFA was also applied in 12 studies (Gates and Dingwell, 2008; Cowley et al., 2014; Pethick et al., 2015; Pethick et al., 2016; Vázquez et al., 2016; Pethick et al., 2018a; Pethick et al., 2018b; Pethick et al., 2019a; Pethick et al., 2019b; Pethick et al., 2019c; Pethick et al., 2020; Pethick et al., 2021b; Pethick et al., 2021b). The tools that were used the least were, Lyapunov Exponent (Jiang et al., 2019), Recurrence Quantification Analyses (RQA) (Bauer et al., 2017; Hollman et al., 2020; Chatain et al., 2021), and Lempel-Ziv complexity (Jiang et al., 2019).

Data acquisition and processing

Most of the studies (19 out of 25) registered signals at 1,000 Hz (Lin et al., 2014; Pethick et al., 2015; Pethick et al., 2016; Bastida-Castillo et al., 2017; Pethick et al., 2018a; Pethick et al., 2018b; Cruz-Montecinos et al., 2018; Pethick et al., 2019a; Pethick et al., 2019b; Pethick et al., 2019c; Jiang et al., 2019; Pethick et al., 2020; Tyagi et al., 2020; Pethick et al., 2021b; Pethick et al., 2021b; Oliveira et al., 2022) or higher (Chatain et al., 2020; Guzmán-González et al., 2020; Chatain et al., 2021). Lower sampling frequencies (lower than 200 Hz) were used in five of the 25 studies. (Gates and Dingwell, 2008; Cowley et al., 2014; Vázquez et al., 2016; Bauer et al., 2017; Hollman et al., 2020). One study combined a high-frequency sample in signal force and low-frequency sample in acceleration signal (Zhu et al., 2020). Regarding data processing, four studies subsampled the time series at 50 Hz (Oliveira et al., 2022), at 100 Hz (Lin et al., 2014), at 400 Hz (Chatain et al., 2020) and at 500 Hz (Chatain et al., 2021) and two oversampled at 1,080 Hz (Gates and Dingwell, 2008; Cowley et al., 2014). As for filters, none were applied in 13 studies. In those studies which did use filters, the most common one was a low-pass filter with different cut-off frequencies: 6 Hz (Gates and Dingwell, 2008; Cowley et al., 2014; Lin et al., 2014; Bauer et al., 2017), 12 Hz (Cruz-Montecinos et al., 2018; Guzmán-González et al., 2020), 15 Hz (Tyagi et al., 2020; Zhu et al., 2020) and 20 Hz (Chatain et al., 2020; Chatain et al., 2021). Only one study (Zhu et al., 2020) applied a high pass filter on accelerations signals, with a cut-off frequency of 3 Hz. Hollman et al. (2020) applied a Woltring quintic spline filter for smooth trajectories. Moreover, Chatain et al. (2020, 2021) used a Dickey-Fuller test for detecting non-stationarity and Empirical Mode Decomposition to obtain a stationary signal.

Relation between fatigue and force variability

Seventeen studies showed a significant decrease in complexity in all variables in which NLTs were used in the development of fatigue (Pethick et al., 2015; Vázquez et al., 2016; Bastida-Castillo et al., 2017; Pethick et al., 2018a; Pethick et al., 2018b; Cruz-Montecinos et al., 2018; Pethick et al., 2019a; Pethick et al., 2019c; Jiang et al., 2019; Guzmán-González et al., 2020; Hollman et al., 2020; Pethick et al., 2020; Tyagi et al., 2020; Zhu et al., 2020; Chatain et al., 2021; Pethick et al., 2021c; Oliveira et al., 2022). One study (Pethick et al., 2021a) reported a decrease in complexity when the contraction was performed at angles of 60° and 90° at the knee, but not at 30°. Five studies showed different relationships between complexity and fatigue depending on the intensity of the fatigue protocol, the NLTs used, the signal processing or the variable analyzed. Of these five studies two found a decrease in complexity after applying high and sub-maximal relative intensity, but there was no change in complexity with fatigue caused by the application of low intensities (Pethick et al., 2016; Pethick et al., 2019b). Lin, Kuo and Hwang (2014), using MSE, reported a complexity increase at high time scales, and a decrease at low time scales. Chatain et al. (2020) observed a complexity increase due to fatigue in the original signal, but after removing the non-stationarity of the signal, they observed that complexity decreased after fatigue. (Cowley, Dingwell and Gates (2014) found that complexity decreased in the speed variability under general fatigue, but it increased under localized fatigue. On the other hand, two studies showed an increase in complexity due to fatigue (Gates and Dingwell, 2008; Bauer et al., 2017).

Discussion

This review has examined the current knowledge on the application of NLTs to analyze the relationship between the complexity of force variability and the fatigue state of the organism. Most of the studies reviewed reported a decrease in the complexity of force variability along with the development of fatigue. However, some studies did not report the same results. Therefore, it is necessary to review the proposed mechanisms to explain the possible causes of the decrease in complexity, as well as the factors that apparently modulate the results: intensity, type of contraction, recording frequency, and signal processing.

Possible mechanisms involved in the loss of complexity

It has been suggested that force variability reflects the interaction between the components of the neuromuscular system (Slifkin and Newell, 1999) and the control loops governing the force output (Fiogbé et al., 2021). Most included studies found a loss of complexity caused by fatigue in tasks with relatively short duration and sub-maximal to maximum relative intensity. In these tasks, fatigue is expected to be related to peripheral factors. Some studies support this claim by shopping one-sidedly between fatigued and non-fatigued limbs (Oliveira et al., 2022; Pethick et al., 2018b). Thus, some studies in this review have interpreted that a loss of complexity may be caused, or at least be affected, by increased metabolic rate (Pethick et al., 2016; Pethick et al., 2018b; Pethick et al., 2019a; Pethick et al., 2021c), reduced force-producing capacity in the motor units (MU) (Pethick et al., 2015; Pethick et al., 2016), or muscle damage caused by eccentric contractions (Pethick et al., 2019c). Although there is no clear explanation Pethick et al. (2021a) speculated that peripheral fatigue mediated by metabolite accumulation may lead to changes in the discharge of motor units, being responsible for changes in complexity.

Secondly, it has also been pointed out that central mechanisms, such as motor unit synchronization and firing rate, affect the loss of complexity. Different studies in this review agree that one of the main mechanisms that may affect this complexity loss is in MU recruitment (Lin et al., 2014; Pethick et al., 2015; Pethick et al., 2018b; Cruz-Montecinos et al., 2018; Pethick et al., 2019a; Pethick et al., 2019b; Pethick et al., 2021a; Pethick et al., 2021a). This is consistent with other studies that have linked changes in organization and activity of MUs to changes in "motor output" fluctuations (Taylor et al., 2003; Adam and De Luca, 2005; Madeleine and Farina, 2008; Skurvydas et al., 2010). Thus, the decrease in the ability to produce force requires a greater synchronization of motor neurons. This increase in synchronization means that the degrees of freedom of the system are reduced, thus reducing complexity. It should be noted that some authors have observed that, although timing is strongly related to variability, it seems that common input also influences changes in variability (Farina and Negro, 2015). On the other hand, some studies have related the loss of complexity to changes in firing rate, which may be modulated by factor such as relative intensity or time contraction. However, literature shows disparate results regarding the relationship between fatigue and the firing rate (Adam and De Luca, 2005; Babault et al., 2006; Boyas and Guével, 2011; Castronovo et al., 2015). Some studies have related this loss of complexity with an increase in the firing rate (Lin et al., 2014; Cruz-Montecinos et al., 2018), while other studies interpret it as a decrease in this rate (Pethick et al., 2015; Bastida-Castillo et al., 2017). These disparate results may be due to the heterogeneity of the protocols used (Boyas and Guével, 2011).

In addition to the above mechanisms, some studies support the influence of central factors on the loss of complexity as they report that with increasing cognitive demands (central level) there was a greater decrease in complexity in force production compared to tasks with lower cognitive demands (Cruz-Montecinos et al., 2018; Guzmán-González et al., 2020; Tyagi et al., 2020). Furthermore, caffeine consumption, which affects the central nervous system, has also been shown to slow down the loss of complexity that is caused by the onset of fatigue (Pethick et al., 2018a).

Different authors have discussed the relationship between fatigue of central and peripheral origin, with one affecting the other (Gandevia, 2001; Boyas and Guével, 2011). It has been suggested that changes at the peripheral level produced by fatigue are compensated by changes at the central level (Taylor and Gandevia, 2008). For example, when the capacity to produce force is reduced due to alterations at the peripheral level, the increase in active MU is activated as a compensation mechanism (Gandevia, 2001; Pethick et al., 2015; Pethick et al., 2019b). It has also been suggested that afferent outputs from the muscle affect central levels (Taylor and Gandevia, 2008; Boyas and Guével, 2011), so changes in a central level due to fatigue would be useful to protect the muscle from further peripheral fatigue (Gandevia, 2001). Therefore, attempting to understand changes in force complexity solely based on of the central or peripheral origin of fatigue may not adequately portray the process that triggers fatigue mechanisms, which are not independent elements, but are interconnected. Furthermore, Lin et al. (2014) considered that the loss of complexity observed at the shorter time scale (1–5) could be related to the increase in active motoneurons d, and to the increase in excitatory impulses coming from the central nervous system compensating for the loss of force. Meanwhile, the increase in complexity observed over longer time scales (25–40) could result from motor noises associated with fatigue. The opposing time-scale trends in completeness with the development of fatigue could reflect the interaction of at least two regulatory systems, one voluntary and one involuntary, operating over a wide range of time scales, and it could reflect the central and peripheral mechanisms mentioned above. Thus, as suggested by Pethick et al., (2021b), both peripheral and central processes appear to be involved in the loss of complexity at the onset of fatigue. We suggest understanding this as a feedback loop in which different peripheral triggers leading to a decrease in force production are compensated by central mechanisms, resulting in a decrease in complexity. This could be caused by the reduction of the degrees of freedom needed to meet the task demands. Thus, the complexity in the different force production signals would decrease due to fatigue, indicating that the organism is in a situation where it is less flexible and has a reduced adaptive capacity.

Intensity and type of contraction

The intensity of the contraction seems to be one relevant factor involved in the change in complexity due to fatigue. Most studies assessing actions at sub-maximal or maximum intensity have reported a decrease in complexity after the fatigue protocol (Pethick et al., 2015; Pethick et al., 2016; Vázquez et al., 2016; Bastida-Castillo et al., 2017; Pethick et al., 2018a; Pethick et al., 2018b; Cruz-Montecinos et al., 2018; Pethick et al., 2019a; Pethick et al., 2019b; Pethick et al., 2019c; Guzmán-González et al., 2020; Pethick et al., 2020; Tyagi et al., 2020; Zhu et al., 2020; Chatain et al., 2021; Pethick et al., 2021c; Oliveira et al., 2022). One study (Pethick et al., 2021a) reported a loss of complexity at submaximal intensity (50% MVC) in knee extension when the knee was at 90° and 60° of extension (0° full extension), but not at 30°. The authors state that in other studies, to achieve similar responses at 90° of extension, the relative intensity had to be increased to 30°.

Only one study showed contradictory results according to the time scale analyzed using MSE (Lin et al., 2014). It should be noted that this type of analysis allows us to analyze how complexity behaves at different temporal scales, which could be related to different system elements involved. Moreover, according to Stergiou (2016), if entropy (SampEn in this case) tends to decrease with increasing time scale, it could mean that the relevant information is only at low time scales, which could be related to the voluntary control mentioned above. In this case, the contradictory results may be because they performed sinusoidal isometric contractions, as reported by Vaillancourt and Newell (2003) who found different trends depending on whether constant or sinusoidal isometric actions were performed. It may also be the case that, while entropy measures typically analyze a single time scale, the MSE examines different scales within the same time series (Costa et al., 2005). As mentioned above, this could be related to the type of control (voluntary or involuntary). Thus, it may be that this type of actions may lead to an increase in complexity in involuntary control, but a decrease in complexity in voluntary control.

Papers that analyzed exercises carried out at low relative intensity did not follow the aforementioned trend between fatigue and complexity, revealing no significant differences (Pethick et al., 2016; Pethick et al., 2019a; Pethick et al., 2019b) or even showing an increase in complexity with the development of fatigue (Gates and Dingwell, 2008). These differences depending on relative intensity could be because the fact that the organism would not be in a sufficiently compromised situation to show a loss of complexity during low-intensity exercises. For instance, it has been found that there is an inverse relationship between metabolic rate and complexity (Pethick et al., 2019b). If the metabolic rate is not increased enough at low relative intensity, complexity may not decrease. The same applies to muscle oxygenation (Pethick et al., 2019b) and changes in movement patterns depending on the relative intensity required (Gates and Dingwell, 2008; Cowley et al., 2014). Consequently, if these changes are irrelevant, the central control mechanisms will adjust the system's requirements without significant loss of complexity. Pethick et al. (2016) noticed that loss of complexity happens because of intensities exceeding the critical torque, which is approximately 20–25% of the MVC. In another study, it was found that this critical torque is not an exact threshold but a transition phase (Pethick et al., 2021b). It is important to keep this in mind, since below this critical torque or critical power, the organism may not have important changes in homeostasis (Enoka and Duchateau, 2016). Moreover, as noted above, they may even be sensitive to the angle at which the force is produced, as the relative intensity for an effort will change as a function of factors such as the length of the cross-bridge or lever arm, for example. Thus, while they may be a development of fatigue, it may not be significant enough to affect complexity or the effect may be minimal. This could explain why the NLTs seem to be less sensitive at low intensities, thus showing no loss of complexity.

Another aspect that seems to affect the results is the type of muscle activation. Most studies measured isometric actions at sub-maximal and high intensities, resulting in a decrease in complexity due to fatigue (Pethick et al., 2015; Pethick et al., 2016; Vázquez et al., 2016; Pethick et al., 2018a; Pethick et al., 2018b; Cruz-Montecinos et al., 2018; Pethick et al., 2019a; Pethick et al., 2019b; Jiang et al., 2019; Chatain et al., 2020; Guzmán-González et al., 2020; Pethick et al., 2020; Tyagi et al., 2020; Zhu et al., 2020; Pethick et al., 2021a; Chatain et al., 2021; Pethick et al., 2021c; Oliveira et al., 2022). But only one study, Pethick et al. (2019c), analyzed eccentric and isometric contractions, reporting greater fatigue and muscle damage after the eccentric contractions, and longer recovery time in eccentric actions (Pethick et al., 2019c). In that study, linear measures of variability, such as standard deviation and coefficient of variation, returned to baseline in a shorter period of time (10 and 30 min, respectively) than measures of complexity. ApEn and DFA maintained low complexity values for a longer period showing that the organism had not yet recovered, although it is possible that it is due to a greater extent to muscle damage. Thus, this study also suggests that the NLTs are more sensitive than traditional measures of variability.

In addition, there were five studies that analyzed dynamic actions and only two of these five studies found a loss of complexity due to fatigue (Bastida-Castillo et al., 2017; Hollman et al., 2020). The rest of them showed controversial results. Two studies found an increase in complexity (Gates and Dingwell, 2008; Bauer et al., 2017), one study found an increase or decrease of complexity depending on the variable analyzed (Cowley et al., 2014). It has to be pointed out that two of the studies that found an increase of complexity due to fatigue, conducted actions at low intensities (Gates and Dingwell, 2008; Cowley et al., 2014), and it is possible that these results are mediated by relative intensity, as mentioned above. Is should also be noted that two of the studies (Bauer et al., 2017; Hollman et al., 2020) used body weight loading as part of the fatigue protocol and found opposite results. These studies found contrary results, with Bauer et al. (2017) reporting an increase in complexity, while Hollman et al. (2020) reported a decrease. Both fatigued the lumbar musculature, using the Biering-Sorensen test, in the fatiguing protocol, but in the pre- and post-tests there was a greater involvement of the hip extensors. It should be noted that Hollman et al. (2020) compared the lumbar muscle fatigue protocol with a control protocol (push-up to failure protocol) and reported that changes in complexity only occurred in the lumbar muscle protocol, which was more specific than the other. We interpret that these controversial results in dynamic actions have three causes. Firstly, the methodological heterogeneity of the studies. Secondly, because of the influence of relative intensity, as mentioned above. Finally, due to the differences between dynamic and isometric actions. Differences in the involvement of the central and peripheral levels in fatigue have been reported, depending on whether the actions are isometric or concentric (Allen et al., 2008). Furthermore, given the nature of dynamic actions, it is to be expected that these have a higher non-stationarity component than isometric actions. This increased non-stationarity will affect the results, since some NLTs follow algorithms that assume a higher degree of stationarity (Stergiou, 2016). Thus, in order to obtain robust and reliable results, some of the HNLs mentioned above need stationarity in the time series in which they are applied (e.g., the LyE and entropy measures) (Caballero et al., 2014). Therefore, signal processing can play an important role in the study of complexity and its relation to fatigue.

Influence of signal recording and processing

Both the nature of the signal and its processing (e.g., sample frequency, filtering) are significant factors when using NLTs (Stergiou, 2016). In order to select the most appropriate sample frequency, both the purpose of the analysis and the system's behavior (Stergiou, 2004, 2016) should be considered. Although the studies analyzed in this review have not looked into this matter, the results seem to suggest that it is advisable to use high recording frequencies to capture the dynamics of fluctuations in force production. Forrest et al. (2014) found that frequencies below 200 Hz were not suitable for ApEn analysis on force signals. It appears that recording frequencies below this threshold may modify the shape of the recorded signal and prevent capturing the dynamics of variations in force production. Most of the studies in this review that used recording frequencies higher than 200 Hz (n = 20) reported a loss of complexity along with the development of fatigue (Pethick et al., 2015; Pethick et al., 2016; Pethick et al., 2018a; Pethick et al., 2018b; Cruz-Montecinos et al., 2018; Pethick et al., 2019a; Pethick et al., 2019b; Pethick et al., 2019c; Guzmán-González et al., 2020; Pethick et al., 2020; Zhu et al., 2020; Pethick et al., 2021b; Pethick et al., 2021c), exception the study by Chatain et al. (2020). Although Chatain et al. (2020) found an increase in complexity in the original signal after the fatigue protocol, they found a decrease in complexity when the non-stationarity of the signal was eliminated. Studies using recording frequencies of 200 Hz or lower (n = 6) reported results in different directions (Lin et al., 2014; Vázquez et al., 2016; Bauer et al., 2017; Hollman et al., 2020; Zhu et al., 2020; Oliveira et al., 2022). Two of these studies oversampled the signal, increasing the length of the data sets obtained in the record, and reported that fatigue caused an increase in complexity in some measured variables (Gates and Dingwell, 2008; Cowley et al., 2014), and a decrease in others (Cowley et al., 2014). Furthermore, it has been observed that in previous reviews on the use of NLTs, these have shown the disadvantage of obtaining non-reliable results when the length of time series is artificially increased as this signal processing may significantly influence the results of the analysis, which is not advisable (Stergiou, 2016).

