UNIVERSIDAD MIGUEL HERNÁNDE DE ELCHE

DEPARTAMENTO DE PSICOLOGÍA DE LA SALUD

Programa de Doctorado en Psicología de la Salud

Variability, performance and the ability to adapt in balance tasks

Doctoral Thesis

A dissertation presented by
Carla Caballero Sánchez

Graduate in Physical Activity and Sport Science

Elche, 2016

El Dr. D. Juan Carlos Marzo Campos, director del Departamento de Psicología de la Salud de la Universidad Miguel Hernández de Elche.

AUTORIZA:

Que el trabajo de investigación titulado: "VARIABILITY, PERFORMANCE AND THE ABILITY TO ADAPT IN BALANCE TASKS" realizado por Dña. Carla Caballero Sánchez bajo la dirección de Dr. D. Francisco Javier Moreno Hernández sea depositado en el departamento y posteriormente defendido como Tesis Doctoral en esta Universidad ante el tribunal correspondiente.

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Título de la Tesis

VARIABILITY, PERFORMANCE AND THE ABILITY TO ADAPT IN BALANCE TASKS

Tesis Doctoral presentada por:

Dña. Carla Caballero Sánchez

Dirigida por el Dr. D. Francisco Javier Moreno Hernández

El Director **El Doctorando**

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A mi Abuelo

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"Me enseñaron que el camino del progreso no es ni rápido ni fácil"

"Lo importante es no dejar de hacerse preguntas"

Albert Einstein

ABSTRACT

Postural control analysis has been one of the most studied research fields in motor control. Specifically, balance tasks have been frequently used to assess motor coordination due to the fact that maintaining balance is a frequent activity and, at the same time, it is also a complex ability that involves controlling many neuromuscular components. In the literature, postural control is commonly analyzed though the analysis of the variability of the center of pressure (CoP) fluctuations in balance tasks. Variability of the human movement has been frequently interpreted as an error of the system that should be reduced as much as possible. However, current studies have outlined movement variability as a functional characteristic of the system, boosting the individual´s ability to adapt to the environment. Under this perspective, several studies have tried to find out if there is a relationship between motor variability, performance and the ability to adapt. With this purpose, motor variability has been analyzed through many measures, among which we can find traditional variables used to assess the amount of variability. Recently, new variables have been used to assess the variability structure by mathematical nonlinear tools. Despite the large number of studies on the reliability of these variables, there is still controversy about which variables better characterize postural control. The first study presented in this doctoral thesis analyses the reliability of different tools, both traditional and nonlinear, usually used to measure postural control in standing balance tasks. The results indicated that, in balance tasks, nonlinear variables show greater reliability than traditional scattering variables in the CoP analysis. In addition, mean velocity of CoP shows higher reliability values than scattering variables, showing similar values to nonlinear variables.

After knowing which variables are better to characterize postural control in balance tasks, the next step was to analyze the relationship between variability and performance. In the literature we can find controversial results about whether variability is related to greater or lower performance and how it is linked to the ability to adapt. One of the possible reasons for this controversy can be that the structure of variability depends on the different constraints from the organism, the environment and the task. In order to test this hypothesis, we

outlined a study in which different task constraints were manipulated to observe their effect on motor variability and its relationship with performance. This study allowed us to verify that the relationship between the structure of CoP variability and the performance in a standing balance task is dependent on the task difficulty and the availability of biofeedback. Therefore, constraints should be taken into account to analyze motor variability and its relationship with performance and the ability to adapt.

Finally, according to current studies, it seems that variability can be related to the ability to adapt and the learning process. The third study presented in this thesis tried to check this hypothesis developing two experimental protocols in balance tasks in which a practice period was applied to promote learning. The results of both experiments showed that motor variability structure in balance tasks seems to reveal the system´s ability to learn based not only on exploration processes but also on error sensitivity.

Future studies should go in depth into the analysis of the motor variability structure as an index for predicting performance, the ability to adapt and learning, taking into account the task constraint effects and different motor tasks in order to extrapolate the results of this doctoral thesis.

RESUMEN

El análisis del control postural es un campo de trabajo muy estudiado dentro del control del movimiento. En concreto, las tareas de equilibrio han sido muy utilizadas para la valoración de la coordinación motriz, ya que el mantenimiento del equilibrio es una actividad usual y, a su vez, muy compleja que implica la coordinación de numerosos componentes neuromusculares. En la literatura, frecuentemente se analiza el control postural a través del análisis de la variabilidad de las fluctuaciones del centro de presiones en tareas de equilibrio. Podemos encontrar autores que indican que la variabilidad del movimiento humano es un error que debe ser reducido lo máximo posible, mientras que los estudios más actuales indican que la variabilidad presenta un rol funcional, favoreciendo la capacidad del individuo para poder adaptarse a las condiciones del entorno. Bajo esta última perspectiva, numerosos estudios han tratado de analizar si existe relación o no entre la variabilidad del movimiento y el rendimiento o capacidad de adaptación. Para conseguir este objetivo, la variabilidad ha sido analizada a través de numerosas medidas, entre las que podemos encontrar medidas tradicionales utilizadas para analizar la magnitud de la variabilidad, y otras medidas más novedosas, utilizadas para analizar la estructura de la variabilidad a través de herramientas matemáticas no lineales. A pesar de los numerosos estudios sobre la fiabilidad de dichas medidas, aún existe controversia sobre cuáles pueden caracterizar mejor el control postural. Por ello, el primer estudio presentado en esta tesis doctoral se centró en el análisis de la fiabilidad de diferentes herramientas de medida del control postural, tanto tradicionales como no lineales, en tareas de equilibrio en bipedestación. Los resultados nos indicaron que en tareas de estabilidad, las herramientas no lineales muestran una mayor fiabilidad que las medidas tradicionales de dispersión. Además, la velocidad media del centro de presiones es más fiable que las variables de dispersión, presentando valores similares a los de las herramientas no lineales.

Tras conocer cuáles serían las variables más adecuadas para caracterizar las tareas de equilibrio, el siguiente paso fue analizar la relación entre la variabilidad y el rendimiento. En la literatura podemos encontrar cierta

controversia acerca de si la variabilidad está relacionada con un mayor o menor rendimiento, y con la capacidad de adaptación. Uno de los posibles motivos de dicha controversia puede ser que la estructura de la variabilidad dependa de diferentes constreñimientos procedentes del organismo, del entorno y de la tarea. Para poder contrastar esa hipótesis planteamos un estudio en el que se manipularon diferentes constreñimientos de la tarea, pudiendo observar su efecto sobre la variabilidad y su relación con el rendimiento. Este estudio nos permitió confirmar que la relación entre la estructura de la variabilidad y el rendimiento en una tarea de equilibrio es dependiente de la dificultad de la tarea y de la disponibilidad de *biofeedback*, por lo que los constreñimientos de la tarea deben ser tenidos en cuenta para el análisis de la variabilidad motora y su relación con el rendimiento y la capacidad de adaptación.

Por último, de acuerdo con los actuales trabajos, parece ser que la variabilidad puede estar relacionada con la capacidad de adaptación y con el aprendizaje. El tercer estudio presentado en este trabajo trató de contrastar dicha hipótesis a través del desarrollo de dos protocolos de tareas de equilibrio en los que se aplicó un período de práctica para provocar un proceso de aprendizaje. Los resultados de ambos experimentos indicaron que la estructura de la variabilidad en tareas de equilibrio parece revelar la capacidad de los individuos para aprender, basándose, no sólo en los procesos exploratorios, sino también en la sensibilidad al error.

Futuros estudios deberán ir encaminados en profundizar en el análisis de la capacidad predictiva de la variabilidad motora, tanto del rendimiento como de la capacidad de adaptación, teniendo en cuenta el efecto de más constreñimientos de la tarea y en diferentes habilidades motrices para poder extrapolar los resultados de esta tesis doctoral.

PREFACE

The present thesis titled *Variability, performance and the ability to adapt in balance tasks* covers three experimental works performed between 2012 and 2016 at the Research Sport Center of Miguel Hernandez University, Department of Health Psychology. Part of the work developed in this doctoral thesis was carried out during a research visit in the laboratory of the Centre d'Etudes des Transformations des Activités Physiques et Sportives (CETAPS), of the Faculty of Sport Sciences at the University of Rouen, France, under the supervision of Dr. Ludovic Seifert from April to June 2014, and in the Centre for Sports Engineering Research at Sheffield Hallam University, UK, under the supervision of Professor Keith Davids from January to March 2015. Three original experimental studies are included in this manuscript. The first one was published in the international peer-reviewed *Journal of Motor Behavior*, the second one was accepted in the international peer-reviewed journal *Experimental Brain Research* and the third study has been presented as a preliminary manuscript that will be submitted in the following months.

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ABBREVIATIONS

AP: Antero-Posterior.

ApEn: Approximate Entropy.

BVE: Bivariate Variable Error.

CNS: Central Nervous System.

CoG: Center of Gravity.

CoP: Center of Pressure.

DFA: Detrended Flutuation Analysis.

DOF: Degrees of Freedom

FE: Fuzzy Entropy.

ICC: Intersession Intraclass Correlation.

LyE: Lyapunov Exponent.

ML: Medio-Lateral.

MV: Mean Velocity.

MVM: Mean Velocity Magnitude.

PCA: Principal Component Analysis.

PE: Permutation Entropy.

RD: Resultant Distance.

RQA: Recurrence Quantification Analysis.

SC: Stable Condition.

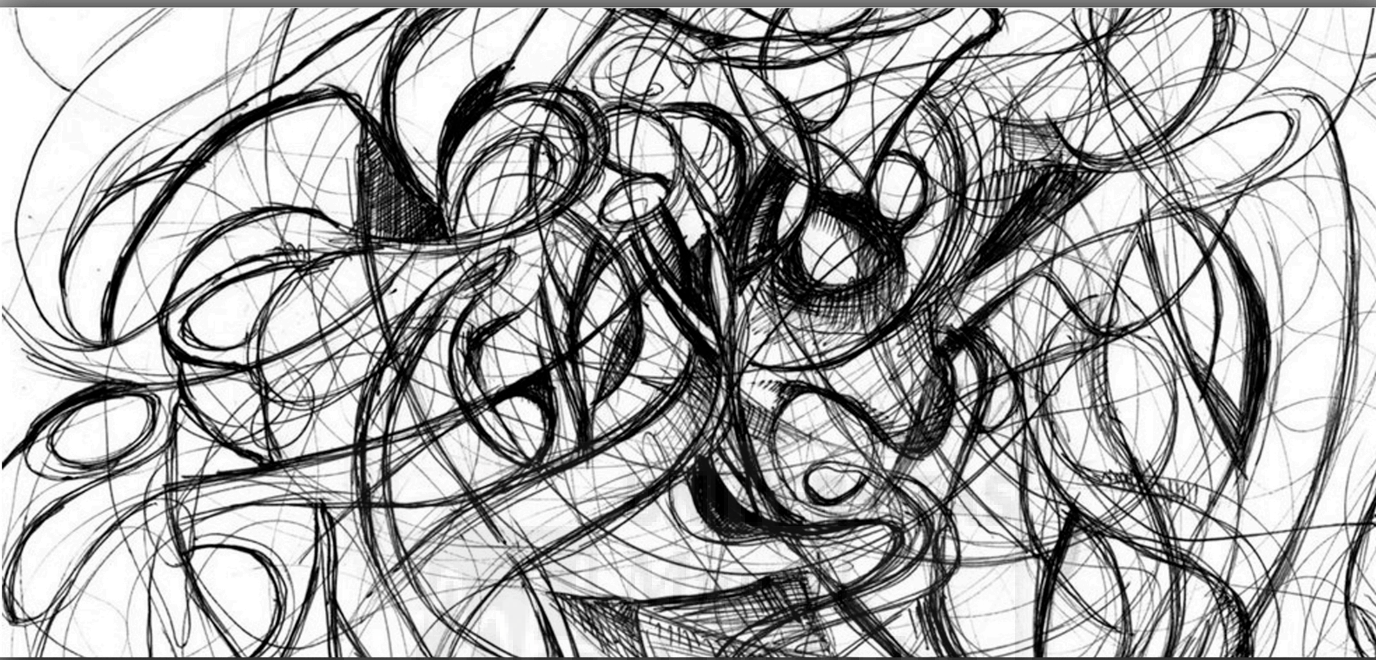
SD: Standard Deviation.