Once the recording frequency has been determined, the application of a filter can be considered. To consider the need for a filter we have to know the characteristics of the signal (e.g., how noisy it is). On this basis the type of filter will also be decided. While in some cases it has been recommended to avoid filtering signals to analyze the structure of the variability of a time series (Caballero et al., 2014; Stergiou, 2016), one of the most commonly applied treatments is the low-pass filter to prevent the occurrence of "unwanted" noise. The analyzed studies reported low-pass filters with cut-off frequencies of 6 Hz (Gates and Dingwell, 2008; Cowley et al., 2014; Lin et al., 2014; Bauer et al., 2017), 12 Hz (Cruz-Montecinos et al., 2018; Guzmán-González et al., 2020), 15 Hz (Tyagi et al., 2020; Zhu et al., 2020), 20 Hz (Chatain et al., 2020; Chatain et al., 2021), and in one of the studies a Woltring quintic spline filter (Hollman et al., 2020) was used. Two of these studies showed a clear increase in complexity (Gates and Dingwell, 2008; Bauer et al., 2017), three showed mixed results (Cowley et al., 2014; Lin et al., 2014; Chatain et al., 2020), and five revealed a decrease in complexity (Cruz-Montecinos et al., 2018; Guzmán-González et al., 2020; Hollman et al., 2020; Tyagi et al., 2020; Chatain et al., 2021). It seems that when the filter cut-off is made at a frequency of 6 Hz the results become less consistent. This could be because, as some authors have pointed out (Singh et al., 2010; Novak and Newell, 2017), frequencies ≤4 Hz reflect voluntary control loops, while frequencies between 8 and 12 Hz reflect involuntary control loops such as physiological tremor. Based on this, Zhu et al. (2020) used a high-pass filter with a 3 Hz cutoff frequency to analyze the complexity of the tremor, reporting loss of complexity in both the force signal and tremor in the acceleration signal. Thus, if we use low-pass filters above 12 Hz it is possible that the signal hardly varies at all, and therefore the results are more consistent. On the other hand, it can be interesting to analyze the signals at different frequency widths to find out how the different voluntary and involuntary control systems affect the complexity of the signal.

Finally, it should be noted that NLTs are sensitive to the stationarity of the time series (Peng et al., 2009; Caballero et al., 2013), which may have influenced the results reported by the studies reviewed. Two studies (Chatain et al., 2020; Chatain et al., 2021) applied Empirical Mode Decomposition (EMD) to reduce the non-stationarity of the signal. The comparison between the original and the treated signal was only performed in one of them (Chatain et al., 2020). In that study the authors observed that complexity decreased due to fatigue when non-stationarity was reduced, while it increased in the original signal. This was observed at low intensities (15% MVC), and it suggests that the non-stationarity of the signal affects the sensitivity of NLTs, although further research is needed to explore this methodological aspect in the application of these tools when analyzing force variability. Moreover, non-stationarity can be expected to have a bigger impact on dynamic actions. Thus, it would be interesting to verify if applying this type of method improves the robustness and reliability of NLTs to analyze fatigue in non-isometric contractions.

Limitations, conclusion and future perspectives

The main limitations of this review were the heterogeneity of protocols, both of the NLTs used and of the different signal treatments, which makes it difficult to draw solid conclusions. The low number of studies on dynamic actions was another significant limitation, which indicating the difficulty of performing non-linear analyses on this type of actions. In addition to the above limitations, some factors can modify the complexity values, such as pathologies (Bauer et al., 2017; Tyagi et al., 2020), or intrinsic characteristics of the participant such as gender (Duan et al., 2018; Chatain et al., 2021).

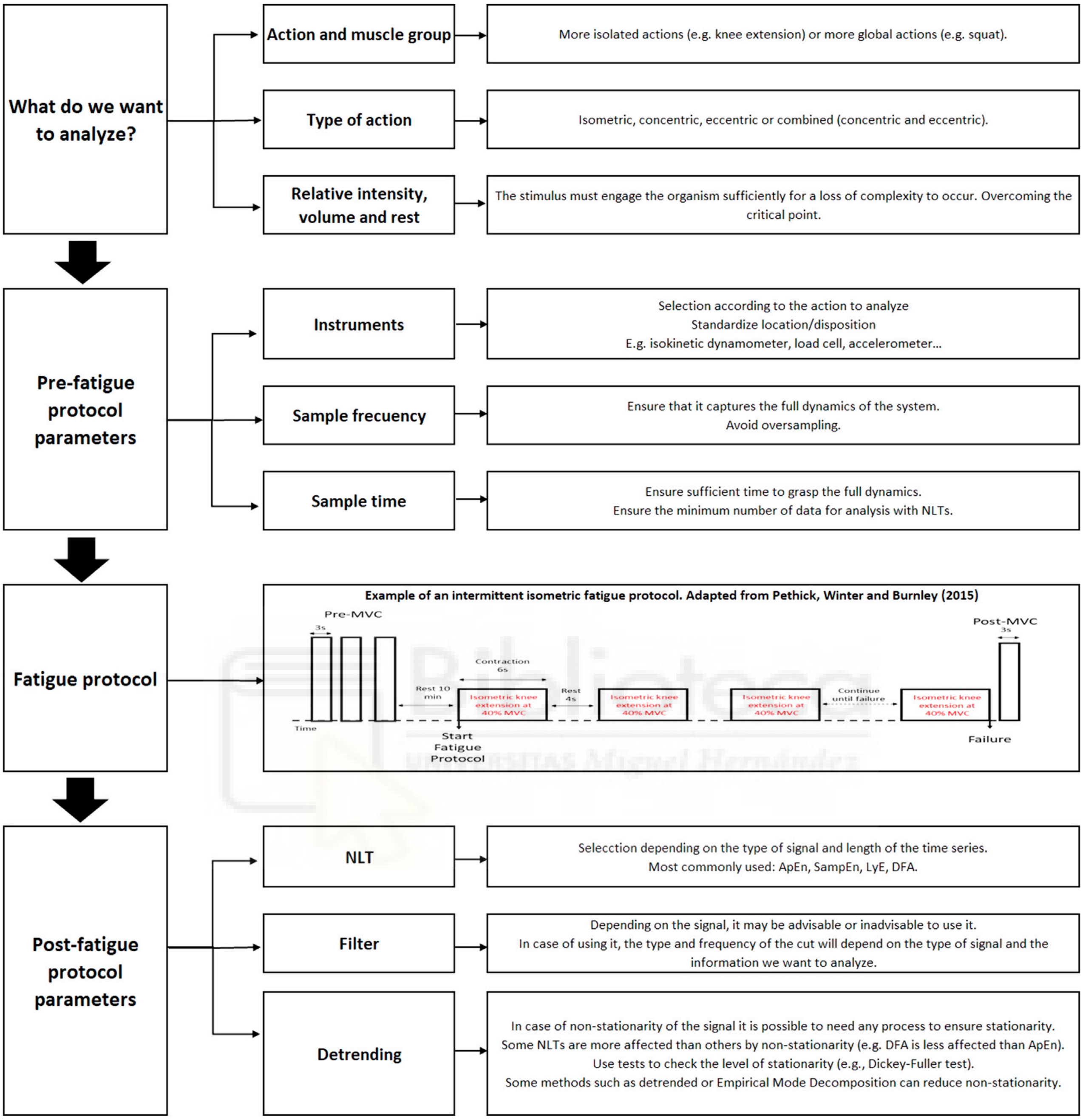

FIGURE 2
Flowchart with the steps to analyse the structure of variability in kinetic and kinematic signals.

Therefore, these variables should be considered in future work relating fatigue to complexity.

As mentioned above, a relationship has been suggested between fatigue and loss of complexity in isometric actions at a relative intensity that engages the body (above the critical point). This loss of complexity appears to reflect changes at the central level that occur to compensate for alterations at the peripheral level. This clear relationship has not been observed in dynamic actions, where factors such as non-stationarity may hinder the application of NLTs. This review has highlighted the importance of proper selection of the recording method and signal processing. Thus, the following are suggested as practical recommendations for analyzing force variability (see Figure 2). Based on the studies reviewed, it is suggested that recording frequencies of 200 Hz are adequate to capture the dynamics of the system. Low-pass filters with cut-off frequencies above 12 Hz do not seem to be particularly influential on the results. And it is also possible that analyzing using filters with cut-off ranges with frequencies of 12 Hz allows different aspects of force control to be studied (e.g., <4 Hz to study voluntary control or 8–12 Hz to study involuntary control). However, non-stationarity should be a factor to be considered, especially in rhythmic isometric or dynamic actions. Methods such as the EMD can be effective in eliminating the non-stationarity of the signal. In addition, it may be advisable to use methods that allow to analyze the structure on different time scales (e.g., MSE), as the way these methods develop in different structures of the system can then be analyzed. Finally, as recommended by some authors (Harbourne and Stergiou, 2009; Caballero et al., 2014; Stergiou, 2016), the use of different NLTs is also advisable, since these can measure complementary aspects of variability (regularity, autocorrelation, etc.).

Further studies are needed in two directions. On the one hand, an in-depth study of dynamic contractions, as they are the most frequently performed in sport and in everyday life, and are the ones about which we have the least information. In this way, it will be possible to know if there is a relationship between fatigue and the loss of complexity in these contractions, as well as to know the correct methodology to apply. On the other hand, it would be convenient to study whether it is possible to use these tools in dynamic and isometric contractions to monitor fatigue in training sessions. In this way, it would be possible to control the state of fatigue in which the organism finds itself, allowing safer and more efficient training programs to be carried out. In addition, since no study specifically addresses the neural mechanisms causing the loss of complexity, it would be desirable to add measures to understand the neural contributions to the loss of complexity, e.g., transcranial magnetic stimulation. It would be interesting to conduct studies with the aim of analyzing the underlying mechanisms. To this end, measures can be added to understand the neural contributions to the loss of complexity, e.g., transcranial magnetic stimulation.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

FG-A carried out the search proposal and the search process. FG-A participated in the decisions of inclusion of articles. FG-A carried out the synthesis of results and the writing of the discussion. CS participated in the search process, in the decision for the inclusion of articles. CS also participated in the synthesis of results and the writing of the discussion. RS supervised the search process, and participated in the decisions for the inclusion of articles. RS supervised the synthesis of results and participated in the writing of the discussion. FM supervised the search process, and participated in the decisions of inclusion of articles. FM supervised the process of synthesis of the results, and participated in the writing of the article. All authors participated in the conception of the review and contributed to the drafting and critical revision of the manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fphys.2022.1074652/full#supplementary-material

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Appendix 2: Assessing Motor Variability during Squat: The Reliability of Inertial Devices in Resistance Training

Study 2: García-Aguilar F, López-Fernández M, Barbado D, Moreno FJ, Sabido R. Assessing Motor Variability during Squat: The Reliability of Inertial Devices in Resistance Training. Sensors (Basel). 2024 Mar 19;24(6):1951. doi: 10.3390/s24061951. PMID: 38514217; PMCID: PMC10965883.

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Assessing Motor Variability during Squat: The Reliability of Inertial Devices in Resistance Training

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Abstract: Movement control can be an indicator of how challenging a task is for the athlete, and can provide useful information to improve training efficiency and prevent injuries. This study was carried out to determine whether inertial measurement units (IMU) can provide reliable information on motion variability during strength exercises, focusing on the squat. Sixty-six healthy, strength-trained young adults completed a two-day protocol, where the variability in the squat movement was analyzed at two different loads (30% and 70% of one repetition maximum) using inertial measurement units and a force platform. The time series from IMUs and force platforms were analyzed using linear (standard deviation) and non-linear (detrended fluctuation analysis, sample entropy and fuzzy entropy) measures. Reliability was analyzed for both IMU and force platform using the intraclass correlation coefficient and the standard error of measurement. Standard deviation, detrended fluctuation analysis, sample entropy, and fuzzy entropy from the IMUs time series showed moderate to good reliability values (ICC: 0.50–0.85) and an acceptable error. The study concludes that IMUs are reliable tools for analyzing movement variability in strength exercises, providing accessible options for performance monitoring and training optimization. These findings have implications for the design of more effective strength training programs, emphasizing the importance of movement control in enhancing athletic performance and reducing injury risks.

Keywords: strength training; variability; inertial sensors; non-linear measures; motor control

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1. Introduction

Muscular force in the field of physical activity is understood as the capacity of a muscle to produce tension when activated [1]. As adequate force levels present benefits in terms of both athletic performance [2,3] and health [4–6], strength exercises are commonly introduced in sport, fitness, and rehabilitation training programs. In order to maximize the benefits and decrease the risks of these strength interventions, most studies have manipulated important parameters related to the exercise load, such as volume, frequency, intensity, etc. [7–9]; however, there is a lack of knowledge about how movement control during strength exercises influences the adaptations caused by these programs.

Movement control, understood as the ability of the nervous and musculoskeletal system to regulate and direct motor actions, exhibits an inherent variability during human movement [10] that seems to reflect how each individual copes with the different task constraints [11]. During strength exercises, movement variations depend on how force is produced and controlled. Force control is the ability to generate accurate and task-relevant force levels and is an important performance factor [12]. During strength exercises, this control is characterized by complex motor fluctuations, which reflect how the different body systems (nervous, musculoskeletal, etc.) adapt motor performance quickly and accurately in response to exercise constraints [13]. These fluctuations are produced at different levels, from the central level, such as recruitment, firing frequency, or coordination of muscle groups, to the effects of peripheral aspects, such as metabolite accumulation [14–17]. The resultant force output produced during any strength exercise constantly fluctuates, reflecting the continuous interaction between individuals and the task demands [18]. Therefore, movement variability during strength exercise not only depends on each individual's features (e.g., skill level, current physical condition, experience, etc.), but is also influenced by different constraints such as fatigue [19–21] or load [22–24], among others.

Non-linear measures have been proposed as relevant tools to analyze movement variability in order to understand how individuals cope with task demands [12]. Specifically, non-linear tools, such as entropy measurements or detrend fluctuation analysis (DFA), have been implemented to describe motor variability during force production tasks [25–27]. Entropy parameters and DFA analyze specific aspects of the variability structure, such as signal regularity and fractality, respectively. These tools have been revealed as useful in detecting changes in force control caused by the manipulation of relevant constraints such as fatigue or load magnitude [18,25]. In addition to force control, postural control was another variable where non-linear measures were applied to determine the effect of conditioning factors such as fatigue in lower limb training [28,29]. However, such studies have been conducted on non-functional tasks, which were either single-joint or unrepresentative sporting or everyday actions (e.g., finger press or knee extension). They have also been studied in laboratory settings, which makes it difficult to extrapolate these results to a training context. Studies analyzing common strength exercises such as the squat have focused on kinematic and kinetic variables related to velocity and power [30] through portable biomechanics IMU; however, no work has studied whether the analysis of movement fluctuations during regular exercises such as the squat can be measured reliably to provide useful information for the planning of strength training.

To the best of the authors' knowledge, no previous research has systematically investigated the reliability of non-linear measures to assess global strength actions using affordable materials. This study aims to fill this gap by examining the reliability of analyzing acceleration signals obtained from accelerometers, specifically in the context of a global movement, involving different joints and the coordination of large muscle groups (e.g., a squat). Our investigation also encompasses assessment of the impact of IMU placement and recording frequency on the reliability of non-linear tools. Furthermore, we explore whether the outcomes of these measurements align with those obtained from a widely used laboratory instrument in sports science, such as a force platform. The significance of this research lies in its potential to establish reliable analysis protocols, which, if validated, can be utilized to investigate the impact of various conditioning factors, including fatigue, loading effects, movement speed, and more.

2. Materials and Methods

2.1. Participants

Eighty-eight healthy young people were initially recruited to participate in the study. Seventeen participants did not complete all measures sessions and were therefore eliminated from further analysis. In addition, for five participants, the records were not obtained correctly and, therefore, could not be analyzed. The final sample consisted of 66 participants, and the descriptive data for the participant set are as follows: 34 males (age = 25.7 ± 4.4 years; height = 174.5 ± 7.4 cm; body mass = 71.7 ± 13.6 kg; one repetition maximum (1RM) in the squat = 116.5 ± 23.2 kg; ratio 1RM/body mass = 1.5 ± 0.2) and 32 females (age = 25.1 ± 5.4 years; height = 160.9 ± 5.3 cm; body mass = 60.4 ± 7.6 kg; 1RM in squat = 76.5 ± 17.4 kg; ratio 1RM/body mass = 1.2 ± 0.2). To ensure that all participants had a stable technique, and to avoid affecting reliability results (e.g., through the learning effect), participants were preferred to have at least one year of strength training experience, including the squat exercise in their training programs. To be included in the study, participants completed a health history questionnaire, guaranteeing that they were free from any disease, illness, or injury that may affect the results of the study. Participants were instructed to maintain their normal lifestyle, including nutritional and hydration states.

Caffeine intake was not allowed in the 3 h previous to measurements. In addition, strength training sessions were not allowed in the 72 h previous to the experimental sessions. To avoid experimental variability, participants were scheduled at the same time for each session. All participants attended three testing sessions separated by at least 72 h. Prior to participation, each subject provided written informed consent, which was approved by the ethics committee of the University (PID2019-109632RB-100) and which adhered to the Declaration of Helsinki.

2.2. Procedures

2.2.1. Day 1—RM Estimation

During their first session, participants were familiarized with the warm-up protocol and performed the 1RM squat test. For this 1RM squat test, participants started from a shoulder-width stance apart with the barbell resting on the upper back, approximately at the level of the acromion, with the knees and hips fully extended. Each participant descended until his thighs were parallel to the ground and, subsequently, ascended to the upright position (Figure 1). Participants were encouraged to return to the upright position at maximum speed. The 1RM estimation was automatically calculated by the specialized software of the linear position transducer (T-Force System, V. 3.70, Ergotech, Murcia, Spain). Several studies have supported the use of movement velocity for 1RM estimation [31–33].