SE: Sample Entropy.

SEM: Standard Error of Measurement.

%SEM: Standard Error of Measurement expresses as a percentage.

UC: Unstable Condition.



1. Introduction

1.1. Postural control

Postural control involves the body´s position in space for dual purposes: 1) to build up posture against gravity and ensure balance, and 2) to fix the orientation and position of the segments that serve as a reference frame for perception and action with respect to the external world (Hassan, Mockett, & Doherty, 2001; Yamamoto et al., 2015). Constantly we are controlling our posture either by maintaining a static corporal position (sitting on a chair) or performing a dynamic task (from daily skills such as walking to complex sports movements such as making a volleyball shot). In all of these cases, stability and the position of the body segments are fundamental in achieving the goal of the motor task. Every motor task is nested on postural regulation and balance, and, for this reason, postural control has been thoroughly studied in motor control.

In this thesis, we are going to focus on the first postural control function: balance. Balance is related to the inertial forces acting on the body and the inertial characteristics of body segments (Winter, 1995). Thus, maintaining balance is based on keeping the Center of Gravity (CoG) projection on the base of support (Manor et al., 2010; Riley & Turvey, 2002; Yamamoto et al., 2015). In order to assess the ability to maintain balance during quiet standing, the fluctuations of the CoG have usually been measured through the time course of the Center of Pressure (CoP) (Figure 1). The CoP is the point of application of the ground reaction force vector, and it seems to be a collective variable that reflects the activities of many neuromuscular components acting together to keep the CoG within the base of support (Manor et al., 2010; Riley & Turvey, 2002; Winter, 1995). The fluctuations or excursions of the CoP correspond to postural sway (Yamamoto et al., 2015) and several studies in postural control have been focused on assessing postural sway in order to evaluate balance (Prieto, Myklebust, Hoffmann, Lovett, & Myklebust, 1996; Ruhe, Fejer, & Walker, 2010; Yamamoto et al., 2015). For example, a quiet stance is characterized by small amounts of postural sway and, therefore, a large postural sway is generally interpreted as a sign of poor balance (Hassan et al., 2001; Samuel, Solomon, & Mohan, 2015).

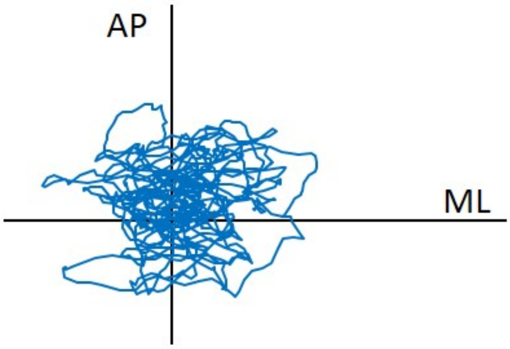


Figure 1. Representation of antero-posterior (AP) and medio-lateral (ML) components of the Center of Pressure (CoP) in a balance task.

In the literature, the CoP has been used to assess motor control performance and other specific domains such as the effects of motor disorders on postural control (Cattaneo et al., 2015; Minamisawa, Takakura, & Yamaguchi, 2009), the reduction of balance according to ageing (Kilby, Slobounov, & Newell, 2014; Zhou et al., 2013), infant development (Dusing, Thacker, & Stergiou, 2013; Harbourne, Deffeyes, Kyvelidou, & Stergiou, 2009) or the relationship between postural control and some sports skills (Hrysomallis, 2011; López et al., 2013). Many of these studies have assessed postural control through the study of the variability of postural sway.

1.2. Motor variability in postural control

1.2.1. Motor variations and control

Motor variability is a very relevant topic in motor control because it is an inherent characteristic of motor behavior (Edelman, 1992; Stergiou & Decker, 2011). These normal variations that occur in motor performance across multiple repetitions of a task reflect changes in both space and time and they are easily observed (Bernstein, 1967; Newell & Slifkin, 1998; Stergiou, Harbourne, & Cavanaugh, 2006).

Movement variation is obvious when the person changes the goal from response to response, amending the chosen motor program (Schmidt, Zelaznik, Hawkins, Frank, & Quinn Jr, 1979) or adapting the emergent motor pattern according to the result obtained from the previous trial. However, even when the subject tries to maintain the same goal and the same pattern in successive trials, variability still appears. It is impossible to perform two identical movements as much as one tries, even though every repetition is successful. In other words, each movement is unique and unrepeatable. But, what is the source of this human variation?

Motor variability appears as a consequence of different sources of variation. One common source of variability in nature comes from the chaotic-mechanical variations of the environment and the interaction between it and the elements of the human system (e.g., tissues, muscles, bones, joints…). The human body is an open thermodynamic system engaged in constant energy transactions and constantly adapting to environmental changes (Davids, Glazier, Araujo, & Bartlett, 2003). In addition, even though the environment remains constant, the elements of the human system are enrolled in continuous internal interactions clearly exhibited in the Central Nervous System (CNS). Neurons throughout the brain show a high degree of variability in their spiking activity even during seemingly constant task conditions (Mandelblat-Cerf, Paz, & Vaadia, 2009). Two types of variation in spike trains of neurons have been recently outlined: stochastic variations or “noise” variability, and trial-by-trial correlated fluctuation or “signal” variability (Lisberger & Medina, 2015). According to Lisberger and Medina (2015), if neuronal variability were just stochastic variations, the large number of neurons at each level of a mammalian sensory-motor system should allow the noise to be averaged. However, neuron-behavior correlations are introduced in this study as the main cause of motor variability because they imply that some of variation in the firing of one neuron is being transmitted all the way to the final output.

Besides these variability sources, we must also take into account the large number of possible configurations that the motor system has available in order to successfully achieve the same motor goal. Our motor system has a huge number of degrees-of-freedom (DOF), which make possible to find a unique solution through different ways. This is due to the fact that any level of description of the neuromotor system is characterized by more elements than are needed to deal successfully with the task constraints. Bernstein (1967) called this characteristic the DOF problem or the problem of eliminating redundant DOF. This problem occurs when the “controller” needs to regulate some DOF functional for achieving a specific task goal and to eliminate less functional system DOF from the coordinative structure used for action (Bernstein, 1967).

With the purpose of explaining motor variability and its role in motor control, researchers have studied it from two different points of view. The first one considers variability to be an error of the system, with the aim of the organism to reduce it as much as possible in order to improve performance (Newell & Slifkin, 1998; Schmidt, 1975; Williams, Davids, & Williams, 1999). That *“error”* is mainly related to the mechanisms involved in the muscle contractions needed to run a motor program, introducing noise and movement inaccuracy (Schmidt, 1975; Schmidt et al., 1979). According to this perspective, as we have indicated before, “the subject may execute the same program over and over on consecutive trials, but noise in the motor system downstream from the motor program makes the produced output different on different attempts” (Schmidt et al., 1979, p.420).

However, in the literature, we can also find that motor variability is interpreted as a functional characteristic of the system. From this perspective, it is suggested that movement systems are based on spontaneous pattern formations between the different system parts, which emerge through processes of self-organization (J. A. S. Kelso, Bergman, Cairns, Nilsson, & Nystedt, 2000). This self-organization is possible due to the system´s ability to freeze or unfreeze the DOF during the chain of movement in order to adapt to the environment (Newell & Vaillancourt, 2001). Then, motor variability may help to exploit the large number of possible configurations offered by the many motor system DOF, and it could play an important role for motor learning and the ability to adapt (Barbado, Sabido, Vera-Garcia, Gusi, & Moreno, 2012; Davids et al., 2003; Lamoth, van Lummel, & Beek, 2009; Mandelblat-Cerf et al., 2009; Moreno & Ordoño, 2010; Zhou et al., 2013). In this sense, variability enables continuous exploration of possible motor states and neuronal configurations that can lead to the desired state by trial and error (Faisal, Selen, & Wolpert, 2008; Fiete, Fee, &

Seung, 2007; Rokni, Richardson, Bizzi, & Seung, 2007; Wu, Miyamoto, Castro, Ölveczky, & Smith, 2014).

These two perspectives have been extrapolated to postural control. The variability of the postural sway shown in balance tasks can be interpreted as mistaken fluctuations of the motor system, which should be reduced, or as functional fluctuations, which reflect exploratory behaviors in adaptation or learning processes. From our point of view, both interpretations are possible. In this sense, different tools for analyzing CoP variability have been used to understand the characteristics of CoP changes. In the next section, we are going to focus on how the variability of CoP has been measured.

1.2.2. Analyzing postural control through CoP variations.

Several variables of the dynamic of CoP have been used to assess postural control. Mainly, two different global dimensions about motor variability have been assessed: the amount of variability, measured by traditional scattering variables, and the structure of the variability, also addressed by its complexity and measured using nonlinear tools (Caballero, Barbado, & Moreno, 2014; Stergiou et al., 2006).

Traditionally, linear scattering measures have been used to provide a description of the amount of CoP variability around a central point, especially the standard deviation (SD) (Borg & Laxåback, 2010; Le Clair & Riach, 1996). Evaluating variability using these tools arises from the idea that the mean is the goal performance and everything away from the mean is error (Stergiou & Decker, 2011). Thus, SD has been used to characterize both the distribution of the data set and the amount of noise present in the perceptual-motor system (Newell & Slifkin, 1998). Other linear measures have been used to describe the sway and the dispersion or area during a given time with a balance task such as the root mean square (Haran & Keshner, 2008), the resultant distance -RD- (Roerdink, Hlavackova, & Vuillerme, 2011), the central tendency measure (Ramdani et al., 2011), the CoP sway area (Hageman, Leibowitz, & Blanke, 1995; Manor et al., 2010), or the mean velocity -MV- (Chiari, Cappello, Lenzi, & Della Croce, 2000; Le Clair & Riach, 1996).