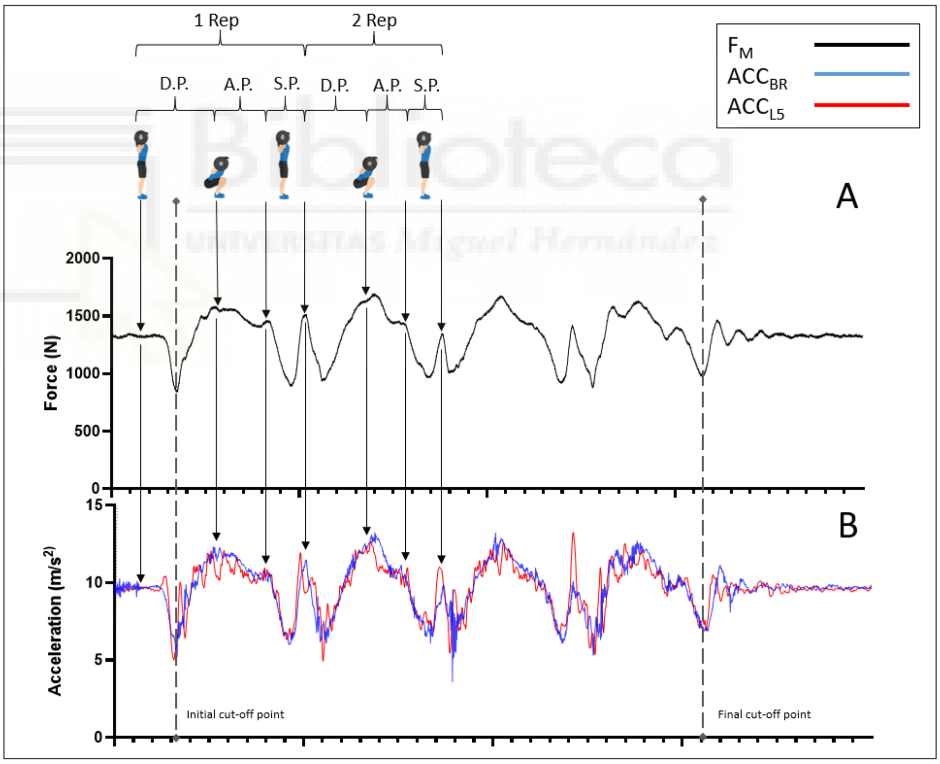

Figure 1. Example of a set of four squats showing the kinetic and kinematic dynamics during the intensity of 70% of the repetition maximum. Illustrated here are the synchronized force and acceleration profiles. The upper graph (**A**) shows the force magnitude (F_M, in Newton), represented by the solid black line. The lower graph (**B**) displays the acceleration magnitude (m/s^2), with the blue line representing acceleration at the barbell (ACC_{BR}) and the red line indicating acceleration at the lumbar region (ACC_{L5}). Dashed vertical lines represent the initial and final cut-off points for data analysis. The phases of the squat movement—ascending (A.P.), descending (D.P.), and stabilization (S.P.)—dotted arrows indicate phase changes approximately. These arrows also relate the graph of F_M to that of acceleration in ACC_{BR} and ACC_{L5}. Additionally, icons at the top illustrate key positions within the squat cycle: standing and the lowest squat point.

2.2.2. Days 2 and 3—Experimental Procedure

During the second and third sessions, participants performed the experimental protocol, which consisted of a total of two sets of four consecutive repetitions in the squat exercise. Participants performed two sets with 30% and 70% of 1RM, respectively, at a preferred velocity, with a rest period of 4 min between the two situations. All repetitions were completed in all sets.

2.3. Data Acquisition

A linear encoder T-ForceTM (T-Force Dynamic Measurement System, Ergotech, Murcia, Spain) was used to calculate RM and monitor mean propulsive velocity during repetitions. During the experimental protocol, the force data were obtained using a Kistler force platform (Winterthur, Switzerland, Mode 9287BA), which was calibrated with InstaCal software V. 7.62 (Measurement Computing Corporation, Norton, MA, USA) before the start of the protocol. The acceleration signal was obtained through two IMUs, which formed part of an inertial motion capture system (iSen, STT Systems Inc., San Sebastián, Spain). One of them was placed in the middle of the barbell with which squats were performed, and the other was placed in the lumbar region at the level of the lumbar vertebra 5 (L5) (Figure 2). The IMUs were synchronized with the iSen software, V. 2023.0. Synchronization between the force platform and the accelerometers was achieved by means of a trigger. The trigger was made by hitting the force platform with an IMU used exclusively for this purpose. Both the IMUs and the force platform recorded at a frequency of 200 Hz.

(**A**) (**B**)

Figure 2. Equipment setup: (**A**) overview; (**B**) placement of the IMUs: one located at the bar and one at L5.

2.4. Data Analysis

The acceleration magnitude of each of the devices was calculated from the three acceleration axes using the following Equation (1):

$$\sqrt{\left(AP^2 + ML^2 + V^2\right)} \tag{1}$$

where AP is the anterior–posterior axis; ML is the medial–lateral axis; and V is the vertical axis. Thus, the acceleration magnitude of the IMUs located at the barbell (ACC_{BR}) and at L5 (ACC_{L5}) was obtained. From the force platform, three axes were also obtained: AP, ML, and V. With these axes, F_M was calculated using Equation (1). On the other hand, the center of pressure magnitude (COP_M), which is the resultant of the moments of force in the medial–lateral and anterior–posterior axis, was calculated using the following Equation (2):

$$\sqrt{\left(Ax^2 + Ay^2\right)} \tag{2}$$

where Ax refers to the medial–lateral component of the center of pressures, and Ay to the anterior–posterior component from the force platform.

All of the aforementioned processing steps were performed using an application created ad hoc with LabView 2012 (National Instruments, Austin, TX, USA). In addition, the same application was used to perform the cuts in the time series. The F_M module was used to detect the beginning of the first squat and the end of the last squat. The initial cut-off point was the point of lowest force in the first squat, and the final cut-off point was the point of lowest force in the last squat (Figure 1). The original length, i.e., with the recording frequency at 200 Hz, was between 874 and 4703 data. Signals were then sub-sampled at 100 and 50 Hz. Sub-sampling was executed by proportionally adjusting the sampling frequency through the selection of points at regular intervals. To reduce from 200 Hz to 100 Hz, one out of every two points was selected, whereas to decrease to 50 Hz, one out of every four was taken, thus ensuring an adequate temporal representation in the subsampled series. This way, analyses were repeated at three different sampling frequencies (200, 100, and 50 Hz). These frequencies were selected on the basis of practical applicability, as most smartphones integrate accelerometers that work at these frequencies. Thus, the results obtained from this work will be applicable to most devices. The amount of variability was calculated using the standard deviation. The structure of the variability of the time series was analyzed. For this purpose, the time series data were analyzed using fuzzy entropy (FuEn) and sampled entropy (SaEn) to analyze regularity or predictability. These two measures were chosen as they have been shown to be more solid to changes in data length, and FuEn has been shown to be more robust to changes in r and noise [34]. Long-term correlations were also analyzed to provide an indicator of the roughness of the movement, for which DFA was used, as it has been shown to be less affected by the signal's non-stationarity [35]. FuEn was calculated using a protocol set out by Chen et al. [36], and SaEn was computed based on Yentes et al. [37]. The parameters m = 2, r = 0.2 × SD, and n = 2 [38] were used to calculate FuEn, and m = 2 and r = 0.2 × SD to calculate SaEn [37]. DFA was calculated according to Peng et al. [35] and using windows of one-second duration. For this purpose, the duration of the windows was adjusted according to the sampling frequency. Thus, at 200 Hz, the initial window was 8 data and the final window was 200 data. For 100 Hz, 4 and 100 data were used, respectively, while for 50 Hz, 4 and 50 data were used. The variability analyses performed in this work were carried out using a code that we developed using the Python programming language.

2.5. Statistical Analysis

The obtained data were analyzed using SPSS (V. 25, IBM Statistics, New York, NY, USA). The normality of the data was confirmed using the Kolmogorov–Smirnov test. Relative reliability was assessed through the intraclass correlation coefficient (ICC) [39]. In this analysis, day 2 was compared with day 3 for each of the variables (SD, DFA, FuEn, and SaEn), and for ACC_{BR}, ACC_{L5}, F_M and COP_M. For the interpretation of these values, we followed Koo and Li [40], who considered an ICC of >0.90 as excellent, 0.75–0.90 as good, 0.50–0.75 as moderate, and <0.50 as poor. Additionally, the absolute reliability was computed for each of the variables in each device using the standard error of measurement (SEM) as the SD of the difference between participants' trials divided by $\sqrt{2}$ [41]. This SEM was used to account for the impact of sample heterogeneity and the influence of systematic errors. In this study, the SEM is expressed in absolute values in order to establish what amount of error we can assume in each of the variables. In addition, two complementary analyses were performed. Pearson's correlation coefficient was calculated to determine the level of correlation between the variables obtained from the force platform and the accelerometers. A two-way ANOVA (intensity and days) was also performed to determine whether the variables studied were sensitive to variations produced by an external factor, in this case, the load. The Bonferroni adjustment was used in the post hoc analysis.

3. Results

Figures 3 and 4 present a summary of the results obtained in the ICC for each device and the SEM for the non-linear variables, respectively. The SEM values of the SD are measured in different units. In summary, in terms of ICC, most of the outcomes calculated from IMUs and F_M showed moderate to good ICC values, but COP_M did not show acceptable ICC values for any variable. The impact of frequency on ICC was minimal, as the differences were generally less than 0.1 for most measures and variables. SEM is shown with absolute values, in m/s^2 for SD and unitless for non-linear variables. A more detailed description of the results shown in each table follows.

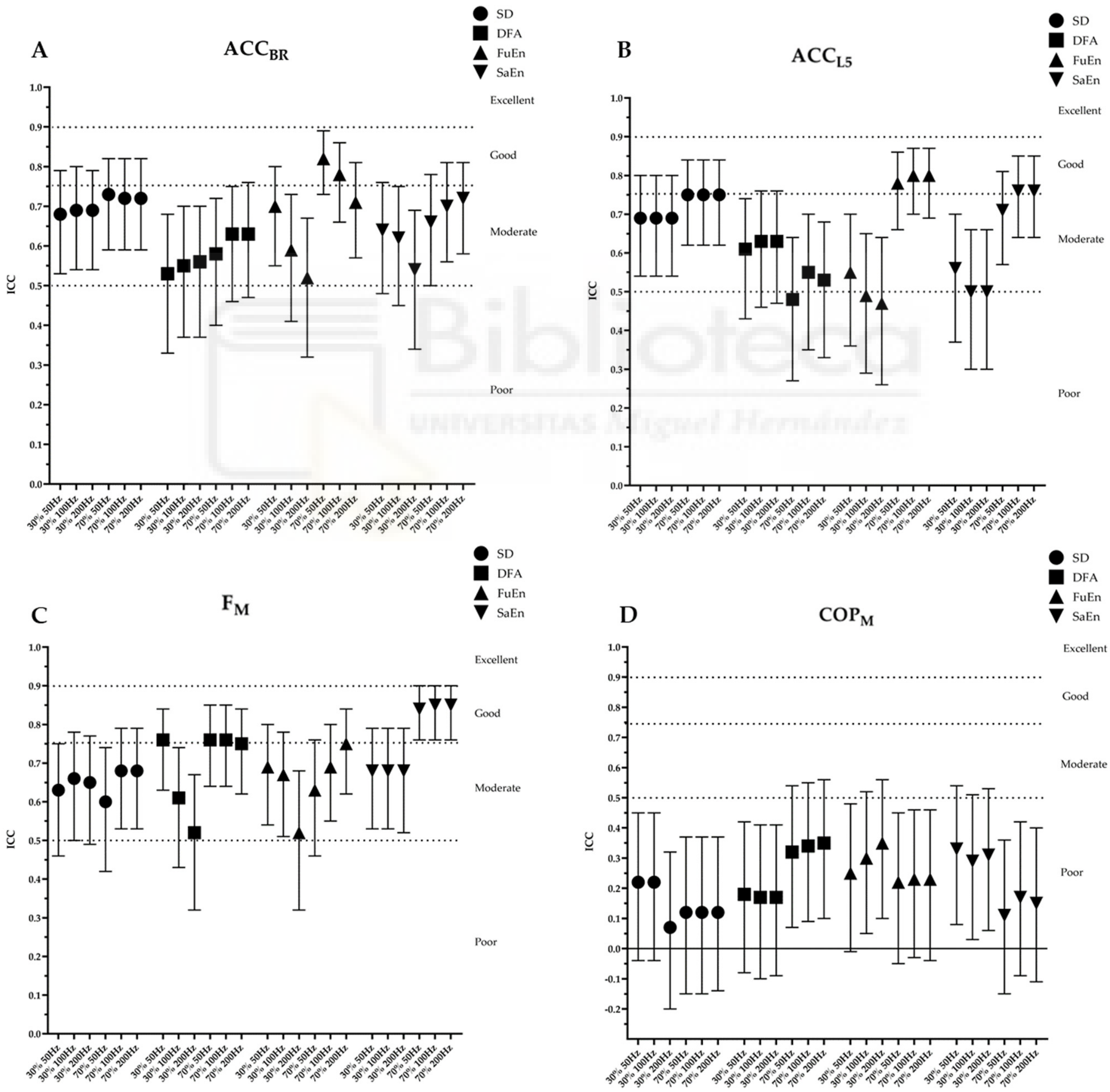

Figure 3. Results of the intraclass correlation coefficient by devices: (**A**) acceleration from the IMU placed on the bar; (**B**) acceleration from the IMU placed on the L5 zone; (**C**) magnitude of the force obtained from the force platform; (**D**) magnitude of the center of pressures obtained from the platform. The graph shows the mean and the upper and lower limits of the 95% confidence interval. The dashed lines indicate the limits for each of the interpretations of the ICC values.

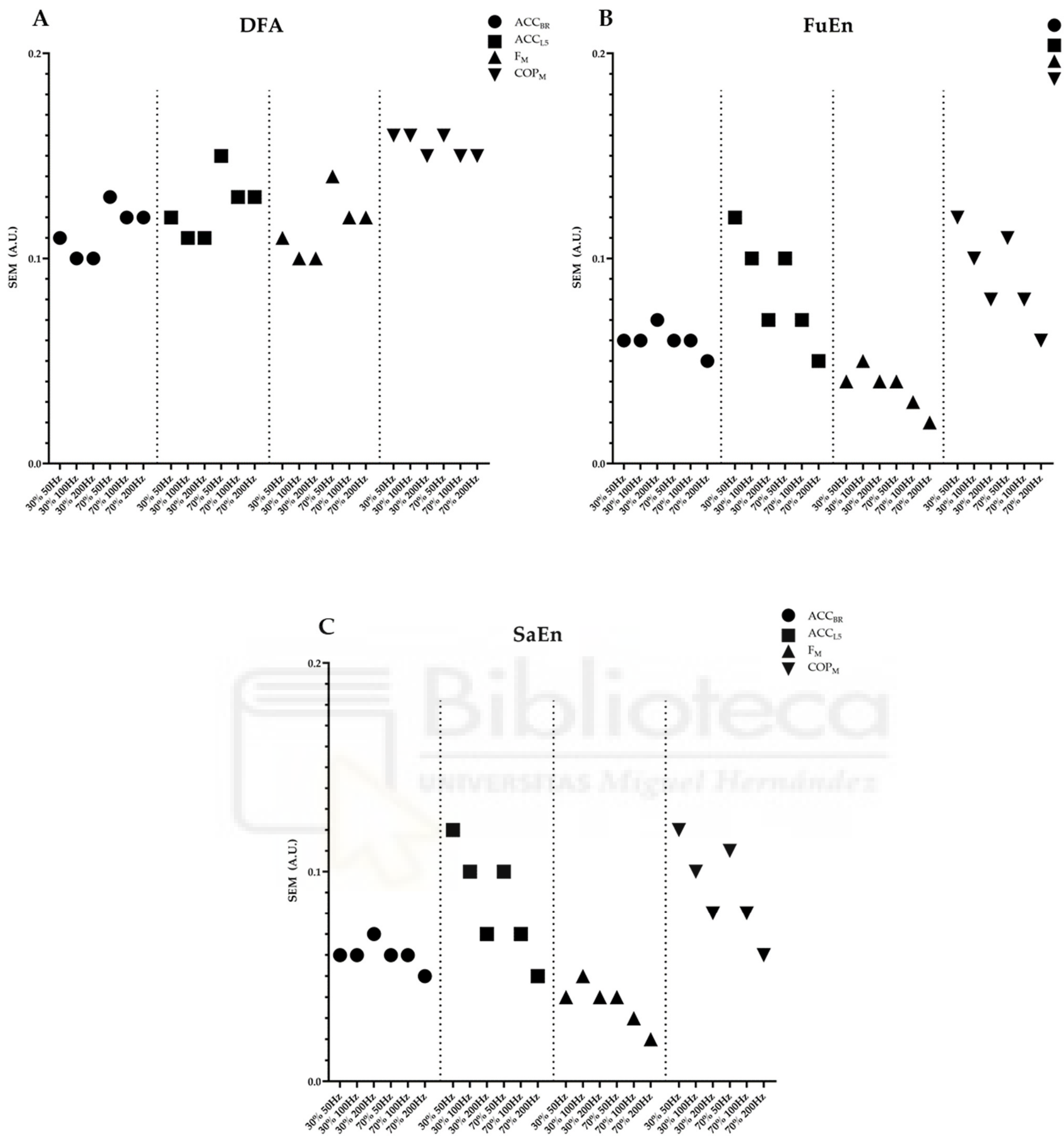

Figure 4. Results of standard errors of measurement by variables: (**A**) detrended fluctuation analysis; (**B**) fuzzy entropy; (**C**) sample entropy. The dashed lines indicate the groupings of the different devices. Note that the SEM standard deviation is not shown in the graphs because given the differences in the measurement magnitudes of each device they are not comparable.

Tables 1 and 2 present the mean values and standard deviation together with the reliability results of the time series obtained from the IMUs placed at the barbell and at L5 area, respectively. The ACC_{BR} showed a moderate to good ICC, with values ranging from 0.52 to 0.82. The ICC values at 70% load were slightly higher than at 30% load. Regarding SEM, the following values were observed for each variable: SD ranged from 0.33 to 0.49, DFA ranged from 0.10 to 0.13, FuEn ranged from 0.05 to 0.07, and SaEn ranged from 0.05 to 0.10. The results are similar to those obtained for ACC_{L5}. For the ICC value, the range for ACC_{L5} was from 0.47 to 0.80. It appears that the trend towards higher ICC values in the 70% load compared to the 30% load was maintained in ACC_{L5} for all variables except DFA.