Even though these types of scattering variables have been used to provide information about motor variability, some authors have suggested that these variables do not provide enough information about the nature of variability (Caballero et al., 2014; Stergiou & Decker, 2011). The valid usage of traditional linear measures to study variability assumes that variations between repetitions of a task are random and independent –of past and future repetitions– (Lomax & Hahs-Vaughn, 2013). However, several studies have suggested that movement fluctuations have deterministic properties (Dingwell & Cusumano, 2000; Dingwell & Kang, 2007; Harbourne & Stergiou, 2003; Miller, Stergiou, & Kurz, 2006), and they may reflect changes in the biological system's behavior in order to adapt to environmental conditions (Clark & Phillips, 1993; Hamill, van Emmerik, Heiderscheit, & Li, 1999; Kamm, Thelen, & Jensen, 1990; A. Kelso, 1995; Thelen, 1995; Thelen, Ulrich, & Wolff, 1991). Several authors have suggested that linear tools are not able to assess these changes (Dingwell & Cusumano, 2000; Dingwell & Kang, 2007; Harbourne & Stergiou, 2009; Miller et al., 2006; Stergiou & Decker, 2011). Thus, complementing traditional variability measures, several mathematical tools have been applied to assess how motor behavior changes over time, addressing its temporal dynamics or its complexity. These measures are called nonlinear tools, and they seem to provide additional information about the variability (Borg & Laxåback, 2010; Buzzi, Stergiou, Kurz, Hageman, & Heidel, 2003; Duarte & Sternad, 2008; Fino et al., 2015). Figure 2 illustrates the different global dimensions of motor variability. Linear variables, such as the range, quantify the amount of variability whereas nonlinear variables, such as Approximate Entropy (ApEn) (see below for more information), are able to quantify the structure of variability, providing more information about the system´s behavior (Harbourne & Stergiou, 2009).

Different statistical tools have been developed to provide information about the variability structure or, such as we have indicated above, about the complexity of the system (Stergiou et al., 2006). Complexity has been defined as the number of system components and the coupling interactions among them (Newell & Vaillancourt, 2001). When we refer to the complexity of the different physiological processes of the human system, some authors define it as the presence of non-random fluctuations on multiple time scales (Costa, Goldberger, & Peng, 2002; Lipsitz & Goldberger, 1992; Manor et al., 2010). The analysis of complexity has been interesting because system complexity has been related to the system state (Goldberger, Amaral, et al., 2002; Lipsitz & Goldberger, 1992; Manor & Lipsitz, 2013; Stergiou & Decker, 2011). Specifically, some of these analyses have been carried out to assess the complexity of postural control (Manor & Lipsitz, 2013; Stergiou & Decker, 2011) through many mathematical tools, and it seems that each of these tools measures different properties of variability (Shelhamer, 2006).

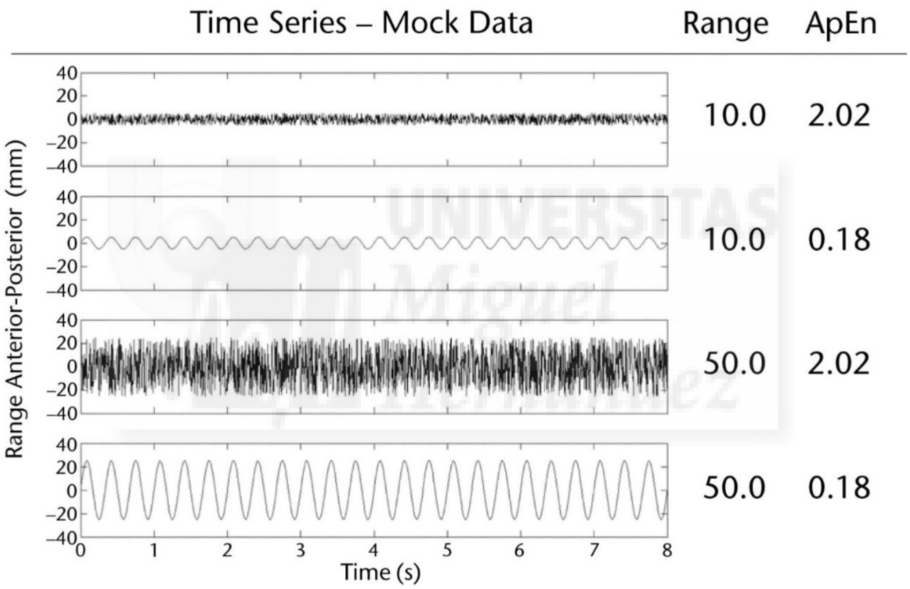


Figure 2. Comparison of linear and nonlinear variables of several signals with the respective values for range and *Approximate Entropy (ApEn)*. Extracted from Harbourne and Stergiou (2009).

One of the most common properties assessed in variability is local dynamic stability (Bruijn, Bregman, Meijer, Beek, & van Dieën, 2012; Buzzi et al., 2003; van Schooten et al., 2011). This property is defined as the degree of sensitivity of the system to small perturbations (Buzzi et al., 2003) and it is usually measured by the *Lyapunov Exponent (LyE)* (Wolf, Swift, Swinney, & Vastano, 1985). When *LyE* values are negative (periodic systems), the trajectories converge, and this convergence represents local stability in a particular direction. When *LyE* values are positive (the attractor is chaotic), the trajectories diverge, and this divergence represents local instability in a particular direction (Eckmann & Ruelle, 1985). Traditionally, higher instability has been linked to higher variability. However, some authors have indicated that variability and stability represent different properties within the motor control process (England & Granata, 2007; Stergiou & Decker, 2011). *LyE* has been used in several studies where the complexity of postural control has been analyzed to assess sitting postural control in infants (Cignetti, Kyvelidou, Harbourne, & Stergiou, 2011), the effect of the amount of attention invested in postural control in the CoP trajectories (Donker, Roerdink, Greven, & Beek, 2007) or the dynamic structure of CoP fluctuations in patients recovering from stroke (Roerdink et al., 2006), among others.

Another property of the variability that is frequently analyzed is the degree of irregularity of the time series (Chen, Wang, Xie, & Yu, 2007; Guerreschi, Humeau-Heurtier, Mahe, Collette, & Leftheriotis, 2013; Huang, Yen, Tsao, Tsai, & Huang, 2014; Richman & Moorman, 2000; Wu et al., 2014). Several tools have been used to assess this characteristic of the system. One of them is *Recurrence Quantification Analysis (RQA)* (Zbilut, Thomasson, & Webber, 2002; Zbilut & Webber, 2006). This tool combines recurrence plots (Eckmann, Kamphorst, & Ruelle, 1987), that is, the visualization of trajectories in phase space, with the objective quantification of system properties (for more information see Zbilut and Webber (2006). Recurrent points that form diagonal line segments are considered to be deterministic (as distinguished from random points that form no patterns), but this graphical representation may be difficult to evaluate. Thus, RQA was developed to provide quantification of important aspects of the plot (Table 1 and Figure 3) (for more information see Zbilut, Webber, Colosimo, and Giuliani (2000) and Zbilut and Webber (2006)). We can find postural control studies where RQA have been used, for example, to explore the influence of vision in the postural sway structure (Riley, Balasubramaniam, & Turvey, 1999) or to describe motor patterns in Parkinson´s disease through the determinism of the CoP (Schmit et al., 2006).

Table 1. Summary of the most commonly used recurrence variables. Extracted from Zbilut and Webber (2006).

Measure	**Definition**
Recurrence, REC	Percentage of recurrence points in an RP, $REC = \left(\frac{1}{N^2}\right)\sum_{i,j=1}^{N} R_{ij}$
Determinism, DET	Percentage of recurrence points that form diagonal lines, $DET = \frac{\left(\sum_{l-l_{min}}^{N} lP(l)\right)}{\sum_{i,j=1}^{N} R_{ij}}$ $P(l)$ is the histogram of the lengths l of the diagonal lines.
Laminarity, LAM	Percentage of recurrences points that form vertical lines, $LAM = \frac{\left(\sum_{v=v_{min}}^{N} vP(v)\right)}{\left(\sum_{v=1}^{N} vP(v)\right)}$ $P(v)$ is the histogram of the lengths v of the vertical lines.
Ratio, RATIO	Ratio between *DET* and *RR*, $RATIO = \frac{N^2\left(\sum_{l=l_{min}}^{N} lP(l)\right)}{\left(\sum_{l=1}^{N} lP(l)\right)^2}$
Averaged diagonal line length, LEN	Average length of diagonal lines, $LEN = \frac{\left(\sum_{l=l_{min}}^{N} lP(l)\right)}{\left(\sum_{l=l_{min}}^{N} P(l)\right)}$
Trapping time, TT	Average length of vertical lines, $TT = \frac{\left(\sum_{v=v_{min}}^{N} vP(v)\right)}{\left(\sum_{v=v_{min}}^{N} P(v)\right)}$
Longest diagonal line, L_{max}	Length of the longest diagonal line, $L_{max} = max(\{l_i; i = 1 \dots N_l\})$
Longest vertical line, V_{max}	Length of the longest vertical line, $V_{max} = max(\{v_l; l = 1 \dots L\})$
Divergence, DIV	Inverse of L_{max}, $DIV = \frac{1}{L_{max}}$ Related to the largest positive Lyapunov Exponent, but does not correspond to it.
Entropy, ENT	Shannon entropy of the distribution of the diagonal lengths $p(l)$, $ENT = -\sum_{l=l_{min}}^{N} p(l) \ln p(l)$
Trend, TREND	Paling of the RP towards its edges, $TREND = \frac{\sum_{i=1}^{N-2}[i-(N-2)][REC_i - \langle REC_i \rangle]}{\sum_{i=1}^{N-2}\left[i = \left(\frac{N-2}{2}\right)\right]^2}$

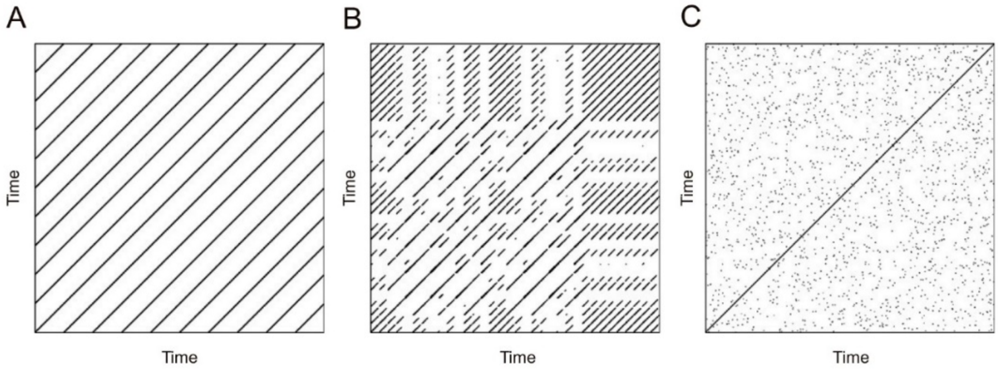


Figure 3. Recurrence plots of (A) a periodic motion with one frequency, (B) the chaotic Rössler system and (C) uniformly distributed noise. Extracted from Marwan, Romano, Thiel, and Kurths (2007).

In addition, a relevant collection of tools called entropy measures have also been used to assess the degree of irregularity. Typically, high values of entropy indicate high irregularity. The first and most used entropy measure applied to human variability has been *ApEn* (Pincus, 1991). This entropy measure has been used in a large number of studies in different research fields, among which we can find postural control analysis (Kee, Chatzisarantis, Kong, Chow, & Chen, 2012). However, this tool is relatively inconsistent and depends on data series length and, due to this fact, Richman and Moorman (2000) developed *Sample Entropy (SE)* as an improved entropy measurement. This tool shows higher consistency than *ApEn* and it has been used in several postural control studies, for example, detecting changes in postural control during quiet standing, measuring postural stability after a cerebral concussion (Cavanaugh, Guskiewicz, & Stergiou, 2005) or assessing the effect of training on postural control (Menayo, Encarnación, Gea, & Marcos, 2014). However, problems still exist in the validity of *SE* because the definition of vectors is very similar to that of *ApEn*. For this reason, Chen et al. (2007) developed a new statistic tool, *Fuzzy Entropy (FE)*. FE shows some advantages such as stronger relative consistency, less dependence on data length, freer parameter selection and more robustness to noise (Chen, Zhuang, Yu, & Wang, 2009). There are few studies where this tool has been used to assess the degree of irregularity in CoP time series. One of these few studies is by Sipko and Kuczyński (2013), in which the authors compared postural control between patients with different levels of chronic back pain.

Another entropy measure is *Permutation Entropy (PE)* (Bandt & Pompe, 2002). *PE* assesses the frequency of the appearance of permutation patterns in a time series, making use of only the order of the time series values. In contrast with the other irregularity variables, *PE* shows high robustness to noise and data length. This tool has not been frequently applied to motor control analysis, and we have just found one study where the structure of CoP fluctuations (calculated through pressure mat data) has been analyzed by *PE* (Leverick, Szturm, & Wu, 2013). These authors assessed the suitability of this tool for characterizing gait dynamics, obtaining strong reliability values.

Nevertheless, although entropy measurement tools have been improved, some authors have argued that the degrees of irregularity of the signal, measured by entropy parameters, are not clearly related to the complexity of system dynamic (Goldberger, Peng, & Lipsitz, 2002; Stergiou et al., 2006). Other nonlinear measures have been proposed to assess the complexity of movement variability by analyzing the long-range auto-correlation of the signal. *Detrended Fluctuation Analysis (DFA)* (Peng, Havlin, Stanley, & Goldberger, 1995) is a scaling analysis method used to quantify long-range correlations in signals. It evaluates the presence of long-term correlations within the time series by a scaling index called *α* (Bashan, Bartsch, Kantelhardt, & Havlin, 2008; Peng et al., 1995). This procedure indicates that an index *α* that is equal to 1 is related to pink noise and fractal characteristics (Holden, 2005), and it has been used to describe the complexity of a process (Goldberger, Amaral, et al., 2002). Specifically, DFA has been used to study the human postural control system during quiet standing in healthy people (Blázquez, Anguiano, de Saavedra, Lallena, & Carpena, 2009) and in people with motor disorders (Minamisawa et al., 2009).

The choice of appropriate tools to analyze motor variability remains controversial. It is still unknown which tool may be the most adequate to that end (Caballero, Barbado, & Moreno, 2013; Goldberger, Peng, et al., 2002; Stergiou & Decker, 2011; Vaillancourt & Newell, 2002). From our point of view, both the amount and the properties of the variability structure can be relevant to characterize the dynamics of the CoP because each one provides different information about the system state. Therefore, variability has to be considered as a multidimensional feature of the motor system (Stergiou & Decker, 2011), and several authors suggest the need to use more than one tool for assessing motor variability (Goldberger, Peng, et al., 2002; Harbourne & Stergiou, 2009; Stergiou & Decker, 2011).

It is possible to use multidimensional approaches to analyze the CoP data and better understand the relationships that emerge among different variables. To that end, we adopt statistical tools such as *Principal Component Analysis* (PCA) and Cluster Analyses. In this way, we can address various possible ways of defining motor variability while tracking fluctuations in the CoP. *PCA* is a multivariate statistical technique used to understand to what extent the based-CoP variables measure different characteristics of the variability. *PCA* allows to reduce the number of nonlinear tools, grouping them in factors that facilitate the analysis and the description of the characteristics of the CoP variability (Harbourne & Stergiou, 2009). On the other hand, *Cluster analysis* was developed to identify patterns in high-dimensional datasets (Rein, Button, Davids, & Summers, 2010), and it could be used to define profiles that group different properties of variability dynamics according to the state of the system.

Another important issue that we have to take into account in working with different measures of variability dynamics is the reliability of the tools used. Several studies have analyzed the reliability of linear tools (T.L. Doyle, Newton, & Burnett, 2005; Kyvelidou, Harbourne, Stuberg, Sun, & Stergiou, 2009; Lafond, Corriveau, Hebert, & Prince, 2004; Lee & Granata, 2008; Lin, Seol, Nussbaum, & Madigan, 2008; Ruhe et al., 2010; Salavati et al., 2009; Santos, Delisle, Lariviere, Plamondon, & Imbeau, 2008; van Dieën, Koppes, & Twisk, 2010). However, the conclusions about which variables are better for characterizing the amount of variability in postural control seem unclear, and there is no agreement about the methodological issues. Furthermore, regarding nonlinear tools, only a few studies have assessed their reliability (Amoud et al., 2007; Kyvelidou et al., 2009; van Dieën et al., 2010).

With these problems in mind, we carried out the first study that is presented in this thesis, where the main aim was to find the most reliable variables to characterize postural control in standing balance tasks.

1.3. Relationship between postural control performance and CoP variability.

During the learning of any motor skill, the amount of motor variability is progressively minimized as long as movement execution is improved (Caballero et al., 2014; Stein, Gossen, & Jones, 2005; Stergiou & Decker, 2011). Thus, we could think that motor variability worsens motor control or motor performance. We have to take into account that, in this case, variability is understood as the amount of variations around a central point or mean error. It seems to be that if error is gradually eliminated or minimized the accuracy and efficiency of the movement pattern will be optimized (Schmidt, 2003; Schmidt & Lee, 1988). In postural control, standing balance reflects postural control and it is considered the ability to stand with as little sway as possible (Gerbino, Griffin, & Zurakowski, 2007). Therefore, a high amount of CoP variability could be related to low performance. Nevertheless, these studies assessed CoP variability just through its amount and, as we have indicated above, the amount of variability provides only biased information. In other words, we also need to analyze the structure of CoP variability in order to obtain complete information about the system.

There are some studies that have tried to find the relationship between postural control performance (the fluctuations around a central point) and motor variability structure (Barbado et al., 2012; Cattaneo et al., 2015; Schmit et al., 2006). This relationship has been applied to different research fields, especially in health studies, where motor variability has been used to detect, for example, motor coordination diseases (Cattaneo et al., 2015; Roerdink et al., 2006; Schmit et al., 2006) or the effects of aging (Goldberger, Amaral, et al., 2002; Manor & Lipsitz, 2013; Vaillancourt & Newell, 2003). Some of these studies have indicated that greater system complexity in balance control is connected to better performance. This is to say, a loss of complexity is linked to low postural control, understanding postural control as the capacity to keep the CoG over the base of support as precisely as possible (Manor et al., 2010; Massion, 1994; Riley & Turvey, 2002). Some authors have assessed complexity according to the level of cognitive investment, finding that balance tasks with eyes closed implied an increase of postural sway and a decrease in complexity (Donker et al., 2007; Stins, Michielsen, Roerdink, & Beek, 2009). In others studies, low complexity has been related to low postural control due to different motor diseases (Cattaneo et al., 2015; Perlmutter, Lin, & Makhsous, 2010). In this sense, movement variability has been related to the capacity of the system to adapt to environmental changes (Barbado et al., 2012; Davids, Bennett, & Newell, 2006; Davids et al., 2003; Renart & Machens, 2014; Riley & Turvey, 2002), which is connected to better performance.

However, in the literature we find controversial results regarding the relationship between complexity and performance. Some studies have found high values of complexity in CoP fluctuations when participants exhibited low performance in balance tasks (Borg & Laxåback, 2010; Duarte & Sternad, 2008; Santarcangelo, Carli, Balocchi, Macerata, & Manzoni, 2009; Schmit, Regis, & Riley, 2005). Schmit et al. (2005) compared the variability of postural sway in ballet dancers and track athletes and they found that participants showed lower complexity in an eyes-open condition than in an eyes-closed condition, while performance was better with the eyes open. A similar relationship was reported by Santarcangelo et al. (2009), where participants showed lower complexity of CoP while standing on a stable support than on an unstable support.

Another authors have suggested the relationship between complexity and performance is nonlinear because it is dependent on the nature of both the intrinsic dynamics of the system and the task constraints to be satisfied (Newell & Vaillancourt, 2001; Vaillancourt & Newell, 2002, 2003). We consider that this can be one possible reason for the controversial results. These authors examined the time and frequency structure of force output in adult humans to determine whether the changes in complexity with age are dependent on external task demands and they found that the structure of the force output in the older adults group was less complex in a constant-force level task and more complex in a sine wave force task than the younger adults group. Thus, the relationship between performance and complexity seems to be different according to aging and the task constraints in a force task. This result could be explained because the specific performance constraints encountered can cause a reduction in the number of configurations available to the dynamic system through a re-structuring of the state space of all possible configurations available (Davids et al., 2003).

According to this last idea, the second paper presented in this thesis tries to clarify the relationship between postural control performance and CoP variability, paying attention to the constraint influences of tasks and interpreting the results according to the aforesaid task constraints and their effects on the intrinsic system dynamic.

1.4. Relationship between CoP variability and the learning process in postural control.

As we have shown, motor variability has been associated with functional exploratory behaviors (Davids et al., 2006; Davids et al., 2003; Renart & Machens, 2014; Riley & Turvey, 2002). According to Davids et al. (2003), "variability has a functional role in helping individuals adapt to ever-changing constraints imposed on them by environmental, anatomical and physiological changes due to disease, illness, injury and aging" (p. 251). In this sense, recent studies have linked motor variability to the ability to adapt (Dusing et al., 2013; Manor et al., 2010; Zhou et al., 2013) which are frequently related as both the basis and consequence of each other (Moreno & Ordoño, 2015). Some evidence of the relationship between motor variability and the ability to adapt have been indicated by Wu et al. (2014), suggesting that variability could be regulated and indeed amplified in the nervous system to improve learning. Recent work in songbirds suggested that the neural circuits involved in motor variability promote learning by directing the exploration of motor output space (Andalman & Fee, 2009; Warren, Tumer, Charlesworth, & Brainard, 2011). In this sense, the reduced motor learning ability after inactivating the cortical output nucleus of basal ganglia circuits has been related to a reduction in the variability of motor performance (Charlesworth, Warren, & Brainard, 2012; Kao, Doupe, & Brainard, 2005; Olveczky, Andalman, & Fee, 2005). In postural control, it has been found that individuals who showed more complexity of CoP during a standing still condition on a stable surface were able to cope with more difficult but similar tasks (Manor et al., 2010; Zhou et al., 2013). These studies showed that a low baseline complexity in motor variability may indicate control systems that are more vulnerable to changes in the environment (stressors), reducing the functionality of the motor control system.