Regarding SEM, ACC_{L5} reported the following values: SD from 0.30 to 0.44, DFA from 0.11 to 0.15, FuEn from 0.07 to 0.12, and SaEn from 0.05 to 0.14.

Table 1. Descriptive and reliability results of linear and non-linear parameters obtained from the acceleration magnitude time series recorded from IMU placed at the barbell.

Variable	%RM	Frequency	Day 2	Day 3	Reliability Measures	
			M ± SD	M ± SD	ICC (LCL-UCL)	SEM
SD	30	50	2.60 ± 0.90	2.72 ± 0.84	0.68 (0.53, 0.79)	0.49
		100	2.60 ± 0.89	2.72 ± 0.83	0.69 (0.54, 0.8)	0.48
		200	2.60 ± 0.89	2.72 ± 0.83	0.69 (0.54, 0.79)	0.48
	70	50	2.11 ± 0.62	2.15 ± 0.61	0.73 (0.59, 0.82)	0.33
		100	2.13 ± 0.63	2.15 ± 0.61	0.72 (0.59, 0.82)	0.33
		200	2.14 ± 0.63	2.16 ± 0.61	0.72 (0.59, 0.82)	0.33
DFA	30	50	1.29 ± 0.18	1.32 ± 0.15	0.53 (0.33, 0.68)	0.11
		100	1.33 ± 0.17	1.34 ± 0.14	0.55 (0.37, 0.70)	0.10
		200	1.32 ± 0.17	1.34 ± 0.14	0.56 (0.37, 0.70)	0.10
	70	50	1.14 ± 0.22	1.18 ± 0.2	0.58 (0.4, 0.72)	0.13
		100	1.19 ± 0.20	1.21 ± 0.18	0.63 (0.46, 0.75)	0.12
		200	1.18 ± 0.20	1.21 ± 0.18	0.63 (0.47, 0.76)	0.12
FuEn	30	50	0.54 ± 0.12	0.54 ± 0.10	0.70 (0.55, 0.80)	0.06
		100	0.32 ± 0.11	0.32 ± 0.09	0.59 (0.41, 0.73)	0.06
		200	0.19 ± 0.10	0.19 ± 0.08	0.52 (0.32, 0.67)	0.07
	70	50	0.68 ± 0.15	0.67 ± 0.15	0.82 (0.73, 0.89)	0.06
		100	0.44 ± 0.12	0.43 ± 0.12	0.78 (0.66, 0.86)	0.06
		200	0.26 ± 0.11	0.26 ± 0.10	0.71 (0.57, 0.81)	0.05
SaEn	30	50	0.52 ± 0.14	0.52 ± 0.11	0.64 (0.48, 0.76)	0.08
		100	0.34 ± 0.11	0.34 ± 0.09	0.62 (0.45, 0.75)	0.06
		200	0.22 ± 0.10	0.22 ± 0.08	0.54 (0.34, 0.69)	0.06
	70	50	0.59 ± 0.15	0.57 ± 0.19	0.66 (0.5, 0.78)	0.10
		100	0.39 ± 0.12	0.39 ± 0.14	0.70 (0.56, 0.81)	0.07
		200	0.26 ± 0.09	0.25 ± 0.10	0.72 (0.58, 0.81)	0.05

Note. %RM: RM percentage; M: mean; SD: standard deviation; ICC: intraclass correlation coefficient; LCL: lower confidence interval; UCL: upper confidence interval; SEM: standard error of measurement; DFA: detrended analysis fluctuation; FuEn: fuzzy entropy; SaEn: sample entropy.

Table 2. Descriptive and reliability results of linear and non-linear parameters obtained from the acceleration magnitude time series recorded from IMU placed at the L5.

Variable	%RM	Frequency	Day 2	Day 3	Reliability Measures	
			M ± SD	M ± SD	ICC (LCL-UCL)	SEM
SD	30	50	2.31 ± 0.84	2.42 ± 0.77	0.69 (0.54, 0.8)	0.44
		100	2.32 ± 0.85	2.42 ± 0.77	0.69 (0.54, 0.8)	0.44
		200	2.32 ± 0.85	2.42 ± 0.77	0.69 (0.54, 0.8)	0.44
	70	50	1.95 ± 0.6	2 ± 0.54	0.75 (0.62, 0.84)	0.30
		100	1.96 ± 0.6	2 ± 0.54	0.75 (0.62, 0.84)	0.30
		200	1.96 ± 0.6	2 ± 0.54	0.75 (0.62, 0.84)	0.30
DFA	30	50	1.19 ± 0.21	1.18 ± 0.18	0.61 (0.43, 0.74)	0.12
		100	1.22 ± 0.2	1.21 ± 0.17	0.63 (0.46, 0.76)	0.11
		200	1.22 ± 0.2	1.2 ± 0.17	0.63 (0.47, 0.76)	0.11
	70	50	0.96 ± 0.2	0.99 ± 0.21	0.48 (0.27, 0.64)	0.15
		100	1 ± 0.19	1.01 ± 0.19	0.55 (0.35, 0.7)	0.13
		200	1 ± 0.19	1.01 ± 0.19	0.53 (0.33, 0.68)	0.13

Table 2. *Cont.*

Variable	%RM	Frequency	Day 2	Day 3	Reliability Measures	
			M ± SD	M ± SD	ICC (LCL-UCL)	SEM
FuEn	30	50	0.87 ± 0.22	0.84 ± 0.15	0.55 (0.36, 0.7)	0.12
		100	0.55 ± 0.17	0.52 ± 0.12	0.49 (0.29, 0.65)	0.10
		200	0.29 ± 0.11	0.27 ± 0.08	0.47 (0.26, 0.64)	0.07
	70	50	1.09 ± 0.21	1.05 ± 0.21	0.78 (0.66, 0.86)	0.10
		100	0.72 ± 0.16	0.69 ± 0.15	0.80 (0.7, 0.87)	0.07
		200	0.4 ± 0.11	0.38 ± 0.1	0.80 (0.69, 0.87)	0.05
SaEn	30	50	0.89 ± 0.23	0.83 ± 0.17	0.56 (0.37, 0.7)	0.14
		100	0.58 ± 0.17	0.55 ± 0.13	0.50 (0.3, 0.66)	0.11
		200	0.35 ± 0.11	0.33 ± 0.08	0.50 (0.3, 0.66)	0.07
	70	50	1.05 ± 0.24	1.01 ± 0.24	0.71 (0.57, 0.81)	0.13
		100	0.72 ± 0.19	0.69 ± 0.19	0.76 (0.64, 0.85)	0.09
		200	0.43 ± 0.11	0.42 ± 0.11	0.76 (0.64, 0.85)	0.05

Note. %RM: RM percentage; M: mean; SD: standard deviation; ICC: intraclass correlation coefficient; LCL: lower confidence interval; UCL: upper confidence interval; SEM: standard error of measurement; DFA: detrended analysis fluctuation; FuEn: fuzzy entropy; SaEn: sample entropy.

Tables 3 and 4 show the mean values and standard deviations together with the reliability results of the time series F_M and COP_M, respectively. The two types of time series were obtained from the force platform. In the same way as IMUs, the F_M ICC values were also moderate to good (from 0.52 to 0.85). And the SEM values had SDs between 37.22 and 47.16, DFA between 0.10 and 0.14, FuEn between 0.02 and 0.05, and SaEn between 0.03 and 0.07. Contrary to the other measures, the ICC scores for COPM outcomes were low for all variables (ICC < 0.35). With respect to SEM, the values reported for COP_M were 5.48–9.67 for SD, 0.15–0.16 for DFA, 0.06–0.12 for FuEn, and 0.07–0.12 for SaEn.

Table 3. Descriptive and reliability results of linear and non-linear parameters obtained from the force magnitude time series.

Variable	%RM	Frequency	Day 2	Day 3	Reliability Measures	
			M ± SD	M ± SD	ICC (LCL-UCL)	SEM
SD	30	50	197.89 ± 85.64	207.28 ± 73.48	0.68 (0.53, 0.79)	46.55
		100	198.3 ± 85.9	208.09 ± 73.69	0.68 (0.53, 0.79)	46.86
		200	199.35 ± 85.68	207.87 ± 73.76	0.68 (0.52, 0.79)	47.16
	70	50	240 ± 88	242.29 ± 84.19	0.84 (0.76, 0.9)	37.23
		100	240.75 ± 88.31	242.92 ± 84.44	0.85 (0.76, 0.9)	37.24
		200	241.08 ± 88.47	243.01 ± 84.53	0.85 (0.76, 0.9)	37.22
DFA	30	50	1.27 ± 0.18	1.3 ± 0.17	0.63 (0.46, 0.75)	0.11
		100	1.31 ± 0.18	1.32 ± 0.16	0.66 (0.5, 0.78)	0.10
		200	1.31 ± 0.18	1.32 ± 0.16	0.65 (0.49, 0.77)	0.10
	70	50	1.1 ± 0.23	1.13 ± 0.24	0.60 (0.42, 0.74)	0.14
		100	1.14 ± 0.22	1.17 ± 0.22	0.68 (0.53, 0.79)	0.12
		200	1.14 ± 0.22	1.16 ± 0.22	0.68 (0.53, 0.79)	0.12
FuEn	30	50	0.49 ± 0.09	0.49 ± 0.09	0.76 (0.63, 0.84)	0.04
		100	0.29 ± 0.07	0.28 ± 0.07	0.61 (0.43, 0.74)	0.05
		200	0.15 ± 0.06	0.15 ± 0.06	0.52 (0.32, 0.67)	0.04
	70	50	0.44 ± 0.08	0.43 ± 0.08	0.76 (0.64, 0.85)	0.04
		100	0.27 ± 0.06	0.27 ± 0.06	0.76 (0.64, 0.85)	0.03
		200	0.14 ± 0.05	0.14 ± 0.04	0.75 (0.62, 0.84)	0.02

Table 3. *Cont.*

Variable	%RM	Frequency	Day 2	Day 3	Reliability Measures	
			M ± SD	M ± SD	ICC (LCL-UCL)	SEM
SaEn	30	50	0.47 ± 0.12	0.47 ± 0.12	0.69 (0.54, 0.8)	0.07
		100	0.31 ± 0.1	0.31 ± 0.1	0.67 (0.51, 0.78)	0.06
		200	0.2 ± 0.08	0.2 ± 0.08	0.52 (0.32, 0.68)	0.06
	70	50	0.35 ± 0.1	0.34 ± 0.1	0.63 (0.46, 0.76)	0.06
		100	0.24 ± 0.08	0.23 ± 0.07	0.69 (0.55, 0.8)	0.04
		200	0.16 ± 0.06	0.15 ± 0.06	0.75 (0.62, 0.84)	0.03

Note. %RM: RM percentage; M: mean; SD: standard deviation; ICC: intraclass correlation coefficient; LCL: lower confidence interval; UCL: upper confidence interval; SEM: standard error of measurement; DFA: detrended analysis fluctuation; FuEn: fuzzy entropy; SaEn: sample entropy.

Table 4. Descriptive and reliability results of linear and non-linear parameters obtained from the center of pressure magnitude time series.

Variable	%RM	Frequency	Day 2	Day 3	Reliability Measures	
			M ± SD	M ± SD	ICC (LCL-UCL)	SEM
SD	30	50	18.71 ± 6	16.72 ± 5.42	0.22 (−0.04, 0.45)	5.49
		100	18.73 ± 5.99	16.72 ± 5.42	0.22 (−0.04, 0.45)	5.48
		200	20.57 ± 11.07	16.73 ± 5.43	0.07 (−0.2, 0.32)	9.67
	70	50	22.64 ± 9.89	19.9 ± 6.79	0.12 (−0.15, 0.37)	7.74
		100	22.66 ± 9.89	19.93 ± 6.8	0.12 (−0.15, 0.37)	7.72
		200	22.67 ± 9.9	19.99 ± 6.83	0.12 (−0.14, 0.37)	7.74
DFA	30	50	1.35 ± 0.18	1.38 ± 0.19	0.18 (−0.08, 0.42)	0.16
		100	1.37 ± 0.17	1.4 ± 0.17	0.17 (−0.1, 0.41)	0.16
		200	1.37 ± 0.17	1.4 ± 0.17	0.17 (−0.09, 0.41)	0.15
	70	50	1.28 ± 0.2	1.32 ± 0.17	0.32 (0.07, 0.54)	0.16
		100	1.31 ± 0.19	1.34 ± 0.16	0.34 (0.09, 0.55)	0.15
		200	1.31 ± 0.19	1.34 ± 0.16	0.35 (0.1, 0.56)	0.15
FuEn	30	50	0.48 ± 0.14	0.5 ± 0.14	0.25 (−0.01, 0.48)	0.12
		100	0.28 ± 0.13	0.3 ± 0.12	0.3 (0.05, 0.52)	0.10
		200	0.16 ± 0.12	0.18 ± 0.09	0.35 (0.1, 0.56)	0.08
	70	50	0.45 ± 0.13	0.45 ± 0.13	0.22 (−0.05, 0.45)	0.11
		100	0.24 ± 0.1	0.25 ± 0.09	0.23 (−0.03, 0.46)	0.08
		200	0.12 ± 0.08	0.13 ± 0.06	0.23 (−0.04, 0.46)	0.06
SaEn	30	50	0.52 ± 0.15	0.52 ± 0.15	0.33 (0.08, 0.54)	0.12
		100	0.41 ± 0.14	0.43 ± 0.13	0.29 (0.03, 0.51)	0.12
		200	0.21 ± 0.13	0.22 ± 0.1	0.31 (0.06, 0.53)	0.09
	70	50	0.46 ± 0.12	0.47 ± 0.12	0.11 (−0.15, 0.36)	0.11
		100	0.37 ± 0.12	0.37 ± 0.11	0.17 (−0.09, 0.42)	0.10
		200	0.16 ± 0.08	0.17 ± 0.06	0.15 (−0.11, 0.4)	0.07

Note. %RM: RM percentage; M: mean; SD: standard deviation; ICC: intraclass correlation coefficient; LCL: lower confidence interval; UCL: upper confidence interval; SEM: standard error of measurement; DFA: detrended analysis fluctuation; FuEn: fuzzy entropy; SaEn: sample entropy.

The results of Pearson correlation are shown in Table 5. The acceleration values from the IMUs showed strong correlations between SD ($0.94 < r < 0.98$) and DFA ($0.74 < r < 0.83$) in both load intensity conditions. Entropy measures exhibited correlations ranging from weak ($0.23 < r < 0.39$) for 30% RM to strong ($0.63 < r < 0.79$) for 70% RM. The correlation values between F_M and the IMUs ranged from −0.17 to 0.96 (F_M-ACC_{BR}: −0.17–0.096; F_M-ACC_{L5} sacrum: 0.18–0.82). In F_M, a strong correlation was reported with both ACC_{BR} and ACC_{L5} for SD and DFA ($0.71 < r < 0.96$) for both intensities. In the entropy measurements, the correlation was weak to moderate ($-0.17 < r < 0.48$) for both ACC_{BR} and ACC_{L5} with

F_M. Regarding COP_M correlations, no significant results were obtained in the analysis of the remaining variables.

Table 5. Correlations between devices.

		ACC_{BR}-ACC_{L5}	F_M-ACC_{BR}	F_M-ACC_{L5}	COP_M-ACC_{BR}	COP_M-ACC_{L5}	COP_M-F_M
%RM	**Frequency**	**Variable**					
		SD					
30	50 Hz	0.98 **	0.78 **	0.74 **	0.29 *	0.27 *	0.32 *
	100 Hz	0.97 **	0.78 **	0.73 **	0.28 *	0.27 *	0.32 *
	200 Hz	0.97 **	0.78 **	0.73 **	0.28 *	0.27 *	0.32 *
70	50 Hz	0.94 **	0.73 **	0.77 **	0.2	0.19	0.07
	100 Hz	0.94 **	0.73 **	0.77 **	0.18	0.15	0.04
	200 Hz	0.94 **	0.73 **	0.77 **	0.21	0.18	0.07
		DFA					
30	50 Hz	0.83 **	0.96 **	0.82 **	0.09	0.03	0.14
	100 Hz	0.82 **	0.95 **	0.82 **	0.13	0.08	0.2
	200 Hz	0.83 **	0.95 **	0.82 **	0.13	0.08	0.2
70	50 Hz	0.78 **	0.94 **	0.75 **	0.28 *	0.23	0.22
	100 Hz	0.75 **	0.96 **	0.71 **	0.32 *	0.29 *	0.26 *
	200 Hz	0.74 **	0.96 **	0.72 **	0.29 *	0.24	0.25
		FuEn					
30	50 Hz	0.39 **	0.45 **	0.45 **	0.03	0.07	0.22
	100 Hz	0.28 *	0.06	0.34 **	0.04	0.11	0.22
	200 Hz	0.23	−0.17	0.18	0.03	0.14	0.18
70	50 Hz	0.79 **	0.43 **	0.35 **	0.20	0.23	0.15
	100 Hz	0.65 **	0.31 **	0.29 *	0.19	0.14	0.16
	200 Hz	0.55 **	0.12	0.24 *	0.14	0.14	0.08
		SaEn					
30	50 Hz	0.39 **	0.43 **	0.42 **	−0.02	0.14	0.28 *
	100 Hz	0.34 **	0.2	0.36 **	0.02	0.11	0.16
	200 Hz	0.32 **	−0.01	0.25 *	0.07	0.25	0.28 *
70	50 Hz	0.74 **	0.48 **	0.46 **	0.11	0.12	0.11
	100 Hz	0.63 **	0.36 **	0.36 **	0.13	0.09	−0.07
	200 Hz	0.66 **	0.26 *	0.35 **	0.13	0.13	0.1

Note. %RM: RM percentage; SD: standard deviation; DFA: detrended analysis fluctuation; FuEn: fuzzy entropy; SaEn: sample entropy. COP_M: center of pressure magnitude; F_M: force magnitude; ACC_{BR}: acceleration magnitude from IMU barbell; ACC_{L5}: acceleration magnitude from IMU L5; *: $p < 0.05$; **: $p < 0.01$.

The ANOVA revealed significant differences ($p < 0.05$) between the 30% and 70% RM conditions for different devices and variables. Notably, there were no significant differences between days, except for the FuEn of ACC_{L5} and SD in COP_M, although the trends in both measures were similar. It is worth noting that the trends resulting from increasing intensity only aligned with DFA, where an escalation in intensity corresponded to a decrease in DFA values. In the remaining variables, trends diverged between measurements obtained from the F_M and COP_M compared to those from the IMUs, encompassing both ACC_{BR} and ACC_{L5}. For example, while SD increased with a higher load in the F_M and COP_M measurements, it decreased in the IMUs. Conversely, in the 70% RM condition, FuEn and SaEn values decreased in the F_M and COP_M but increased in the IMU, compared to the 30% RM condition.

4. Discussion

This study was conducted to investigate whether movement variability measured through inertial sensors can provide reliable information on movement control during a strength exercise such as the squat. Specifically, on the one hand, we assessed relative reliability through the ICC to determine whether participants could be classified properly according to their movement variability. On the other hand, we analyzed absolute reliability to define the range threshold that can help to determine whether changes in movement variability during the squat are caused by individuals´ inherent variability or an external factor (i.e., learning, adaptation, fatigue, etc.).

Firstly, the ICC was used to determine the relative reliability and consistency of the measurements. A high ICC suggests consistency and agreement between different measurements, indicating that it allows for ranking [41]. While the ACC_{BR} and ACC_{L5}, together with the F_M, showed acceptable to good values for practically all variables, the COP_M showed the lowest reliability values, as the ICC did not reach an acceptable threshold in any case. We have not found studies that have analyzed the relative reliability of movement control variability in strength tasks, whether with linear or non-linear measurements. To provide some references, we can examine related works. When assessing relative reliability using the ICC in strength tasks with accelerometers measuring variables such as velocity, power, or force, reported results have ranged from good to excellent in most of the studies, and only one of the studies reviewed showed poor ICC values in velocity variables [30]. It is noteworthy that in ACC_{BR}, ACC_{L5}, and F_M, ICC values are slightly higher at higher loads for most variables. The only exception to this trend is observed in DFA of ACC_{L5}. This might suggest that higher loads pose a greater challenge, consequently allowing for better classification. Regarding the COP_M, although some studies have shown the reliability of non-linear tools in balance tasks, with ICC values between acceptable and good [42–46], our results suggest that, in strength tasks, they are not reliable (ICC < 0.50). We propose several explanations. The first is the difference in postural adjustments that occur when performing a dynamic task with weight, such as a squat, and those that occur when performing a static balance task with body weight only. Another reason for this may be the greater non-stationarity of the squat signal compared to the balance signals. Finally, in terms of frequency, the differences are minimal, typically less than 0.1 units, indicating that recording between frequencies of 50 and 200 Hz does not appear to affect relative reliability. With this in mind, it can be suggested that ACC_{BR}, ACC_{L5}, and F_M show acceptable relative reliability, indicating that motion analysis involving linear and non-linear variables can be measured consistently, allowing for the classification of subjects.

Secondly, to determine the precision of the measurement, the SEM was used to quantify the absolute reliability. The SEM makes it possible to define the range within which the true value of the measurement should lie [47], and, thus, to determine whether the changes (or lack thereof) are an effect of the intervention or caused by random errors in measurement. It is important to note that the SEM depends on the magnitude of the measurement. In other words, if a measurement yields large values, a larger SEM can be accepted, and vice versa. For instance, the acceptability of an SEM for DFA is different from that for SD when the measurement values differ significantly. The ranges of SEM are different between variables in SD; in IMUs, the SEM is between 0.30 and 0.49; in F_M, the range is between 37.22 and 47.16; and in COP_M, it ranges between 5.48 and 9.67. In non-linear measurements, the values are more similar between ranges of 0.30 and 0.49. Thus, the SEM complements the reliability information provided by the ICC, offering an index of the variations required in measurements to determine whether a change resulting from an intervention is genuinely due to that intervention and not merely a random error. Considering that the SEM is contingent on the type of measurement, and given the limited literature on variability in acceleration signals during strength actions, we are unable to directly compare the precision of these measures. However, based on the descriptive data presented in Tables 1–4, it can be suggested that these measures are capable of detecting changes. However, when comparing SEM values in FuEn and SaEn, given their similar nature, minimal differences are observed (never exceeding 0.05), suggesting a comparable margin of error in both measurements. On the other hand, DFA also exhibits SEM values relatively close to those of entropy measures. Considering that DFA values tend to be higher, DFA is likely a more robust measure against measurement error. Across all variables, the SEM is consistently smaller than the between-subject standard deviation, implying that the measurement is responsive to changes. Previous studies have reported variations in SEM values for non-linear variables. Lin et al. [44] reported lower SEM values (0.04 < SEM < 0.06) in DFA during balancing tasks, while Mazaheri et al. [48] observed greater SEM ranges (0.20 < SEM < 0.37) in entropy measurements, also in the context of balancing tasks. This divergence in SEM values across studies employing similar tasks could be attributed to differences in the measurements (DFA versus entropy). When we compare these findings with our research, it appears that SEM values may fluctuate based on the nature of the task, even when the analysis is performed through analogous variables. These discrepancies could be due to factors similar to those mentioned above for the ICC, including task-specific adjustments, non-stationarity, and variances in the variable's value range. Importantly, the SEM provides critical insight into the expected measurement error, offering valuable information for interpreting the reliability and precision of the data.

Additionally, frequency is an important factor that can modify entropy and DFA values [49,50]. For this reason, we compared the results of the non-linear measures at different frequencies. The reported findings indicate that, while there are variations in the absolute values when changing frequencies, the same trends persist. Similar results are presented in the study by Caballero et al. [51], whereas in our study, an increase in SaEn values and a decrease in DFA values were reported with increasing frequency, but without significantly influencing the results. Furthermore, the reliability values (ICC, SEM) remained consistent. This suggests that different frequencies can be used interchangeably. For the analyses to be valid, the frequency must be adjusted to the movement and/or process to be analyzed [50,51]. However, it should be noted that if we wish to compare absolute values, it is essential to compare values within the same frequency.

The correlation analysis revealed strong correlations between the two IMUs and between the F_M and each of the two IMUs in the variables of SD and DFA. By contrast, for the FuEn and SaEn variables, a strong correlation (r > 0.50) was reported between the two IMUs at the 70% RM load condition, while a weak correlation was observed at the 30% RM load condition. Meanwhile, correlations between the IMUs and the F_M varied from moderate to non-existent. The COP_M showed weak or non-existent correlations with all measures. Other studies have analyzed the validity of accelerometers by comparing them with gold standards such as the center of pressure (COP) [52,53] motion capture systems [54] or gait analysis systems [55], reporting moderate to high correlation values. Our results differ in terms of COP, as in no case do the correlations reach moderate. It is possible that this is due to differences in the task (squat vs. balance) mentioned above. Nevertheless, we observed moderate to high correlations between force modulus and IMUs, particularly in dynamic actions with substantial force requirements. This suggests that both F_M and IMUs can effectively capture the variability structure in tasks such as the squat. Furthermore, it relates body oscillations, reflected in acceleration, to fluctuations in force production, reflected in F_M.

Finally, the conducted ANOVA demonstrated differences between load conditions in all variables and measures. This suggests that these protocols are sensitive to changes in load. Additionally, the absence of differences between days in the majority of variables, and when differences exist, observing consistent trends, further reflects the day-to-day validity of these measures.

5. Conclusions

The main objective of this study was to assess the reliability of different measures of variability in a strength movement such as the squat. While we successfully achieved this goal, contributing valuable insights, it is important to acknowledge certain limitations. Firstly, given that the study focused on a single task (squat) and modified a single factor (load), the results should be approached with caution when extrapolating them to other tasks or conditions. Therefore, further research is needed to investigate these measures in tasks with additional independent variables such as a broader range of loads, fatigue, level of expertise, etc. Additionally, consideration should be given to the characteristics of the time series, which are of variable length and non-stationary. Lastly, when interpreting results and drawing conclusions, the lack of literature addressing similar tasks poses a challenge. Therefore, continued research is essential to establish a robust knowledge base in this field.

Both force and acceleration magnitude, whether measured on the barbell or close to the L5 area, are reliable variables for assessing variability in tasks involving substantial force, such as squats. However, the use of the COP_M is not recommended for this purpose. The most robust measure across all three devices is DFA, as it consistently yields results ranging from acceptable to good across the two reliability metrics employed in this study (ICC and SEM). The choice of a sampling frequency between 50 and 200 Hz seems to have had no significant impact on the relative results, although it did affect absolute values. Furthermore, these measures can be used interchangeably with both the magnitude force and IMUs, making them accessible to a wider range of users.

Author Contributions: Conceptualization, R.S. and F.J.M.; methodology, R.S., D.B. and F.J.M.; software, F.G.-A., D.B. and F.J.M.; formal analysis, F.G.-A.; investigation, F.G.-A. and M.L-F.; resources, F.G.-A. and M.L.-F.; data curation, F.G.-A.; writing—original draft preparation, F.G.-A.; writing—review and editing, R.S., D.B. and F.J.M.; supervision, R.S. and F.J.M.; project administration, R.S. and F.J.M.; funding acquisition, R.S. and F.J.M. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki and approved by the Office of Responsible Research (OIR). The University's ethics committee approved the research ethics statement under register 2019.417.E.OIR; 2020.34.E.OIR and reference DCD.RSS.02.19.

Informed Consent Statement: Each subject provided written informed consent, which was approved by the ethics committee of the University (PID2019-109632RB-100) and which adhered to the Declaration of Helsinki.

Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request. Similarly, the codes used to perform the variability analyses are available upon request to the corresponding author.

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Conflicts of Interest: The authors declare no conflict of interest.

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Appendix 3: Motor variability as an index of fatigue in dynamic actions: a perspective from the complexity loss theory

Note. This study is under review.

Study 3: García-Aguilar F, López-Fernández M, Barbado D, Moreno FJ, Sabido R. Motor variability as an index of fatigue in dynamic actions: a perspective from the complexity loss theory.

Abstract

Background: Fatigue is a complex process that affects force generation and movement execution and plays a critical role in performance, recovery, and injury risk. Traditional measures, such as countermovement jump height, assess fatigue-induced performance losses but fail to capture compensatory changes in movement patterns. Nonlinear analysis of motor variability, derived from acceleration signals, offers a novel approach to monitoring fatigue by detecting subtle changes during movement execution. This study investigated the impact of fatigue induced by three resistance training modalities—power, hypertrophy, and maximal strength—on motor variability during squats.

Methods: Forty-four participants were recruited to participate in the study. To assess the acute effects of each training modality on performance and motor variability, participants performed a testing task consisting of 10 squats at 70% of their 1RM, which was performed before and after a training session, with follow-up assessments at 24, 48, and 72 hours. Lower back acceleration was recorded using inertial measurement units. Acceleration variability was analyzed using linear methods, including standard deviation (SD), and nonlinear methods, such as fuzzy entropy (FuEn) and detrended fluctuation analysis (DFA). Countermovement jump (CMJ) height is a widely used indicator of neuromuscular fatigue.

Results: Significant reductions in CMJ height were observed after hypertrophy and maximal strength training ($p < 0.01$, small to large effect sizes). Although no significant effect emerged for the power condition in the overall ANOVA ($p = 0.08$), pairwise comparisons revealed a significant pre-post change. No significant changes were observed in standard deviation for any of the training modalities ($p > 0.05$). FuEn increased significantly after hypertrophy training ($p < 0.01$, large effect size) and after maximal strength training ($p = 0.01$, moderate effect size), but no significant change was found following power training ($p = 0.89$). Similarly, DFA decreased after hypertrophy training ($p = 0.02$, moderate effect size) and maximal strength training ($p < 0.01$, moderate effect size), with no significant change observed after power training ($p = 0.59$).

Conclusion: Nonlinear analysis of motor variability via inertial measurement units provides valuable insights into fatigue-induced movement adaptations, complementing traditional performance metrics. This accessible, cost-effective approach has potential applications for optimizing training and rehabilitation programs, particularly in populations where high-intensity assessments are impractical.

Keywords: Fatigue, motor variability, resistance training, inertial measurement units, nonlinear analysis.

1. Introduction

Fatigue is a multifactorial process that leads to a reduced capacity to generate force (1). It results from several interacting mechanisms, including central and peripheral factors such as impaired calcium release, accumulation of metabolic by-products, and alterations in motor unit behavior – such as decreased or compensatory increases in discharge rate – depending on the characteristics of the task (e.g., type of exercise, duration, intensity…) (2–4). This process leads to a decline in performance and an increased risk of injury (5). Moderate levels of fatigue can induce long-term beneficial adaptations, whereas excessive fatigue may reduce the benefits of training or even lead to a state of overtraining (6). In resistance training, the design of the training protocol modulates both physiological adaptations (7,8) and the level of fatigue induced (9–11). While fatigue itself is not the primary goal of resistance training, the degree of fatigue generated is often considered when designing training protocols to achieve the intended adaptations. For instance, when the goal is to improve power or movement velocity, it is generally recommended to avoid excessive fatigue in order to preserve neuromuscular performance (12). In contrast, hypertrophy-oriented programs typically involve greater levels of fatigue (13,14). Monitoring and regulating fatigue are essential for coaches to ensure safe progression and optimize performance (15).

Different tests are available to monitor fatigue, each with its advantages and limitations, including questionnaires, perceptual scales, biomarkers (e.g., lactate, creatine kinase, cortisol levels), electromyography, force production, velocity loss, and field tests (5,16,17). The countermovement jump (CMJ) is widely used for assessing neuromuscular fatigue (18). The primary outcome of this test, jump height, provides valuable information about jumping ability and lower extremity power. However, this parameter is a performance outcome — it reflects the result of the jump — but does not offer insights into the mechanics of its execution (execution outcomes). Since the human system is known to exhibit self-organized behavior (18), fatigue can cause changes in movement strategies even when performance variables, such as jump height, remain unchanged. For instance, some studies (19) have found that fatigue **preserves jumping ability through compensatory movement changes.** In the squat exercise, fatigue has also been shown to induce modifications in movement patterns. For example, one study (19) reported changes in trajectories and timing, while other studies highlighted variations in the involvement of different muscle groups or shifts in the participation (20–23). Although these changes in motor patterns may help in achieving task performance, they may not always be adaptive and could increase the risk of injury. For this reason, the study of kinetic and kinematic variables is a necessary complement to the information provided by the performance outcomes.

Recent studies suggest that assessing motor variability can be used to monitor changes in movement patterns caused by fatigue (24,25). Motor variability is understood as the fluctuations that occur in motor behavior during the execution of an action (26). Although these fluctuations are inherent to human motor function, they can also be influenced by various factors (e.g., pathologies or injuries); thus, analyzing variability provides valuable insights into the organism's state (27,28). The analysis of variability can be approached from two complementary perspectives: the magnitude of variability (i.e., the amount of these fluctuations) and the temporal structure of variability (i.e., how these fluctuations occur over time, across different time scales) (27). Over the past decades, the analysis of the temporal structure of variability –also referred to as complexity, and which we will refer to as complexity throughout this manuscript– has been used in biological signals (e.g., heart rate, electromyography, or kinematics) to monitor different organism states, such as aging and/or disease (29–35), injuries (28,36), or fatigue (35,37). Generally, these studies report a “loss of the complexity" in the variability structure of biological time series. In these works, physiological complexity is typically assessed through entropy measures (e.g., approximate entropy, fuzzy entropy) and DFA. Each of these measures reflects a different aspect of the complexity of biological signal: entropy parameters measure predictability (or regularity) of the signal (38), while DFA quantifies self-similarity and long-range correlations across multiple timescales, providing insight into the persistence and adaptability of the system (39).

Loss of complexity has been associated with reduced adaptive capacity and functionality (29,30,35). This relationship has also been observed in fatigue contexts, where recent reviews (37,40) have provided strong evidence that nonlinear measures are influenced by fatigue in force signals during isometric, single-joint tasks. However, the conclusions of these studies are difficult to apply to field settings, as they rely on highly controlled laboratory settings that use analytical tasks and equipment not readily applicable to real-world conditions. Conversely, the usefulness of nonlinear tools for identifying fatigue-related changes in dynamic and multi-joint actions remains unclear. Some studies have investigated the effect of fatigue on dynamic tasks in variables such as angular velocity (41), knee abduction (24), or kinematic parameters, including velocity and time error (42,43). In contrast to isometric tasks, where there is consistent evidence of increased regularity and autocorrelation in response to fatigue, results in dynamic tasks are more heterogeneous, with some studies reporting decreased regularity and autocorrelation (42–44), and others showing the opposite (25,42,45). Potential differences between isometric and dynamic actions may be due to various causes, including the degrees of freedom involved and differences in fatigue mechanisms. Even if these tendencies differ, according to the model of optimal complexity proposed by Stergiou et al. (28), both overly predictable and overly random outputs reflect a loss of complexity and reduced adaptability. Since most actions in sports and daily life are dynamic, it is interesting to study the changes produced by fatigue in terms of complexity. Additionally, these studies typically rely on laboratory-based instruments, such as motion analysis systems, which are often inaccessible and impractical for regular use.

To overcome this limitation, Inertial Measurement Units (IMUs) have been proposed as an accessible and cost-effective alternative. Using these devices, some studies have reported their usefulness in detecting fatigue states, employing machine learning to analyze acceleration signals (46–48). Regarding studies applying instruments such as IMUs to measure changes in complexity caused by fatigue, it is worth mentioning the study by McGregor et al. (49). These authors reported a decrease in regularity, measured using Control Entropy, across all three acceleration axes – representing center of mass (CoM) movements – during a balance task following a fatigue protocol. McGregor et al. (49) suggested that this type of device may help detect fatigue states. Another study (50) demonstrated that these measures applied to acceleration signals are reliable for detecting changes in squat technique variability caused by modifications in load magnitude.

Fatigue control is crucial for both performance- and health-focused training. Despite evidence supporting IMU and nonlinear tools for monitoring fatigue, no study has analyzed complexity during resistance training exercises such as squats. This study aimed to investigate the complexity of acceleration signals as an indicator of fatigue during lower body resistance training. The effects of fatigue were analyzed in three types of resistance training: power, hypertrophy, and maximum strength. Changes in complexity parameters were compared to countermovement jump height, a method widely used in the field.

The study aims to provide human movement professionals with a practical and accessible tool to monitor the fatigue state of the organism, allowing them to control training or rehabilitation programs to make them safer and more efficient. We hypothesize: 1) Fatigue from all three training types will reduce jump height; 2) Fatigue will increase entropy and reduce DFA in acceleration signals; 3) The recovery profile will differ depending on the type of training, with the fastest recovery expected after power training, followed by hypertrophy training, and the slowest recovery after maximal strength training.