These last findings have led to exploration of the relationship between motor variability and learning processes. Thus, in the most recent works about motor variability, some authors have taken another step forward suggesting that there is a link between motor output variability and motor learning ability across different dynamic environments (Wu et al., 2014). In this study, high motor variability during the baseline period predicted fast learning in humans in different point-to-point reaching tasks and in a force field reaching task (Figure 4). Participants who showed above-average amounts of variability during a baseline period in point-to-point reaching movements exhibited faster learning than participants with below-average variability.

Nevertheless, there are few studies about motor variability and learning processes, and nonlinear tools have not been used to assess motor variability in them. Taking into account the aforesaid information about nonlinear tools and the previous suggestion about their application in identifying exploratory behaviors, the aim of the last study in this thesis was to determine if the structure of motor variability in postural control showed during the early stages of motor learning could be related to the learning process. This idea would make it possible to predict differences in learning ability from baseline performance characteristics in postural control tasks.

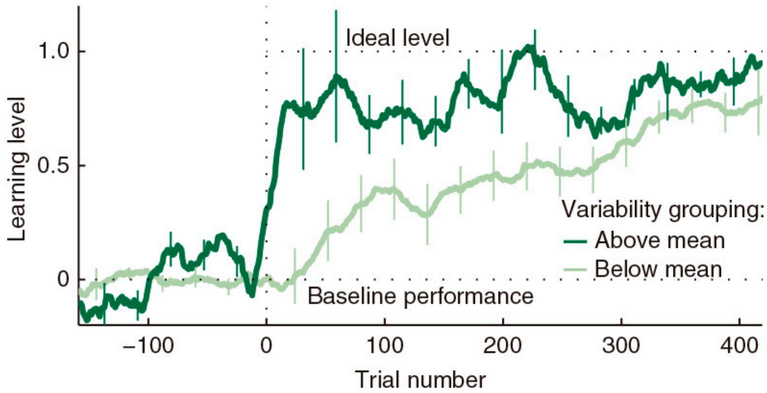
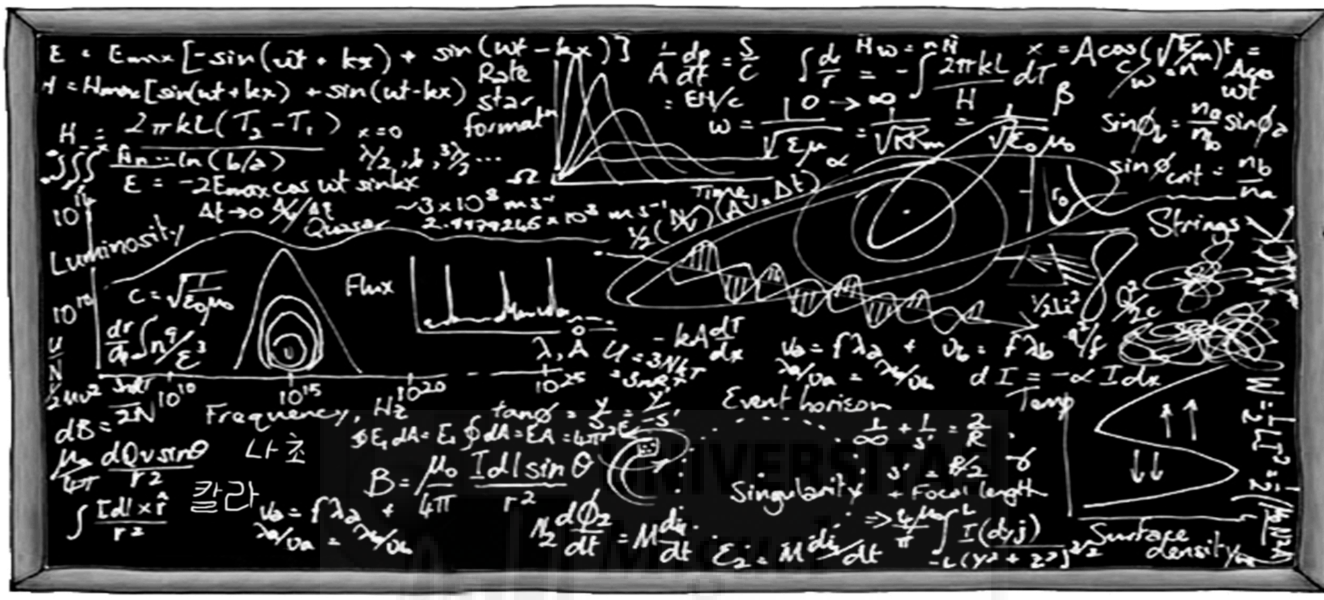


Figure 4. Extracted from Wu et al. (2014). Participants displaying above-average amounts of shape-1 variability (n = 6) during the baseline period in experiment 1 exhibit faster learning than participants with below-average variability (n = 14).



2. Aim and hypothesis

Three studies were proposed to develop this thesis. The key antecedent, main aim and hypothesis from each of them are introduced below:

2.1. What CoP and kinematic parameters better characterize postural control in standing balance tasks? Study I.

Key antecedent I. Different variables of the dynamic of CoP have been used to assess postural control, and despite some studies have explored the reliability of these measures, no single measurement of CoP has clearly emerged as significantly more reliable than the others (Ruhe et al., 2010). The reliability of traditional measures has been questioned (T.L. Doyle, Newton, and Burnett, 2005) and some studies have proposed to analyze COP using nonlinear tools to better assess the interactions of the component of the neuromuscular system (Manor et al., 2010; Mazaheri et al., 2010; Newell & Vaillancourt, 2001).

Aim I. To test the absolute and relative consistency of both traditional measures and nonlinear measures of CoP in a standing balance task under different stability conditions.

Hypothesis I. Nonlinear measures will better characterize postural control showing better absolute and relative consistency than traditional scattering measures in a balance task protocol in upright stance under stable and unstable conditions.

2.2. Variations in task constraints shape emergent performance outcomes and complexity levels in balancing. Study II.

Key antecedent II. The complexity of motor variability has been measured in balance tasks as an index of the capacity of the CNS to re-organize degrees of freedom in order to adapt to perturbations (Barbado et al. 2012; Goldberge, Peng et al. 2002). Thus, less complexity in CoP dynamics has been frequently associated with less capacity to adapt (Manor et al. 2010). However, other studies have found greater complexity in fluctuations of CoP associated with worse task performance (Duarte and Sternad, 2008). Vaillancourt and Newell

(2002, 2003) suggested that increases or decreases in the complexity of CNS behaviors can be functional, but they are dependent on the nature of both the intrinsic dynamics of the system and the task constraints that need to be satisfied.

Aim II. To investigate the extent to which specific interacting constraints of performance might increase or decrease the emergent complexity in a movement system, and whether this could affect the relationship between movement variability and the capacity to adapt to perturbations during balancing.

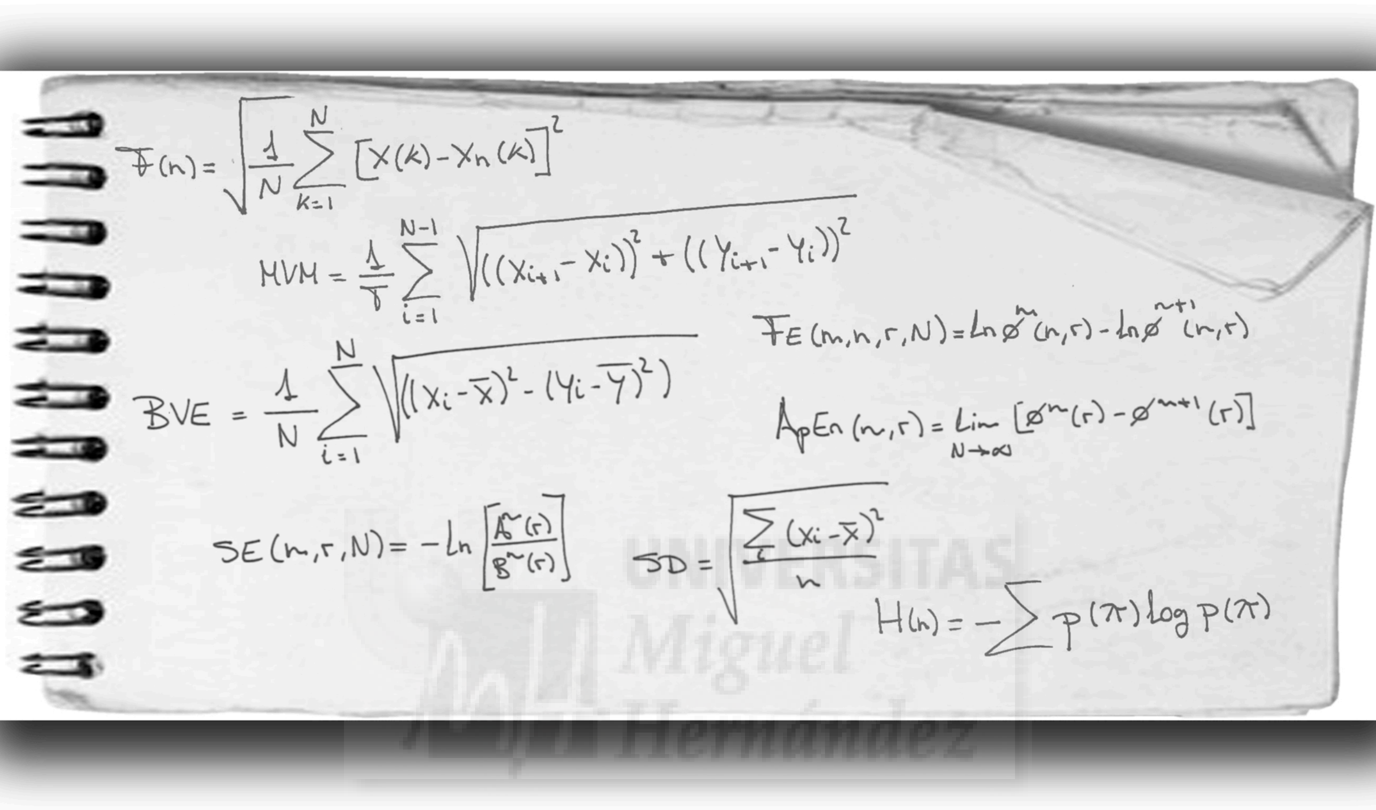
Hypothesis II. The relationship between the complexity of CoP variability and performance in a standing balance task will depend on task constraints; the level of difficulty and the availability of biofeedback.