2. Method

2.1. Experimental Design.

A within-subject repeated-measures design was employed to investigate the acute and short-term effects of fatigue on movement variability and performance following various resistance training protocols. The study duration was four weeks. The first week consisted of two sessions. The initial session was dedicated to familiarizing participants with the tests and collecting informed consent forms. In the second session, the one-repetition maximum (RM) for the squat and hip thrust exercises was estimated. During the following weeks, each participant completed three training sessions corresponding to specific training modalities: hypertrophy, maximal strength, and power. These sessions were distributed over three consecutive weeks. Each training week followed the same structure. Participants performed a pre-test consisting of a countermovement jump and a set of 10 squats at 70% of (RM), followed by the training session, an immediate post-test, and follow-up assessments at 24, 48, and 72 hours after training. This design enabled the comparison of fatigue and recovery profiles across different training conditions within the same individuals. A schematic representation of the experimental timeline is included in Figure 1.

2.2. *Participants*.

Forty-four participants (18 women, 26 men; age = 29.6 ± 9.0 years; height = 169.4 ± 9.1 cm; weight = 72.8 ± 11.6 kg; RM squat = 99.6 ± 34.8 kg) were recruited for this study. The sample size was calculated in advance using the G*Power software (51). Based on previous studies (24,52,53), a moderate effect size was expected. For this reason, the parameters for the statistical power calculation were selected as an effect size of f = 0.20 ($\eta^2 p = 0.04$) for a statistical power of 80%, assuming an inter-measurement correlation of 0.50. A minimum of 30 participants was required for these parameters. The inclusion criteria specified that participants were healthy adults familiar with squat exercises and free from injuries or pathologies for at least 6 months. To ensure eligibility, participants completed a health history questionnaire, confirming their absence of any condition that could influence the study results. Participants provided written informed consent after receiving detailed information about the study. This consent process and procedure were approved by the university's ethics committee (DCD.RSS.02.19) and adhered to the principles outlined in the Declaration of Helsinki.

2.3. Procedures

The RM estimation was automatically calculated using the specialized software of the linear position transducer (T-Force System, V 3.70, Ergotech, Spain). Several studies have supported the use of movement velocity for 1RM estimation (54,55). The distribution of the training weeks is shown in Figure 1. The order was as follows: the first week focused on hypertrophy, the second on maximal strength, and the third on power—the fatigue protocols aimed to emulate lower-body training for each of these strength modalities. During the power session (PS), jump squats and explosive hip thrusts were performed with the toes on the ground. This session involved three sets of six repetitions at 30% of the RM, with three minutes of rest between sets. In the hypertrophy session

(HS), four sets of eight repetitions at 75% of the RM were performed, with a rest period of one minute and 30 seconds between sets for both the back squat and hip thrust exercises. Finally, in the maximal strength session (MS), the same exercises were performed, but the training consisted of three sets of three repetitions at 88% of the RM with three minutes of rest between sets. To avoid circadian changes in strength, all sessions were conducted at the same time each day.

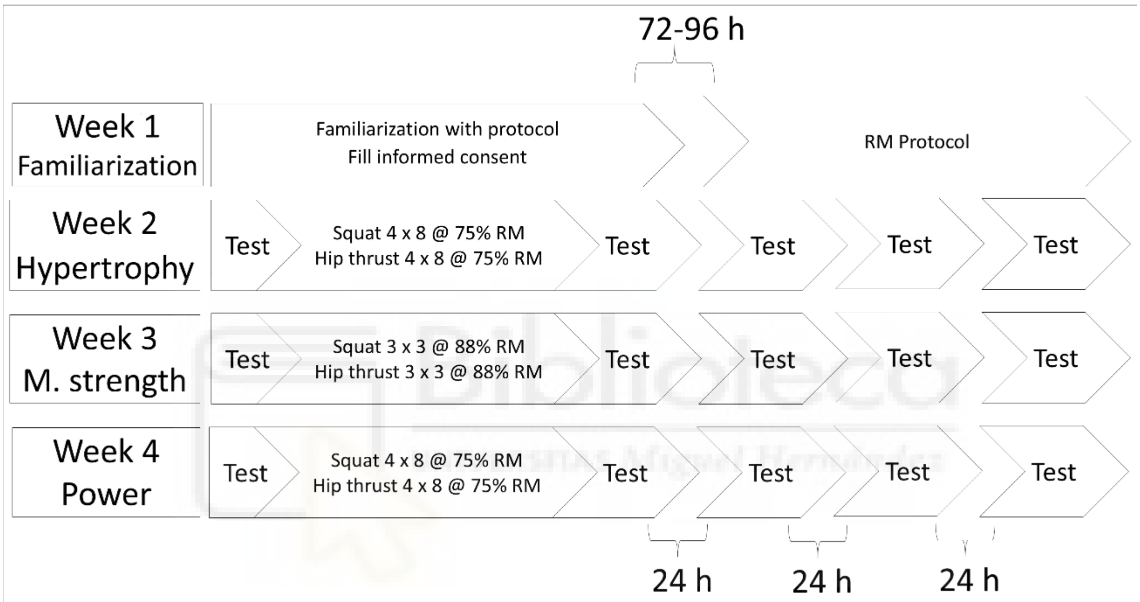

Figure 1. Chronological order of the development of the different weeks. M. strength: maximum strength. RM: repetition maximum. Test: countermovement jump and 10 squats at 70% of the maximal repetition were performed.

The tests involved three CMJs with one minute of rest between jumps and a set of squat exercises. The CMJ was performed with hands placed on the hips, ensuring proper execution by maintaining triple extension and avoiding flexion at the ankles, knees, hips, or trunk to estimate jump height. Six familiarization jumps were performed during the warm-up, and participants were encouraged to jump as high as possible during the tests. The squat test consisted of performing 10 squats at 70% of RM. During the familiarization sessions, the height at which the femur was parallel to the ground was recorded, and this height served as the reference point for the test. Participants were instructed to perform the 10 squats at a preferred velocity, with fluid movement and avoiding pauses between repetitions. Before performing the 70% test, two approach sets of 30% and 50% of RM were performed.

2.4.Data Recording and Analysis

CMJ height was recorded using the ChronoJump contact platform system (Boscosystem, Barcelona, Spain), with an average of three jumps analyzed per subject (56). During the squat repetition tests, low back acceleration was recorded using an IMU (iSen, STT Systems Inc., San Sebastián, Spain) placed at the level of the iliac crests near the L5 area. This area was chosen because various authors (57–59) have highlighted that IMUs placed in this location are a valid tool for detecting changes in the trajectory of the CoM. Since changes in the CoM are associated with variations in movement patterns during the squat exercise (60–62), analyzing the variability of the CoM can provide valuable insights into potential execution changes caused by fatigue. The acceleration signal was recorded at a sampling rate of 200 Hz. After performing a power spectral analysis to identify where 99.9% of the signal power was concentrated, the data were downsampled to 100 Hz. The magnitude of the acceleration (Acc_{L5}) was obtained using the acceleration data from all three axes.

The SD was examined to analyze the magnitude of variability. FuEn and DFA were used to assess complexity. FuEn was selected due to its greater robustness to noise and reduced sensitivity to time series length, as well as higher reliability on acceleration signals compared to other entropy methods (50,63), which made it particularly suitable for analyzing relatively short and noisy IMU acceleration signals. The FuEn was calculated according to Chen (63) using the following parameters: m = 2, r = 0.2 × SD, and n = 2 (64). The DFA was calculated based on the proposal by Peng et al. (39), with the windows adjusted to a duration of one second. For this purpose, windows from 4 to 100 data points (1 s) were analyzed. The IMU location, as well as the recording frequency and parameters for the DFA and FuEn were selected because a previous study (50) reported moderate to good reliability values measured through interclass coefficient correlation (ICC) (SD: ICC = 0.75; FuEn: ICC = 0.80; DFA: ICC = 0.55) and relatively low standard error values (SEM) (SD: SEM = 0.30; FuEn: SEM = 0.07; DFA: SEM= 0.13).

2.5.Statistical analysis.

The data obtained were analyzed with SPSS software (V. 25, IBM Statistics, New York, USA). The normality of the data was confirmed by the Saphire-Wilk test. Although a few variables did not follow a normal distribution, given the relatively large sample size (n > 25/30), it was assumed that ANOVA would be sufficiently robust in this context (65,66). Thus, a repeated measures ANOVA was performed with five-time points for each of the weeks (pre-test, post-test, retest 24 hours, retest 48 hours, and retest 72 hours), including four variables: CMJ, SD, FuEn, and DFA. Since no sphericity was assumed for most variables in the ANOVA tests, the Greenhouse-Geisser adjustment was applied to adjust significance levels. Additionally, the effect size was reported using partial Eta squared (η^2p) obtained from the ANOVA. The effect size was interpreted as small when $\eta^2p \approx 0.01$, medium when $\eta^2p \approx 0.06$, and large when $\eta^2p \approx 0.14$ (67). All data are reported as mean ± standard deviation unless otherwise specified.

3. Results

Some participants were unable to attend some of the retest sessions due to personal reasons. When this happened, those participants were excluded from the statistical analyses. As a result, 38 participants completed all tests during the power week, 35 during the hypertrophy week, and 41 during the maximal strength week. Regarding the acceleration signals, the length of the recordings ranged from 928 to 2959 data points.

A summary of the main results is presented in Table 1. In summary, no significant main effect of time was observed for CMJ height in the PS. However, a significant difference was found between the pre-and post-training values, which suggested a transient drop in performance immediately after the session. Significant effects were noted in the HS and MS. Fatigue did not have a significant effect on the magnitude of variability, as measured by SD, in any of the weeks. However, in terms of complexity, no significant change was observed in FuEn or DFA during the PS, whereas changes were detected during the HS and MS sessions.

Table 1. Descriptive data and results for each of the variables according to the type of fatigue protocol.

CMJ (cm)									
Week	**N**	**PRE**	**POST**	**24h**	**48h**	**72h**	**F**	**p**	**η^2p**
Power	38	27.2±8.7[b]	26.3±8.4	26.7±8.3	27.4±8.7	27.5±8.0	2.32	0.08	0.06
Hypertrophy	35	26.2±8.3[b]	23.4±7.7[c,d,e]	25.6±8.3	25.6±8.3	26.1±8.1	16.55	<0.01**	0.03
Maximal	41	27.0±8.1[b]	26.1±8.3[d,e]	27.0±8.3	27.5±8.0	27.8±7.8	8.17	<0.01**	0.17
SD (m/s^2)									
Week	**N**	**PRE**	**POST**	**24h**	**48h**	**72h**	**F**	**p**	**η^2p**
Power	38	2.43±0.59	2.48±0.64	2.45±0.61	2.51±0.60	2.56±0.66	1.66	0.18	0.04
Hypertrophy	35	2.09±0.57[d]	2.07±0.77	2.20±0.70	2.25±0.62	2.19±0.58	1.74	0.17	0.05
Maximal	41	2.25±0.66	2.24±0.69	2.29±0.60	2.30±0.61	2.34±0.62	1.13	0.35	0.03
FuEn (A.U.)									
Week	**N**	**PRE**	**POST**	**24h**	**48h**	**72h**	**F**	**p**	**η^2p**
Power	38	0.35±0.07	0.36±0.08	0.35±0.09	0.35±0.08	0.35±0.10	0.20	0.89	<0.01
Hypertrophy	35	0.47±0.18[b]	0.51±0.19[c,d,e]	0.46±0.16	0.45±0.17	0.46±0.19	7.08	<0.01**	0.17
Maximal	41	0.36±0.10[b]	0.39±0.11	0.37±0.11	0.36±0.10	0.36±0.10	3.67	0.01*	0.08
DFA (A.U.)									
Week	**N**	**PRE**	**POST**	**24h**	**48h**	**72h**	**F**	**p**	**η^2p**
Power	38	1.20±0.19	1.18±0.20	1.17±0.20	1.18±0.21	1.19±0.21	0.64	0.59	0.02
Hypertrophy	35	1.16±0.18[b]	1.10±0.22[e]	1.12±0.23	1.13±0.23	1.15±0.21	3.39	0.02*	0.09
Maximal	41	1.21±0.20[d]	1.18±0.19	1.17±0.22	1.15±0.21	1.19±0.21	3.95	<0.01**	0.09

Note. N: sample size for that strength manifestation; A.U.: arbitrary units; PRE: pre-test measurement, POST: post-test measurement; 24H: 24-hour retest measurement; 48H: 48-hour retest measurement; 72H: 72-hour retest measurement. The values presented in the tests are Mean ± Standard Deviation. *: P < 0.05; **: P < 0.01; b: significant differences with Post-test; c: significant differences with 24h-test; d: significant differences with 48h-test; e: significant differences with 72h-test.

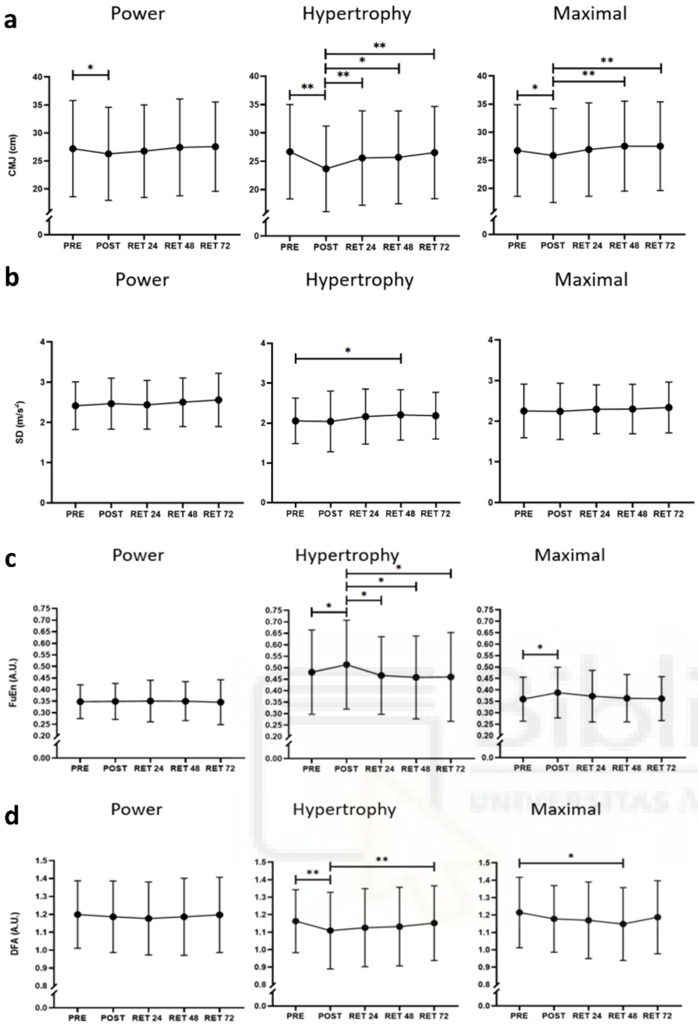

Figure 2. Plots of the means and standard deviation of the results of height from CMJ and SD, FuEn and DFA from Acc_{L5} in squat tests. Significant differences between the different time points obtained from the pairwise comparison are marked in the figure. *: $p < 0.05$; **: $p < 0.01$. A.U.: arbitrary units.

Although the overall effect on PS was not significant, Figure 2.a showed a slight decrease in CMJ jump height immediately after training. In the HS, there was a decrease in jumping height between the pre-and post-tests, which appeared to recover by 24 hours, as no significant differences were found between the pre-test and subsequent time points. In MS, there was also a significant decrease in jump height following the fatigue protocol;

however, at 24 hours, no differences were observed between the pre-and post-tests, while at 48 and 72 hours, significant differences persisted relative to the post-test.

Figure 2.b shows the results of the pairwise comparisons for the SD of Acc_{L5}. In none of the weeks was a significant effect found. Based on these results, the magnitude of variability, as measured by SD, is not sensitive to the fatigue-induced changes observed in other variables. Figures 2.c and 2.d display the results obtained for the complexity measures and their pairwise comparisons. No changes in nonlinear measurements were observed in PS after the fatigue protocol was applied. In the HS, FuEn increased and DFA decreased in the post-test following the fatigue protocol. FuEn values seemed to return to pre-fatigue values at 24 hours, while DFA did not return to baseline levels until 72 hours. Finally, a similar trend to that shown in HS was observed in MS. Thus, FuEn values increase in MS between pre- and post-fatigue, but in this case, no significant differences were found between post and the other time points. DFA in MS showed a tendency to decrease, similar to that found in HS; however, significant differences were only observed between the pre-and 72-hour tests.

4. Discussion

This study aimed to analyze the acute and short-term effects of fatigue induced by different resistance training modalities (power, hypertrophy, and maximal strength) on motor variability, using linear and nonlinear measures derived from acceleration data. Specifically, we hypothesized that (1) all training modalities would reduce CMJ height; (2) fatigue would increase entropy and reduce DFA, reflecting a loss of complexity; and (3) recovery patterns would differ by training type, with the fastest recovery in the power session and the slowest in maximal strength. The results partially supported these hypotheses. Hypothesis 1 was confirmed across all training modalities, as significant pre-to-post reductions in CMJ height were observed in each condition. However, it should be noted that the main effect of time in the ANOVA was not significant for the power session. Hypothesis 2 was only confirmed in the hypertrophy and maximal strength sessions, where significant changes were observed in both performance and variability measures. In contrast, minimal fatigue in the power session did not lead to meaningful changes. Hypothesis 3 was confirmed: the recovery of CMJ and complexity measures was slower following hypertrophy and maximal strength compared to power training. These findings are discussed in existing literature and theoretical frameworks below.

4.1.Effects of Fatigue on Countermovement Jump and Motor Variability

Previous research has shown that resistance training induces muscle fatigue due to physiological and biochemical responses (68). Depending on the type of training, fatigue is produced through different pathways and with varying recovery times (8,10,16,69,70). Overall, the fatigue effects and recovery times reported in this study are consistent with those reported in other research. Specifically, the Power Session protocol induced only mild fatigue immediately after the session, as evidenced by a significant decrease in jump height between the pre-and post-tests. However, this difference was not reflected in the main effect of time in the ANOVA, likely due to the absence of persistent changes in the subsequent time points. This is consistent with other studies that reported no significant effect of fatigue after power session protocols (71–75) or even an increase in jump height (76). In studies where a fatigue effect was observed, it was typically minimal and usually recovered within 6 hours (77) or 24 hours at most (78,79). In contrast, the Hypertrophy Session and Maximal Strength Session protocols produced a significant fatigue effect. The greatest post-fatigue height loss was observed in the Hypertrophy Session, which aligns with the findings of Kotikangas et al. (76). However, there are some discrepancies in terms of recovery times. Some works coincide with ours and found a complete recovery at 24 hours (71,76). At the same time, most studies report recovery times longer than 48 hours (12,69,71,76) and up to 72 hours (75,78–80). We suggest that these discrepancies may be due to the type of protocol, as the studies requiring longer recovery times involved higher volumes or were taken to failure. Although the loss in jump height in the Maximal Strength Session was qualitatively smaller (on average, -1 cm, while in hypertrophy, it was -3 cm), a longer recovery time was required, as full recovery was not achieved until 48 hours. This finding is in agreement with other studies (72,76,77,81), although it should be noted that some research has reported a 24-hour recovery time (76,80). In general, the results obtained in the CMJ are consistent with those reported in other studies, and the recovery times fall within the expected time range for each type of training.

In terms of the variability analysis from Acc_{L5}, the magnitude of movement variability (measured by SD) was not sensitive to the effects of fatigue in any of the types of training. Regarding the nonlinear measures of variability, it appears that they were sensitive to the fatigue generated in the Hypertrophy and Maximal Strength Sessions, but not in the Power Session, possibly because it was a low-fatigue session. The different measures of variability used give us different information. In this case, it appears that the nonlinear measures are more sensitive to the changes induced by fatigue, whereas the linear measures are not. Although the observed changes should be interpreted with caution, as they were statistically significant with a large effect size, the magnitude of the changes was smaller than the SEM reported in previous studies. Moreover, those SEM values were derived from comparisons between different load conditions, not from fatigue-related changes. Specifically, in the Hypertrophy Session, fatigue led to significant changes in FuEn (increase) and DFA (decrease), with FuEn returning to baseline within 24 hours and DFA showing a delayed recovery, requiring up to 72 hours. In the Maximal Strength Session, these changes were less pronounced but exhibited a slower recovery, with FuEn remaining elevated and DFA showing partial recovery at 72 hours. These findings align with the CMJ results, where Hypertrophy appears to have a faster recovery profile than Maximal Strength. However, variability measures indicate that fatigue has prolonged effects compared to performance metrics. Based on these results, it seemed that the recovery profile of motor variability is longer than that of CMJ. It should be noted that CMJ is a measure of performance, and performance can sometimes be maintained even when signs of fatigue (4). For example, when performing a squat, fatigue may alter the contribution of the muscle groups involved (23). That is, in the face of fatigue, changes in motor patterns may occur to maintain performance. It is possible that FuEn and DFA reflect changes in movement patterns. Concretely, the effect of fatigue appears to have led to less predictable (higher FuEn) and less auto-correlated (lower DFA) behavior. This might reflect an exploration of different pathways(49) to compensate for fatigue and perform the motor task (in this case, ten squats at 70% RM), which would translate into a greater number of movement adjustments (82,83). Since FuEn and DFA measure different aspects of complexity — predictability and autocorrelation respectively — they provide different information about movement, making it likely that the recovery profiles of these measures differ.

4.2. *The theory of fatigue-induced loss of complexity in dynamic actions*

The "Loss of Complexity Theory" proposed by Goldberger et al. (29,30) posits that under non-optimal conditions—such as disease, injury, aging, or fatigue—the organism exhibits reduced complexity across various physiological signals (29,30,35,84–88) **)**. In the context of force control, studies using isometric tasks have consistently reported reductions in complexity, typically expressed as more predictable and autocorrelated force outputs (37,40). However, findings in dynamic actions remain inconsistent. Fatigue has been shown to reduce complexity through both increased regularity (25,42,45) and increased randomness (41–43), depending on the specific task and measurement conditions. According to Stergiou et al. (28), both overly rigid (highly predictable) and overly noisy (highly random) behaviors represent a loss of complexity. Considering the results of this and previous studies, there does not appear to be a universal decrease in regularity or autocorrelation in biological signals resulting from fatigue. Rather, it should be noted that the term "loss of complexity" has been related to a state in which the organism has a reduced capacity for adaptation or diminished flexibility and adaptability.

Most of the physiological explanations for the fatigue-induced loss of complexity have been derived from studies involving isometric, single-joint tasks. In these constrained contexts, a reduction in complexity—interpreted as a loss of adaptability and functional capacity—has been consistently associated with increased motor unit synchronization, likely reflecting a greater reliance on common synaptic input (37). This increased synchronization reduces the range of available motor strategies, limiting neuromuscular variability and resulting in more regular and autocorrelated outputs. These changes are typically reflected by decreased entropy and increased DFA values, and have been proposed as markers of peripheral neuromuscular fatigue (89). However, as Cortes et al. (24) noted, this explanation may only apply to highly controlled isometric tasks involving a single joint and limited muscle groups with a single functional role (e.g., knee extension). In multi-joint and dynamic tasks, the situation may differ substantially. Given that the number of degrees of freedom has been shown to influence the behavior of nonlinear measures (90), a key question arises: What physiological mechanisms can explain the different complexity responses observed between isometric and dynamic actions under fatigue?

One possible explanation for this divergence is that different nested components of movement control may predominate at distinct temporal scales depending on the nature of the task. In isometric tasks, due to the absence of joint displacement and stable muscular demands, fluctuations are mainly determined by processes on low time scales, i.e., higher frequency neuromuscular dynamics. In contrast, dynamic tasks involve joint movements, varying muscular contributions, and continuously evolving coordination patterns. These characteristics lead to a predominance of behaviors at high time scales, i.e., lower frequency processes. However, when fatigue sets in—originating at the neuromuscular level—the resulting increase in motor unit synchronization may introduce variability that disrupts the smooth execution of the global movement. This neuromuscular "noise," when projected onto the slower timescale of joint coordination, manifests as increased unpredictability and reduced autocorrelation. Furthermore, fatigue-induced compensatory strategies may contribute to this loss of structure at the global level. Such strategies may include alterations in joint kinematics (e.g., at the hip or knee) (20,21,91), shifts in muscle group contributions (23,92), changes in activation patterns (93), or reorganization within intermuscular networks between trunk and lower limb muscles (94,95). These compensations add variability to the system, potentially explaining the divergent complexity responses to fatigue in dynamic versus isometric tasks.

Thus, in dynamic actions, the increase in irregularity and the decreased autocorrelation would reflect how the different parts of the organism organize on different time scales. Results reported in a recent paper (96) indicate that increasing the load during a squat resulted in higher FuEn and DFA values, supporting the idea that the system increases its irregularity and decreases its autocorrelation to cope with a constrained situation. This suggests that this type of strategy is not only used to cope with states of fatigue but also in response to demands for greater effort. It seems that less autocorrelated movements indicate a greater number of adjustments (83). This observation could suggest that in more demanding situations, such as fatigue, the organism needs to make a greater number of adjustments to complete the task. Although this framework remains theoretical, it provides a plausible basis for understanding the divergent patterns observed in nonlinear measures of motor variability under fatigue in isometric versus dynamic tasks.

5. Limitations and Perspectives for Study

It is essential to acknowledge that this study has some limitations. Firstly, analyzing the data using a two-way ANOVA requires complete data at all 15-time points (3 conditions x 5-time points), which means that missing a single session result in exclusion from complete factorial analyses. For this reason, a one-way ANOVA was performed for each condition. Future studies should consider strategies to minimize data loss, allowing for direct statistical comparisons between training modalities. Moreover, the sample was relatively heterogeneous in terms of gender and training level. In future studies, it should be analyzed whether there may be any effect of gender in the analysis of variability. In addition, the participant's fitness level should be further defined to detect possible differences for two reasons: firstly, because fatigue may affect complexity differently, and secondly, although the intensity was adjusted to the individual, the volume was not, which could have influenced the results. Another potential limitation is the variable duration of the time series during squat execution, which may affect the application of nonlinear analyses. Although this variability better reflects real training conditions, it should be acknowledged and considered when interpreting the results. Based on our results, we cannot determine whether changes in complexity indicate more or less adaptive behavior. Therefore, protocols could be conducted until exhaustion, as this would ensure that changes in variability reflect a decrease in the organism's functionality. In addition, to determine precisely the clinical relevance of the loss of complexity, studies should examine different physiological variables, such as EMG, biomarkers, or kinematics, to gain a deeper understanding of the physiological significance of the changes in complexity.

6. Conclusions

This study showed that lower-body resistance training induces measurable changes in motor variability, which can be detected through acceleration signals collected at the lower back using inertial sensors. Specifically, nonlinear measures such as fuzzy entropy and detrended fluctuation analysis proved sensitive to fatigue-related changes, particularly after hypertrophy and maximal strength sessions. These changes reflect alterations in the organization of motor output and may signal a reduced capacity to adapt to physical demands. In contrast, the power-oriented session induced mild fatigue in the performance measure, producing no change in that variability, which highlights the modality-dependent nature of fatigue effects. Although this was not the primary aim of the study, our results tentatively suggest that the loss of complexity may manifest differently in isometric versus dynamic tasks. Our findings suggest that nonlinear metrics derived from wearable accelerometers can capture subtle motor adaptations caused by fatigue, complementing traditional indicators such as countermovement jump performance.

6.1. Practical Applications

Nonlinear analysis of motor variability provides a promising tool for monitoring fatigue in field and clinical settings. It offers two key advantages:

1. It enables fatigue assessment in populations where maximal or high-impact tests are not feasible (e.g., injured or elderly).
2. It allows for accessible and low-cost implementation using wearable sensors or smartphones.

These insights may contribute to safer and more effective training or rehabilitation strategies by enabling more individualized load management and injury prevention.

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Appendix 4: How does fatigue affect handstand balance? A non-linear approach to study fatigue influence in handstand performance

Study 4: Sabido R, García-Aguilar F, Caballero C, Moreno FJ. How does fatigue affect handstand balance? A non-linear approach to study fatigue influence in handstand performance. J Neuroeng Rehabil. 2024;21:171. doi: 10.1186/s12984-024-01442-6. PMID: 38888977; PMCID: PMC11111293.

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RESEARCH **Open Access**

How does fatigue affect handstand balance? a non-linear approach to study fatigue influence in handstand performance

Rafael Sabido[1], Fernando García-Aguilar[1*], Carla Caballero[1] and Francisco J. Moreno[1]

Abstract

Background The handstand is an essential skill in acrobatic sports. This skill requires the athlete to maintain an inverted upright stance with only the hands supported, which requires a great effort of muscular coordination and motor control. Several factors influence the ability to control the posture, including fatigue, which is a bit studied constraint of handstand performance.

Research question With the aim to find out whether variability in movement control can be an indicator of fatigue, the present study was carried out.

Method Fourteen male acrobatic gymnasts were required to perform handstands. The time series for analyzing variability were capturing using Force Platforms, which is a traditional laboratory instrument, and Inertial Measurement Units (IMU), which is a more recent and less widely used, but more accessible tool. For this purpose, an analysis of the amount of variability was carried out, using the standard deviation. And analysis of the structure of variability (or complexity), using Detrended Fluctuation Analysis (DFA) and Fuzzy Entropy (FuEn).

Results Our results reveal that fatigue causes significant increases in the amount of variability in the medio-lateral axis on the force platform, and in the IMU located in the area of the L5 vertebra. These changes are accompanied by increased auto-correlation in the medio-lateral axis of the force platform, and more unpredictable behavior in the L5 IMU.

Key points

- Amount of variability can discriminate between non-fatigued and fatigued states in force platform.
- Structure of variability can discriminate between non-fatigued and fatigued states in force platform.
- Movements are most affected in the medio-lateral axis.
- Forces produced to maintain balance exhibit smoother adjustments in fatigue state.
- Acceleration in the L5 tends to be less predictable in fatigue state.

Keywords Variability, Complexity, Balance, Motor Control, Gymnastic skills

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Introduction

Handstand task is defined as the action of maintaining the body in an inverted vertical stance with the hands in contact with the support surface [55]. Handstand is one of the most important skills in acrobatic sports [28]. Correct execution of a handstand implies a body position with a straight back and legs to maintain posture enduringly [52], trying to maintain the Centre of Mass (COM) vertical projection within the support area created by hands [53].

To execute the handstand, the performer realizes minimal changes in hand pressure and limb actions to control the balance position. The ability to maintain an inverted posture as the handstand requires complex muscle coordination and a high motor control of many degrees of freedom [55]. Several neurophysiological and biomechanical control processes are key to the performance of successful handstand performance [53]. Research studies about biomechanics and motor control in the handstand have been center on individual or coordinated structures, for example, the control in several joints such as hips, shoulders, or wrists [48]. Nevertheless, the role of macroscopic variables as the center of pressure (COP) has been less studied in opposite to upright balance studies where is a common variable.

Human motor control is characterized by complex nonlinear dynamics, where a multitude of constraints influence performance. In the case of handstand, different variables have been studied to know their influence on motor control of that skill. Some of those variables are performer experience [53, 55], visual availability [50], suit characteristics [15] or the surface where handstand is executed [3]. One key performance variable is upper limb strength [28] because the antigravitational function is not proper for those muscles. This function requires great muscle activity of the upper extremities [33], so those muscles succumb early to fatigue [28]. Fatigue is an important constraint in acrobatic sports because affects several aspects (biomechanical response, perception, injury tolerance, etc.) during training and competition [6, 40]. Nevertheless, to the best of the authors' knowledge, no study has analyzed the influence of fatigue on handstand performance.

The study of the relationship between fatigue and motor control has been extended in the last years, in the health field [11, 26] as many as sports performance field [2, 29]. An important number of articles about fatigue have studied its influence on upright balance [16, 19, 27]. Most of those studies found an increase in variables such as COP area and velocity displacement after fatigue conditions [12, 39]. In addition to these variables, nonlinear analysis of balance control has been considered during balance tasks [4, 13, 31]. Several authors have exposed the utility of nonlinear tools as entropy or detrend fluctuation analysis (DFA), to obtain different information during balance tasks [8]. So, while entropy analysis can assess the regularity of COP during balance tasks [51], DFA analysis can support information about the complexity of COP signal [9]. Recently these tools have been proposed such as variables sensitive to fatigue in different tasks [24]. Generally, the analysis of movement variability, whether for the detection of fatigue or other sub-optimal states of the body, has been performed using expensive and difficult to access instruments such as force and isokinetic platforms, which limits its applicability in clinical and sporting contexts [13, 31, 47]. Therefore, the present study is exploratory in nature, with the aim of evaluating the usefulness of movement variability analysis using IMU, seeking a more accessible and practical alternative.

The purpose of the present study was to investigate the influence of the fatigue process on handstand performance comparing the information from linear and non-linear analysis. We hypothesized that while COP Area and Velocity increase with fatigue, a lower irregularity and higher autocorrelation from COP signal will be observed during handstand performance.

Methods

Participants

Fourteen (n = 14) male acrobatic gymnasts were recruited for this study. The participants were aged 25.77 ± 5.82 years (mean ± SD), with a mass of 69.66 ± 8.78 kg and a height of 1.74 ± 0.09 m. G*Power software version 3.1.9.4 [21] was used to decide the sample size. Based on previous studies we expected fatigue to have a high effect size (at least dz = 0.80) [16, 50]. And it was set to expect a statistical power of 80%. Based on these parameters the sample should be at least 12 participants. No participants had any history of nervous system or muscular dysfunction at the time of measurements. Written informed consent was obtained from each participant before the experiment. The study was following the Declaration of Helsinki and was approved by a University Office for Research Ethics Testing protocol (DCD.RSS.02.19).

Experimental procedure

To preserve the integrity of the research process, all the tests were carried out in the same morning hour. The measurements were carried out in a laboratory room, in conditions that ensure the isolation of acoustic or visual stimuli that could interfere with postural control during the study. Athletes were wearing gymnastic costumes without shoes.

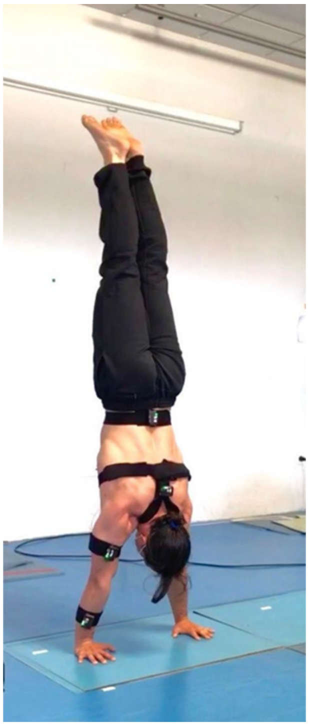

Fig. 1 Shows the set where the measurements were performed, showing the four IMUs and the force platform

To assess postural stability during the handstand task, ground reaction forces were recorded by a force platform (Kistler, Switzerland, Model 9287BA) and four IMUs (STT-System, Spain). Two IMUs were mounted on the forearm and arm from the dominant limb, and the other two near the seventh cervical vertebra (C7) and the fifth lumbar vertebra (L5). Figure 1 shows the arrangement of the devices.

After a 15-min warm-up with general movements and specific exercises for the handstand task (including 10 trials of swinging up to the handstand to familiarize themselves with the task and conditions in the lab), participants performed two 30-s trials separated by a fatigue procedure. Three minutes after the pre-test trial, two sets of 15 push-ups at a preferred velocity were done with a rest of one minute between both sets. Later the two sets of push-ups to induce fatigue the post-test trial was measured. For a schematic overview of the procedure see Fig. 2.

The participant performed a handstand with a rebound of one leg and a swing of the other leg. Stability measurement was recorded when the lower limbs were joined in a vertical position. A trigger in force plate recording was included when the participant was in vertical position. Participants were asked to stand "as still as possible" during the test. Participants must maintain balance in the handstand by using the wrist strategy and not another one (e.g., the hip or elbow strategy) which means the control was reached by movements in the wrist joint [32].