2.3. Can the structure of motor variability predict learning rate? Study III.

Key antecedent III. Recent approaches have indicated that motor variability could reflect the motor system's ability to explore different motor configurations looking for an optimal solution that includes adaptive (Barbado et al., 2012; Manor et al., 2010; Zhou et al., 2013) and learning processes (Wu et al., 2014). Wu et al. (2014) found, in a reward-based learning protocol, that high motor variability during the baseline period predicted faster learning of different reaching tasks in the future. Nevertheless, when motor variability during a novel task is analyzed, it is difficult to estimate the extent to which motor variability is a consequence of an avoidable stochastic neuromuscular system function (Churchland et al., 2006; Harris and Wolpert, 1998; Osborne et al., 2005; Schmidt et al., 1979) or whether it is the result of an active behavior centrally regulated to promote learning (Mandelblat-Cerf et al., 2009; Sober et al., 2008). The use of nonlinear tools has revealed functional properties of motor variability, but its relation with motor learning, when a low amount of variability is required to properly perform the task, is still under discussion.

Aim III. To test if the structure of motor variability in balancing can be related to the learning process.

Hypothesis III. Motor learning rate will be related not only to the initial performance level but also to the initial structure of movement variability exhibited by learners.



3. Study I

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WHAT CoP AND KINEMATIC PARAMETERS BETTER CHARACTERIZE POSTURAL CONTROL IN STANDING BALANCE TASKS?

Carla Caballero, David Barbado and Francisco J. Moreno.

3.1. Abstract.

The authors’ aim was to determine which variables allow for the characterization of motor balance behavior. Traditional measures and nonlinear measures of CoP (n = 30) and kinematics (n = 10) were tested in their absolute and relative consistency in a 30 s standing balance task protocol under stable and unstable conditions. Regarding CoP variables, MV, PE and DFA exhibited high consistency between trials and ranked individuals more accurately compared with other metrics. In the kinematic signal MV, PE and DFA had good intrasession reliability values in unstable conditions. Overall, the intrasession reliability values were better in the unstable condition than in the stable condition and the measures calculated using derived data had better intrasession reliability values. In conclusion, MV, PE, and DFA allow for the good characterization of motor balance behavior in a simplified protocol where velocity time series are analyzed.

Key words: Postural control, nonlinear measures, reliability, center of pressure, kinematics.

3.2. Introduction.

The dynamic of CoP while standing is a collective variable, responsible for posture and balance (Riley and Turvey, 2002; Winter, 1995) that reflects the activities of many neuromuscular components acting together to keep the CoG within the base of support (Manor et al., 2010; Riley and Turvey, 2002).

Traditionally, different variables of the dynamic of CoP have been used to assess postural control. These traditional measures are used to describe the sway or dispersion or area during a given time in a balance task. Some of these traditional measures are SD (Borg and Laxaback, 2010; Le Clair and Riach, 1996), root mean square (Haran and Keshner, 2008), RD (Roerdink et al., 2011), central tendency measure (Ramdani et al., 2011), CoP sway area (Hageman et al., 1995; Manor et al., 2010), or MV (Chiari et al., 2000; Le Clair and Riach, 1996).

Reliability analysis has frequently been used to evaluate the consistency of CoP measurements. The reliability of a variable consists of both absolute and relative consistency. Absolute consistency allows us to know the extent to which a variable maintains its value between trials of the same task. Relative consistency allows us to know the extent to which a variable is able to rank individuals in the group relative to others (Weir, 2005).

Some studies have shown high reliability for the MV measure (Lafond et al., 2004; Lin et al., 2008), although no single measurement of CoP appeared significantly more reliable than the others (Ruhe et al., 2010). T. L. Doyle et al. (2005) indicated that the reliability of the traditional measures is questionable. However, Ruhe et al. (2010) in a review of CoP measures concluded that traditional CoP parameters show acceptable reliability values under specific conditions in the study design. In fact, they indicated different recommendations for the study design to improve the reliability of the traditional measures. There are no standard recommendations regarding foot position or instruction prior to the recording, but the most frequent instruction given to the participants was to stand as still as possible. A wide range of sampling rate frequencies have been reported in the literature, but frequencies higher than 100 Hz are not frequently recommended (R. J. Doyle, Hsiao-Wecksler, Ragan, and Rosengren, 2007;

Lafond et al., 2004; Santos et al., 2008). Some authors (Ruhe et al., 2010) recommend a sampling duration of 90 s, whereas other studies have obtained good reliable results in simplified protocols of balance tasks with sample durations between 10 and 60 s (Le Clair and Riach, 1996; Schmid, Conforto, Camomilla, Cappozzo, and D'Alessio, 2002).

Additionally, some studies have tried to analyze the interactions of the neuromuscular component system by analyzing the complexity of the CoP fluctuations through nonlinear tools (Manor et al., 2010; Mazaheri, Salavati, Negahban, Sanjari, and Parnianpour, 2010; Newell and Vaillancourt, 2001). Many authors have suggested that complexity is related to the capacity of the system to generate adaptive responses to stressors (Barbado et al., 2012; Goldberger, 1996; Goldberger, Amaral, et al., 2002). In this sense, greater system complexity is connected to better performance, and a loss of complexity is thought to be linked to a reduced ability to adapt (Goldberger, 1996; Manor et al., 2010). However, few studies have assessed the consistency of CoP complexity variables.

Some studies have measured the complexity of CoP through the predictability of the signal (Barbado et al., 2012; Borg and Laxaback, 2010; Duarte and Sternad, 2008; Stergiou and Decker, 2011). For this purpose, the most used nonlinear measure has been ApEn (Pincus, 1991). This tool, when applied to CoP, has shown good reliability in assessing postural control. For example, Kyvelidou et al. (2009), in an analysis of the development of sitting postural control in infants, concluded that ApEn had higher intra- and intersession intraclass correlation coefficient (ICC) values than did the traditional parameters and another predictability measure, the LyE (Wolf et al., 1985). However, LyE showed better values of reliability than did ApEn when the aim was to assess cerebral palsy infants under the same conditions (Kyvelidou et al., 2009).

Due to the relative inconsistency and the dependence of the results of ApEn on the length of the data series Richman and Moorman (2000) suggested another statistic, SE, to relieve the bias caused by self-matching. van Dieën et al. (2010) analyzed the reliability of SE for a sitting balance task and this tool was sufficiently reliable. However, the similarity of the definition of vectors in this method is based on a Heaviside function as in ApEn. This function leads to a type of conventional two-state classifier, where an input pattern's its belongingness to a given class is judged by whether it satisfies certain precise properties required of membership. However, in the real physical world boundaries between classes may be ambiguous, and it is difficult to determine whether an input pattern completely belongs to a class (W. Chen, Wang, Xie, and Yu, 2007). This *Heaviside function* still has problems with the validity of the entropy definition, particularly when small tolerance ranges are involved (W. Chen, Zhuang, Yu, and Wang, 2009). W. Chen et al. (2007) recently developed a new related family of statistics, FE. This measure shows some advantages because it has demonstrated stronger relative consistency, less dependence on data length, freer parameter selection and more robustness to noise (W. Chen et al., 2009).

Bandt and Pompe (2002) presented PE as a parameter of average entropy. PE is based on assessing the frequency of the appearance of permutation patterns in a time series, using only the order of the time series values (Zanin, Zunino, Rosso, and Papo, 2012). This nonlinear tool has been shown to be an appropriate complexity measure for chaotic time series, particularly in the presence of dynamical and observational noise (Bandt and Pompe, 2002). In contrast to all known complexity parameters, a small noise does not essentially change the complexity of a chaotic signal. PE can be calculated for arbitrary real-world time series. Another advantage of PE over ApEn is its independence from the data length because it measures the entropy of sequences of ordinal patterns that are derived from *m-dimensional* delay embedding vectors (Frank, Pompe, Schneider, and Hoyer, 2006). Because the method is extremely fast and robust, its use seems preferable when there are huge data sets and no time for parameter preprocessing and fine-tuning (Bandt and Pompe, 2002). Nevertheless, the reliability results of SE, FE, and PE tools in assessing postural control in standing balance tasks have not been reported.

Conversely, some authors have argued that the predictability of the signal, measured by entropy parameters, is not clearly related to the complexity of the signal (Goldberger, Peng, et al., 2002). In this sense, other nonlinear measures are frequently used to assess the complexity of the CoP by analyzing the long-range auto-correlation of the signal, such as stabilogram diffusion analysis (Collins and De Luca, 1993) or DFA (Peng et al., 1995). For example, DFA has been applied to analyze the changes in CoP fluctuation with aging and disease (Goldberger, Peng, et al., 2002). Amoud et al. (2007) assessed the reliability of these measures, and DFA appeared to show better reliability values than stabilogram diffusion analysis. Van Dieën et al. (2010) analyzed the reliability of DFA compared with entropy measures showing similar values in sitting balance tasks. Nevertheless, little is known about the reliability of these tools assessing postural control in standing.

Finally, although CoP analysis has been shown to be a useful procedure to indicate changes in postural control, postural stability, or risk of falling (Maki, Holliday, and Topper, 1991), this type of measure can be limited in its ability to discern different postural strategies and movement patterns (Kuo, Speers, Peterka, and Horak, 1998). Therefore, it would be necessary to use additional measures to improve the knowledge of kinematic patterns. For this reason, some authors (Kuo et al., 1998; Madigan, Davidson, and Nussbaum, 2006) have suggested using kinematic measures to analyze postural sway.

The aim of our study was to determine which variables allow for the characterization of motor balance behavior when a short time test is available during the assessment session. In this way, we assessed the absolute consistency and relative consistency of CoP and kinematic parameters that characterize postural control during short sessions in a balance task protocol in an upright stance under stable and unstable conditions.

3.3. Methods.

3.3.1. Participants.

Thirty healthy volunteers took part in this study (age = 27 ± 6.48 years; height = 1.74 ± 0.09 m; mass = 73.94 ± 10.77 Kg), 11 women (age = 25.18 ± 6.86 years; height = 1.65 ± 0.06 m; mass = 64.93 ± 5.79 Kg) and 19 men (age =

28.05 ± 6.19 years; height = 1.79 ± 0.07 m; mass = 79.17 ± 9.47 Kg). They had no previous experience in the balance task used in this study.

Written informed consent was obtained from each participant prior to testing. The experimental procedures used in this study were in accordance with the Declaration of Helsinki and were approved by the ethics standards of the committee on Human Experimentation of Miguel Hernandez University.

3.3.2. Experimental Procedure and Data Collection.

To assess postural stability, ground reaction forces were recorded at 20 Hz by a force platform (Kistler, Switzerland, Model 9287BA). When analyzing the CoP dynamic using nonlinear measures signal oversampling could lead to artificial collinearities that would affect the dynamics of the CoP and mask the real values (Rhea et al., 2011). Therefore, using sampling frequencies close to the CoP dynamic is recommended (Caballero, Barbado, and Moreno, 2013).

Synchronized kinematic data were collected from ten of the participants, using a 6-camera 100 Hz VICON MXSystem with the associated workstation software (Vicon, Oxford, England). According to the plug-in gait model (Vicon), we placed 19 markers (Figure 5): over the incisura jugularis, on the right and left shoulder, on the acromioclavicular joint, on the right and left anterior superior iliac spines, on the right and left posterior superior iliac spine, on the right and left midthigh stick, on the lateral epicondyle of the right and left knee, on the right and left midshank stick, on the right and left lateral malleolus of the ankle along an imaginary line that passes through the transmalleolar axis, on the right and left heel, on the back of the heel such that the line joining it to the forefoot marker reflects the long axis of the foot, on the right and left toe, and finally over the second metatarsal head. The positions of the markers were marked to enable researchers to relocate their exact position in case any markers were lost during a measurement. Joint angles of hip, knee and ankle were calculated using the Nexus 1.7 software (Vicon MX, Oxford, UK).