Data analysis and reduction

We collected 30 s of data at 100 Hz with a force plate and IMUs, but the first 5 s and last 5 s of each trial were discarded to avoid nonstationary signal [54]. The signal was subsampled at 50 Hz. So, the length of time series analyzed was 1000 data points. No filtering was performed on the data because filtering could affect the nonlinear results [34]. Postural performance was

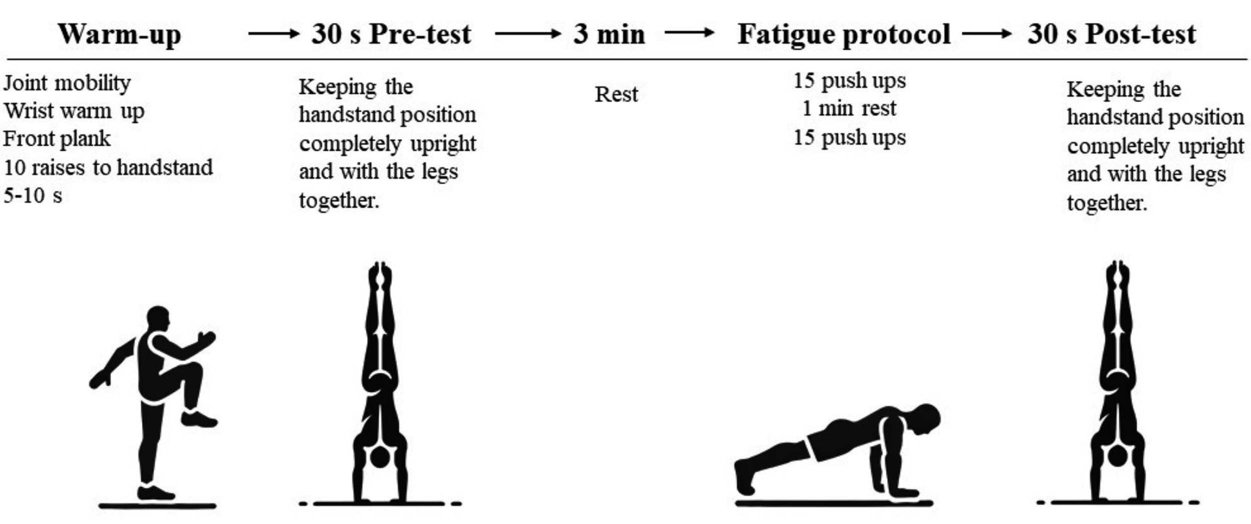

Fig. 2 Outline of the measurement procedure

assessed using bivariate variable error (BVE) and mean velocity magnitude (MVM) in the force plate. BVE was measured as the mean of the displacement to each participant's own midpoint, and MVM was measured as the average COP velocity [10]. Postural modifications on the floor were analyzed through COP area and force distributions measured by force plate. On the other hand, body behavior was measured through standard deviation (SD) from resultant acceleration collected by IMUs. The variables used to assess the complexity of force plate signals and acceleration from IMUs were FuEn, and DFA. FuEn indicates the degree of irregularity in the signal through to calculate the repeatability of vectors. On the other hand, DFA evaluates the presence of long-term correlations within time series [18]. FuEn was calculated using the formula (1) proposed by Chen et al. [14], with the following parameters m = 2, r = 0.2 and N = 2.

$$\mathrm{SampEn(m, r, N)} = -\ln\left(\frac{\mathrm{A}^{m}(\mathrm{r})}{B^{m}(r)}\right) \quad (1)$$

While the DFA following the algorithm (2) of Peng et al. [45], where windows from 4 to 50 data were calculated, which would be equivalent to one second.

$$\mathrm{F(n)} = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\mathrm{y(k)} - y_n\mathrm{(k)}]^{2}} \quad (2)$$

Statistical analysis

Data normality was evaluated with Kolmogorov–Smirnov test with the Lilliefors correction. A paired *t*-test was performed to study the possible significant influence of fatigue in handstand task. Results are expressed as means ± SD. Given the large number of variables analyzed, it was decided to apply the Bonferroni adjustment to determine significance; as this was an exploratory study, we adjusted the p-values by grouping them by device. Thus, the p-value was set at $p < 0.007$ to assume that the differences were significant. Effect size was calculated using standardized mean difference, Cohen's d, to provide a proportion of the overall variance that is attributable to the factor. Values of effect size ≥ 0.80 were considered strong, ≥ 0.50 moderate, and ≥ 0.20 were considered small [23]. All data were analyzed using the SPSS statistical package (v.22, SPSS Inc, Chicago, IL).

Table 1 Comparison between pre and post-fatigue protocol of linear measurements

Variable	Pre Mean ± SD	Post Mean ± SD	p	t	d
BVE	13.679 ± 2.818	14.854 ± 2.566	0.191	−1.378	−0.369
MVM	151.792 ± 35.641	154.271 ± 23.660	0.784	−0.280	−0.075
SD IMU FA	0.401 ± 0.196	0.416 ± 0.168	0.412	−0.847	−0.226
SD IMU AR	0.414 ± 0.181	0.402 ± 0.126	0.628	0.496	0.133
SD IMU C7	0.279 ± 0.121	0.294 ± 0.125	0.451	−0.778	−0.208
SD IMU L5	0.358 ± 0.146	0.412 ± 0.172	0.041	−2.146	−0.574
SD PLA X	7.428 ± 1.983	7.689 ± 1.534	0.339	−0.990	−0.265
SD PLA Y	4.246 ± 0.691	4.787 ± 0.823	0.007*	−3.160	−0.845
SD PLA Z	17.382 ± 3.359	18.327 ± 3.113	0.217	−1.300	−0.347
SD PLA AX	14.083 ± 2.811	14.808 ± 2.243	0.372	−0.930	−0.249
SD PLA AY	6.447 ± 1.660	7.756 ± 2.321	0.034	−2.370	−0.633
SD PLA MF	17.383 ± 3.360	18.325 ± 3.112	0.219	−1.290	−0.345
SD PLA MC	11.813 ± 3.724	13.400 ± 2.184	0.043	−2.130	−0.569

The values presented in Table 1 depict the comparison between pre- and post-fatigue protocol of linear measurements. Mean values and standard deviations (SD) are reported for each variable. The statistical analysis results include the p-value (p) and the outcomes of paired Student's t-test (t). The effect size measure (d) is utilized to assess the magnitude of the observed differences.

BVE: Bivariate variable error; MVM: Mean velocity magnitude; SD: Standard deviation; IMU: Inertial measurement unit; PLA: force platform; FA: Forearm; AR: Arm; C7: Seventh cervical vertebra; L5: Fifth lumbar vertebra; X: Antero-posterior axis of force platform; Y: Medium-lateral axis of force platform; Z: Vertical axis of force platform; AX: Antero-posterior axis of center of pressure; AY: Medio-lateral axis of center of pressure; MF: Modulus of force axis; MC: Modulus of center of pressure

*p < 0.007 indicates a significant difference.

Results

Before presenting the results of the analyses conducted on the complete 20-s signal, we conducted a comparative assessment to distinguish whether potential changes were induced by the fatigue protocol rather than the inherent handstand task. This comparison entailed examining the first and last 10 s of each measurement, both pre- and post-fatigue protocol, through t-tests. The primary aim was to confirm that any disparities between the pre- and post-fatigue periods were attributable to the fatigue protocol and not to accumulated fatigue during the task itself. Our analysis revealed no significant differences between the initial and final 10 s of the pre and post-fatigue measurements. This observation supports the conclusion that the previously noted differences in the pre-fatigue measure can be attributed to the fatigue protocol.

Table 1 presents the comparison from linear measurements between pre- and post-fatigue protocol. In terms of linear measurements, significant differences were observed only in the mediolateral axis (PLA Y) from the force plate, which showed an increase from pre to post-fatigue situations with a strong effect size. Conversely, other variables, such as the SD of L5 IMU, COP displacement in axis Y (AY), and modulus of COP (MC) from the force plate, while not reaching the new significance threshold, displayed strong trends. The effect sizes for these variables were moderate to strong, indicating a meaningful tendency towards significance.

Significant differences were found in DFA in the mediolateral (PLA Y) axis of the force platform, which exhibited a large effect size. For the other variables, such as DFA in the vertical axis (PLA Z) of the force platform, DFA in the MF, and FuEn in the sacral IMU, while the p-values did not meet the stricter significance threshold, these variables demonstrated moderate to strong trends supported by their large effect sizes. In the remaining nonlinear variables, no significant changes or potential trends were observed, with effect sizes ranging from small to medium.

Table 2 Comparison between pre and post-fatigue protocol of non-linear measurements

Variable	Pre Mean ± SD	Post Mean ± SD	p	t	d
DFA IMU FA	0.206 ± 0.140	0.200 ± 0.090	0.777	0.290	0.077
DFA IMU AR	0.326 ± 0.140	0.306 ± 0.098	0.588	0.556	0.148
DFA IMU C7	0.400 ± 0.067	0.421 ± 0.163	0.658	− 0.454	− 0.121
DFA IMU L5	0.184 ± 0.116	0.184 ± 0.075	0.988	0.015	0.004
DFA PLA X	0.907 ± 0.093	0.905 ± 0.077	0.922	0.100	0.027
DFA PLA Y	0.916 ± 0.173	1.056 ± 0.158	0.004*	− 3.459	− 0.924
DFA PLA Z	0.318 ± 0.126	0.486 ± 0.219	0.015	− 2.809	− 0.751
DFA PLA AX	1.252 ± 0.101	1.24 ± 0.108	0.531	0.644	0.172
DFA PLA AY	1.375 ± 0.152	1.376 ± 0.111	0.990	− 0.013	− 0.003
DFA PLA MF	0.318 ± 0.126	0.486 ± 0.219	0.015	− 2.806	− 0.750
DFA PLA MC	1.273 ± 0.098	1.238 ± 0.107	0.049	2.169	0.580
FuEn IMU FA	0.293 ± 0.161	0.305 ± 0.140	0.445	− 0.788	− 0.211
FuEn IMU AR	0.290 ± 0.125	0.286 ± 0.092	0.778	0.287	0.077
FuEn IMU C7	0.189 ± 0.081	0.199 ± 0.083	0.200	− 1.350	− 0.361
FuEn IMU L5	0.229 ± 0.104	0.267 ± 0.116	0.011	− 2.958	− 0.791
FuEn PLA X	1.401 ± 0.149	1.413 ± 0.142	0.741	− 0.337	− 0.090
FuEn PLA Y	1.445 ± 0.154	1.402 ± 0.202	0.366	0.937	0.250
FuEn PLA Z	2.014 ± 0.219	1.995 ± 0.247	0.742	0.336	0.090
FuEn PLA AX	0.557 ± 0.148	0.541 ± 0.123	0.629	0.495	0.132
FuEn PLA AY	0.543 ± 0.150	0.539 ± 0.111	0.861	0.179	0.048
FuEn PLA MF	2.014 ± 0.219	1.996 ± 0.247	0.744	0.334	0.089
FuEn PLA MC	0.620 ± 0.139	0.593 ± 0.124	0.491	0.708	0.189

The values presented in Table 2 depict the comparison between the pre- and post-fatigue protocol of non-linear measurements. Mean values and standard deviations (SD) are reported for each variable. The statistical analysis results include the p-value (p) and the outcomes of paired Student's t-tests (t). The effect size measure (d) is utilized to assess the magnitude of the observed differences.

DFA: Detrended fluctuation analysis; FuEn: Fuzzy entropy; IMU: Inertial measurement unit; PLA: force platform; FA: Forearm; AR: Arm; C7: Seventh cervical vertebra; L5: Fifth lumbar vertebra; X: Antero-posterior axis of force platform; Y: Medium-lateral axis of force platform; Z: Vertical axis of force platform; AX: Antero-posterior axis of center of pressure; AY: Medio-lateral axis of center of pressure; MF: Modulus of force axis; MC: Modulus of center of pressure

*$p < 0.007$ indicates a significant difference

Discussion

In the present study, we investigated the influence of fatigue in the complexity of movement system variability during the performance of a handstand task. The non-linear analysis of the fluctuations of movement in the base of support is sensitive to the effects of fatigue in postural control as a complementary procedure to the traditional variables of analysis.

In the author's knowledge, this is the first study about the influence of fatigue during handstand task. Several constraints have been studied during handstand execution [3, 50]. Most of the studies found a change in behavior with different constraints application (e.g. type of surface, open-closed eyes or place vision), resulting in an increase in force production [3], COP displacement [17], or COP variance [25]. Our results are in partial agreement with these studies, finding a significant increase in the dispersion of forces applied in the base of support and COP way in the Y-axis (PLA Y) after the fatigue protocol. Similar results were found by Gautier et al. [25] during closed eyes or peripheral vision strategies as constraints during handstand. Furthermore, other variables such as the SD of L5 IMU, COP displacement in axis Y (AY), and MC from the force plate, while not reaching the new significance threshold, displayed strong trends. The effect sizes for these variables were moderate to high, indicating a meaningful tendency towards significance. IMU devices are new technologies recently applied in the gymnastic field [37], and they have been proven to be useful to provide feedback during gymnastic execution [5, 7]. Our results about the variability detected in L5 with IMUs can only be compared with studies where the hip has been studied with cinematography [22], showing a similar trend towards increased variability of the joint angle with a constraint related to head position.

Research on the application of non-linear analysis of movement using DFA or Entropy to analyze handstand performance is still scarce. Previously, only Pryhoda et al. [49] have applied non-linear tools to handstand description. Similar to our results, Pryhoda et al. found a reverse trend between complexity and SD when joint angles were analyzed during the handstand task. Isableu et al. [30] applied entropy to study COP regularity in gymnasts but during bipedal tasks. These authors exposed the utility of complexity analysis to show qualitative differences between gymnasts' and control participants' behavior, in a task where quantitative differences did not find. Our results are according to this idea because fatigue constraints led to some significant differences, especially in force plate variables. The loss of complexity observed through DFA increase after fatigue protocol according to previous studies. So, Pau et al. [44] found a decrease in COP complexity during upright balance after fatigue tasks in firefighters in accordance with the results from our study. Similar results were obtained by Lee et al. [36] after mental and physical fatigue using DFA as a variable to study COP complexity in quiet standing tasks. These authors found a decrease in DFA exponent in COP approached statistical significance after a 30-min mental fatigue-inducing task and calf raise task until exhaustion.

These results about a decrease in postural control complexity have been found in other tasks such as running [41] or isometric muscle contractions [46]. Results from those studies and ours would be according to the "loss of complexity hypothesis" which suggests a reduction in qualitative motor variability is produced by a reduction of degrees of freedom during a task [38]. Nevertheless, some authors have found opposite results showing an increase in entropy of COM accelerations during single-legged stance after fatigue induced by two Wingate tests [42]. These authors expose that fatigue can produce a diversion of attention during post-test situation, assuming the idea of Donker et al. [20] who defend an increase in postural complexity when attention is diverted during a dual task. However, in our study we did not observe the aforementioned reduction in complexity. Perhaps given the increased attention requirement due to the difficulty of the task, i.e. maintaining the handstand position compared to standing, it is possible that more attention is required, and thus the complexity tends to increase, as in the studies of Donker et al., even with the development of fatigue.

Nevertheless, the information about non-linear analysis from the accelerometer signal is different from that of the force plate. In this case, a trend towards a significant increase in FuEn has been observed after fatigue, reflecting a higher irregularity in this measure. According to previous studies, information from accelerometers and force plates could be different and complementary [35]. Non-linear analysis from a force plate informs about a freeze in degrees of freedom with fatigue (higher DFA), while entropy analysis from the L5 accelerometer shows a tendency towards higher irregularity as a result of fatigue. Accelerometer in L5 are more sensible to hip actions during handstand, a strategy not allowed to control balance in our protocol, but it is usual to observe this strategy when postural sway becomes too great [32] just as occurs in fatigue condition.

The use of accelerometers to measure motor variability has grown in the last few years. The possibility of providing alternative or complementary information to force plates in balance studies [1], and the low cost of these devices versus force plates [43] are reasons to find a high number of studies using accelerometry to assess balance tasks. In our study, data from accelerometers and force plates showed similar sensitivity to quantitative changes after fatigue induction. Thus, the IMU located at L5, close to the COM site, and the Y-axis or MC variables seem to be good indicators of fatigue influence, similar to the study by Adlerton et al. [1], who analysed COP displacement as a force plate variable. On the other hand, when the structure of motor variability is analyzed, results from force plate variables can be more sensitive to detect fatigue regarding data from IMUs, because only FuEn in IMU L5 showed a trend towards differentiation between pre and post fatigue constraints. In this way, our results indicate a more sensitive measure of the postural adjustments from the force plate versus accelerometry in opposition to the idea from McGregor et al. [41]. This could be explained because force production measured in the force plate results from participant behavior to maintain COM in the support base. In this way, complexity motor analysis reflects as fatigue has an important influence on the participant's ability to show successful behavior.

Conclusions

This study aimed to investigate the influence of fatigue in handstand tasks through force plate and accelerometers and under linear and non-linear analysis. Force plate and one of the accelerometers (ubicated in L5) show a tendency to detect changes in the amount of variability after a fatigue condition. Furthermore, non-linear analysis based on DFA is only sensitive from force plate signal and not from the accelerometer. In the accelerometer signal a trend towards an increase in irregularity can be observed as a possible change of hip control during handstand as a result of fatigue and the increase in COP way. In this way, the accelerometer can be implemented to assess handstand tasks during fatigue protocols through linear analysis (quantitative variability). On the other hand, if coaches or researchers want to detect qualitative changes in variability, a force plate is the recommended device.

It is important to note that this is an exploratory study. More research is needed to fully understand which variables are most useful in detecting fatigue-related changes in handstand tasks. Future studies should aim to validate these findings with larger sample sizes and in different contexts to determine the generalizability and applicability of these measures.

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Author contributions
Conceptualization, R.S.; methodology, R.S, F.G. and F.M.; software, F.G-A. and F.M.; formal analysis, F.G-A.; investigation, R.S. and; resources, R.S. and C.C.; data curation, F.G.; writing—original draft preparation, R.S and F.G-A.; writing—review and editing, C.C. and F.M.; supervision, R.S. and F.M. RS: Conceptualization (equal), Supervision, Writing/Original Draft (equal), Methodology (equal). F G-A: Data Curation (equal), Investigation (equal), Formal Analysis (lead), Writing/Original Draft (equal). CC: Investigation (equal), Methodology (equal), Writing/Review & Editing (equal). FM: Conceptualization (equal), Supervision, Writing/Review & Editing (equal), Methodology (equal).

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Availability of data and materials
The data that support the findings of this study are available from the corresponding author upon reasonable request. Similarly, the codes used to perform the variability analyses are available upon request to the corresponding author. The data is available to any reader upon request to the corresponding author.

Declarations

Ethics approval and consent to participate
The study was conducted in accordance with the Declarationof Helsinki and approved by the Office of Responsible Research (OIR). The University's ethics committee approved the research ethics statement under register 2019.417.E.OIR; 2020.34.E.OIR and reference DCD.RSS.02.19. Each subject provided written informed consent, which was approved by the ethics committee of the University (PID2019-109632RB-100) and which adhered to the Declaration of Helsinki.

Consent for publications
All authors have read and agreed to the published version of the manuscript.

Competing interests
The authors declare no competing interests.

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Publisher's Note

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Seguimos dándole duro.

Fer.