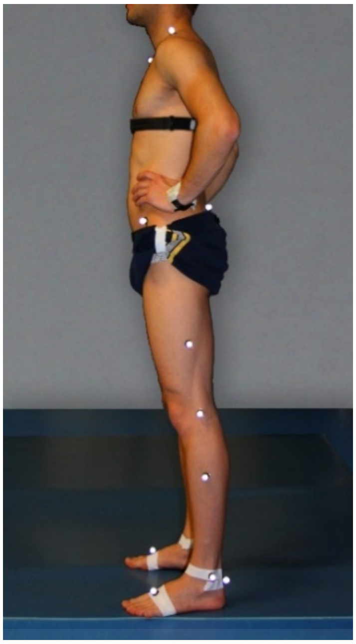


Figure 5. Placement of 19 markers to assess the kinematic parameters.

Participants performed two tests separated by 10 min each. Each test consisted of two trials in two different sway tasks conditions (Figure 6): (a) standing still on a force platform (stable condition) and (b) standing on a foam surface (unstable condition). In both conditions participants were asked to stand as still as possible (Cavanaugh, Mercer, and Stergiou, 2007; Duarte and Sternad, 2008; Ruhe et al., 2010) and their feet placed 30 cm apart, and with their hands resting on their hips. The feet position was such that the line between their heels coincided with the mediolateral axis of the platform. The task was performed barefoot in front of a clear white wall without any visual reference. This position was kept during all of the trials. In the unstable condition, participants were able to maintain their standing posture without grasping the support rail or stepping in any direction. The main aim of this study was to design a simplified protocol to test the intrasession reliability of different CoP measures. For this reason, in this study, the length of each test trial was 30 s, and the rest period between trials was 1 min.

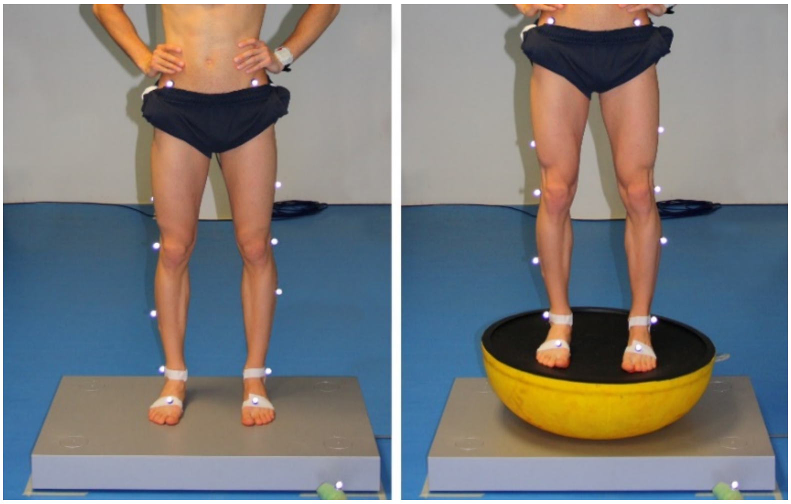


Figure 6. Stable (left) and unstable (right) conditions.

3.3.3. Data analysis and reduction.

We collected 30 s of data at 20 Hz. Prior to the analysis, we discarded the first 5 s of each trial to avoid non-stationarity related to the start of the measurement (Van Dieën et al., 2010). In addition using the protocol of Holden (2005), we used DFA to assess the stationarity of the signal (Tables 2 and 3). DFA values greater than 1 indicate that the signal is a non-stationary process, whereas DFA values less than 1 indicate that the signal is a stationary process. The length of time series analyzed was 500 data points. No filtering was performed on the data because filtering could can affect the nonlinear results (Kyvelidou et al., 2009).

Postural sway was assessed using traditional CoP-based measures in AP and ML displacement: the SD (SD_AP/SD_ML) and MV (MV_AP/MV_ML). These variables were also calculated for the flexion–extension and abduction–adduction angular displacement of the hip and ankle, and the flexion/extension angular displacement of the knee. Furthermore, the MV magnitude (MVM) and bivariate variable error (BVE) were calculated. BVE was measured as the average of the absolute distance to the participant's own midpoint (Hancock, Butler, and Fischman, 1995).

The variables used to assess the complexity of CoP and movement kinematics were SE, FE, PE, and DFA. SE and FE typically return values that indicate the degree of irregularity in the signal: higher SE and FE values indicate greater irregularity in the time domain of the signal whereas lower SE and FE values indicate greater regularity in the signal output. This measure computes the repeatability of vectors of length *m* and *m + 1* that repeat within a tolerance range of r within the standard deviation of the time-series. Higher values of SE and FE thus indicate that vectors of length are less repeatable than are vectors of length *m + 1*, highlighting the lower predictability of future data points, and a greater irregularity within the time series. Lower values represent a greater repeatability of vectors of length *m + 1*, and are thus a marker of higher regularity in the time series. For SE and FE we used the following parameter values: vector length, *m* = 2; tolerance window, *r* = .2*SD; and gradient, *n* = 2 for FE. According to different authors, these parameter values show high consistency, and are thus the most frequently used (W. Chen et al., 2007; Lake, Richman, Griffin, and Moorman, 2002; Pincus, 1991; Yentes et al., 2013).

PE measures the regularity of the time series based on comparisons of neighboring data. It is particularly useful in the presence of dynamical or observational noise because its main features are its robustness with respect to noise that could corrupt the data, and its easy computation. Permutation entropy measures the entropy of sequences of ordinal patterns that are derived from m-dimensional delay embedding vectors (Frank et al., 2006). We used the following parameter values: length, *l* = 4; and delay, *d* = 1. A more detailed introduction to PE can be found in Bandt and Pompe (2002).

DFA is a method based on random walk theory, representing a modification of classic root mean square analysis with random walk to evaluate the presence of long-term correlations within a time series using a parameter referred to as the scaling index *α* (Bashan et al., 2008; Peng et al., 1995). The scaling index *α* corresponds to a statistical dependence between fluctuations at one time scale and those over multiple time scales (Decker, Cignetti, and Stergiou, 2010). This procedure estimates the fractal scaling properties of a time series (Duarte and Sternad, 2008) and it has also been used to describe the complexity of a process (Goldberger, Amaral, et al., 2002). This measure was computed according to Peng et al. (1995). In this study, the slope *α* was obtained from the window range $4 \leq n \leq N/10$ to maximize the long-range auto-correlations and reduce the errors incurred by estimating *α* (Z. Chen, Ivanov, Hu, and Stanley, 2002). Different values of *α* indicate the following: $\alpha > 0.5$ implies persistence (i.e., the trajectory tends to continue in its current direction); $\alpha < 0.5$ implies antipersistence (i.e., the trajectory tends to return to where it came from; Roerdink et al., 2006).

Because the purpose of this study was to assess the intrasession reliability of the different measures of stationary and non-stationary signals, all variables were calculated over the displacement and velocity of CoP data. CoP displacement usually shows non-stationary time series. However, the CoP velocity time series, as the first derivative of the CoP displacement is much more stationary (Costa et al., 2007).

Table 2. Average values (mean ± SD) of variables of CoP in the displacement and velocity signals.

	Displacement					Velocity			
	SC		UC			SC		UC	
	AP	**ML**	**AP**	**ML**		**AP**	**ML**	**AP**	**ML**
SD	2.77 ± 0.9	1.44 ± 0.72	10.95 ± 3.88	10.89 ± 3.49	*MV*	5.66 ± 1.58	4.46 ± 1.3	29.12 ± 11.76	27.35 ± 11.10
BVE	2.75 ± 0.81		13.69 ± 4.32		*MVM*	8.03 ± 1.98		44.68 ± 17.06	
SE	0.43 ± 0.11	0.67 ± 0.23	0.51 ± 0.14	0.5 ± 0.2	*SE*	1.87 ± 0.24	1.98 ± 0.19	1.39 ± 0.21	1.47 ± 0.28
FE	0.37 ± 0.11	0.6 ± 0.22	0.47 ± 0.15	0.45 ± 0.19	*FE*	1.76 ± 0.21	1.85 ± 0.16	1.46 ± 0.22	1.52 ± 0.3
PE	0.76 ± 0.06	0.82 ± 0.05	0.68 ± 0.07	0.72 ± 0.09	*PE*	0.95 ± 0.04	0.97 ± 0.03	0.83 ± 0.04	0.91 ± 0.04
DFA	1.24 ± 0.22	0.93 ± 0.26	1 ± 0.2	1.18 ± 0.19	DFA	0.53 ± 0.13	0.48 ± 0.22	0.55 ± 0.15	0.68 ± 0.18

SC = Stable condition; UC = Unstable condition; AP = antero-posterio axis; ML = medio-latera axis.
Units of CoP measures are as follows: mm (SD and BVE); mm/s (MV and MVM).

Table 3. Average values (mean ± SD) of variables of kinematic in the displacement and velocity signals.

	Body Right side					Body Left side				
	Displacement			Velocity			Displacement			Velocity	
	SC	*UC*		*SC*	*UC*		*SC*	*UC*		*SC*	*UC*
SD_Hip$_{FLEX}$	0.30 ± 0.23	1.55 ± 1.13	**MV_Hip**$_{FLEX}$	0.44 ± 0.24	4.13 ± 4.97	**SD_Hip**$_{FLEX}$	0.27 ± 0.21	1.35 ± 0.92	**MV_Hip**$_{FLEX}$	0.44 ± 0.28	4.17 ± 4.79
SD_Hip$_{ADD}$	0.34 ± 0.16	1.31 ± 0.47	**MV_Hip**$_{ADD}$	1.25 ± 0.40	7.22 ± 5.84	**SD_Hip**$_{ADD}$	0.27 ± 0.15	1.27 ±0.56	**MV_Hip**$_{ADD}$	1.12 ± 0.53	6.86 ± 5.47
SD_Knee$_{FLEX}$	0.14 ±0.09	1.47 ± 0.91	**MV_Knee**$_{FLEX}$	0.39 ± 0.10	4.37 ± 5.02	**SD_Knee**$_{FLEX}$	0.15 ± 0.09	1.32 ± 0.83	**MV_Knee**$_{FLEX}$	0.38 ± 0.20	4.39 ± 4.74
SD_Ankle$_{FLEX}$	0.16 ± 0.06	2.15 ± 1.14	**MV_Ankle**$_{FLEX}$	0.35 ± 0.10	8.02 ± 6.83	**SD_Ankle**$_{FLEX}$	0.18 ± 0.10	1.94 ± 0.74	**MV_Ankle**$_{FLEX}$	0.49 ± 0.91	7.07 ± 5.87
SD_Ankle$_{ADD}$	0.21 ± 0.10	1.26 ± 0.51	**MV_Ankle**$_{ADD}$	1.01 ± 0.20	5.84 ± 4.26	**SD_Ankle**$_{ADD}$	0.23 ± 0.15	1.31 ± 0.57	**MV_Ankle**$_{ADD}$	1.00 ± 0.45	6.63 ± 5.71
BVE_Hip	0.40 ±0.13	2.31 ± 0.89	**MVM_Hip**	1.60 ± 0.61	11.39 ± 8.38	**BVE_Hip**	0.35 ± 0.15	2.15 ± 0.82	**MVM_Hip**	1.47 ± 0.79	10.85 ± 8.06
BVE_Knee	0.25 ± 0.13	1.75 ±1.11	**MVM_Knee**	1.08 ± 0.23	7.77 ± 7.24	**BVE_Knee**	0.21 ± 0.09	1.58 ± 0.83	**MVM_Knee**	1.26 ± 0.98	9.39 ± 9.93
BVE_Ankle	0.24 ± 0.09	2.22 ± 1.02	**MVM_Ankle**	1.21 ± 0.24	11.39 ± 8.57	**BVE_Ankle**	0.25 ± 0.146	2.03 ± 0.71	**MVM_Ankle**	1.30 ± 1.07	11.08 ± 9.01
SE_Hip$_{FLEX}$	0.32 ± 0.33	0.48 ± 0.32	**SE_Hip**$_{FLEX}$	1.76 ± 0.47	1.55 ± 0.41	**SE_Hip**$_{FLEX}$	0.39 ± 0.34	0.51 ± 0.26	**SE_Hip**$_{FLEX}$	1.75 ± 0.48	1.56 ± 0.43
SE_Hip$_{ADD}$	0.73 ± 0.37	0.86 ± 0.37	**SE_Hip**$_{ADD}$	1.83 ± 0.24	1.73 ± 0.34	**SE_Hip**$_{ADD}$	0.78 ± 0.34	0.84 ± 0.32	**SE_Hip**$_{ADD}$	1.85 ± 0.40	1.63 ± 0.36
SE_Knee$_{FLEX}$	0.64 ± 0.30	0.49 ± 0.33	**SE_Knee**$_{FLEX}$	2.01 ± 0.17	1.67 ± 0.34	**SE_Knee**$_{FLEX}$	0.56 ± 0.31	0.52 ± 0.23	**SE_Knee**$_{FLEX}$	1.93 ± 0.24	1.57 ± 0.33
SE_Ankle$_{FLEX}$	0.41 ± 0.15	0.61 ± 0.25	**SE_Ankle**$_{FLEX}$	1.97 ± 0.16	1.45 ± 0.34	**SE_Ankle**$_{FLEX}$	0.35 ± 0.19	0.59 ± 0.28	**SE_Ankle**$_{FLEX}$	1.80 ± 0.40	1.41 ± 0.35
SE_Ankle$_{ADD}$	0.94 ± 0.40	0.76 ± 0.31	**SE_Ankle**$_{ADD}$	1.97 ± 0.19	1.84 ± 0.33	**SE_Ankle**$_{ADD}$	0.94 ± 0.42	0.81 ± 0.40	**SE_Ankle**$_{ADD}$	1.94 ± 0.27	1.76 ± 0.35
FE_Hip$_{FLEX}$	0.29 ± 0.27	0.46 ± 0.34	**FE_Hip**$_{FLEX}$	1.78 ± 0.44	1.78 ± 0.39	**FE_Hip**$_{FLEX}$	0.34 ± 0.28	0.48 ± 0.29	**FE_Hip**$_{FLEX}$	1.76 ± 0.45	1.77 ± 0.36
FE_Hip$_{ADD}$	0.64 ± 0.34	0.80 ± 0.38	**FE_Hip**$_{ADD}$	1.94 ± 0.23	1.93 ± 0.36	**FE_Hip**$_{ADD}$	0.68 ± 0.29	0.80 ± 0.33	**FE_Hip**$_{ADD}$	1.95 ± 0.36	1.87 ± 0.38
FE_Knee$_{FLEX}$	0.55 ± 0.25	0.49 ± 0.39	**FE_Knee**$_{FLEX}$	2.05 ± 0.15	1.90 ± 0.30	**FE_Knee**$_{FLEX}$	0.50 ± 0.31	0.50 ± 0.25	**FE_Knee**$_{FLEX}$	2.00 ± 0.22	1.83 ± 0.30
FE_Ankle$_{FLEX}$	0.35 ± 0.12	0.58 ± 0.26	**FE_Ankle**$_{FLEX}$	2.00 ± 0.13	1.55 ± 0.32	**FE_Ankle**$_{FLEX}$	0.32 ± 0.21	0.57 ± 0.28	**FE_Ankle**$_{FLEX}$	1.84 ± 0.29	1.54 ± 0.33
FE_Ankle$_{ADD}$	0.83 ± 0.34	0.69 ± 0.30	**FE_Ankle**$_{ADD}$	2.05 ± 0.14	1.93 ± 0.32	**FE_Ankle**$_{ADD}$	0.84 ± 0.36	0.76 ± 0.41	**FE_Ankle**$_{ADD}$	2.03 ± 0.22	1.92 ± 0.03
PE_Hip$_{FLEX}$	0.93 ± 0.02	0.83 ± 0.09	**PE_Hip**$_{FLEX}$	0.99 ± 0.00	0.93 ± 0.08	**PE_Hip**$_{FLEX}$	0.83 ± 0.09	0.93 ± 0.02	**PE_Hip**$_{FLEX}$	0.98 ± 0.00	0.92 ± 0.09
PE_Hip$_{ADD}$	0.97 ± 0.01	0.91 ± 0.11	**PE_Hip**$_{ADD}$	0.98 ± 0.00	0.96 ± 0.08	**PE_Hip**$_{ADD}$	0.97 ± 0.01	0.90 ± 0.11	**PE_Hip**$_{ADD}$	0.98 ± 0.00	0.95 ± 0.09
PE_Knee$_{FLEX}$	0.96 ±0.02	0.86 ± 0.07	**PE_Knee**$_{FLEX}$	0.98 ± 0.00	0.94 ± 0.07	**PE_Knee**$_{FLEX}$	0.96 ± 0.02	0.86 ± 0.08	**PE_Knee**$_{FLEX}$	0.98 ± 0.00	0.93 ± 0.07
PE_Ankle$_{FLEX}$	0.92 ± 0.03	0.72 ± 0.09	**PE_Ankle**$_{FLEX}$	0.98 ± 0.00	0.90 ± 0.08	**PE_Ankle**$_{FLEX}$	0.90 ± 0.04	0.74 ± 0.09	**PE_Ankle**$_{FLEX}$	0.98 ± 0.00	0.91 ± 0.08
PE_Ankle$_{ADD}$	0.97 ± 0.02	0.89 ± 0.09	**PE_Ankle**$_{ADD}$	0.98 ± 0.00	0.96 ± 0.07	**PE_Ankle**$_{ADD}$	0.97 ± 0.01	0.88 ± 0.08	**PE_Ankle**$_{ADD}$	0.98 ± 0.00	0.95 ± 0.08
DFA_Hip$_{FLEX}$	1.32 ± 0.23	1.22 ± 0.28	**DFA_Hip**$_{FLEX}$	0.50 ± 0.14	0.46 ± 0.16	**DFA_Hip**$_{FLEX}$	1.33 ± 0.23	1.22 ± 0.28	**DFA_Hip**$_{FLEX}$	0.49 ± 0.13	0.49 ± 0.18
DFA_Hip$_{ADD}$	1.30 ± 0.18	1.13 ± 0.21	**DFA_Hip**$_{ADD}$	0.46 ± 0.20	0.46 ± 0.18	**DFA_Hip**$_{ADD}$	1.26 ± 0.18	1.08 ± 0.15	**DFA_Hip**$_{ADD}$	0.39 ± 0.18	0.40 ± 0.19
DFA_Knee$_{FLEX}$	1.32 ± 0.17	1.24 ± 0.19	**DFA_Knee**$_{FLEX}$	0.46 ± 0.17	0.40 ± 0.17	**DFA_Knee**$_{FLEX}$	1.34 ± 0.19	1.21 ± 0.22	**DFA_Knee**$_{FLEX}$	0.46 ± 0.15	0.42 ± 0.20
DFA_Ankle$_{FLEX}$	1.40 ± 0.17	0.89 ± 0.21	**DFA_Ankle**$_{FLEX}$	0.53 ± 0.10	0.45 ± 0.16	**DFA_Ankle**$_{FLEX}$	1.37 ± 0.22	0.91 ± 0.22	**DFA_Ankle**$_{FLEX}$	0.53 ± 0.15	0.45 ± 0.16
DFA_Ankle$_{ADD}$	1.21 ± 0.14	1.08 ± 0.17	**DFA_Ankle**$_{ADD}$	0.35 ± 0.11	0.43 ± 0.16	**DFA_Ankle**$_{ADD}$	1.22 ± 0.16	1.01 ± 0.21	**DFA_Ankle**$_{ADD}$	0.31 ± 0.11	0.34 ± 0.12

SC = Stable condition; UC = Unstable condition; FLEX = flexion; ADD = Adduction
Units of CoP measures are as follows: mm (SD and BVE); mm/s (MV).

3.3.4. Statistical Analysis.

The normality of the variables was evaluated using the Kolmogorov-Smirnov test with Lilliefors correction. ICCs were used to analyze the relative reliability. Significance was established at $p < .05$. According to Fleiss's classification of ICC values, as adopted by Collins and De Luca (1993), the following general guidelines have been assumed: ICC values above 0.75 represent excellent reliability, values between 0.40 and 0.75 represent fair to good reliability, and values below 0.40 represent poor reliability. The standard error of measurement (SEM) was calculated to quantify the precision of individual scores on a test (i.e., the absolute reliability; Weir, 2005). To judge the relative importance of SEM values better, they were expressed as a percentage (%SEM), where an SEM < 10% is an index of high absolute reliability. However, in postural studies SEMs < 20% could be considered acceptable (Santos et al., 2008). A high SEM indicates a high level of error and implies the no reproducibility of the tested values (Lin et al., 2008).

3.4. Results.

The mean values obtained from the CoP and kinematic variables, under stable and unstable conditions, are presented in Tables 2 and 3. The ICCs and SEM values obtained from the CoP variables of the study under stable and unstable conditions are presented in Tables 4 and 5, respectively. In the stable condition, the relative intrasession reliability of SD and BVE were poor. However, MV produced good values of relative intrasession reliability. For nonlinear variables, PE produced moderate values, whereas the other variables produced poor values or acceptable values only on one axis. With respect to absolute intrasession reliability, SEM indicated that MV showed the best values of the traditional measures and that PE produced the best results of the nonlinear measures. Moreover, PE had better results with respect to SEM than did MV.

In the unstable condition, all of the traditional variables analyzed produced good values of relative intrasession reliability, but MV was again the most reliable variable. Furthermore, PE and DFA seemed to show the best relative intrasession reliability results among the nonlinear variables. It must be noted that in the unstable condition, the variables calculated using velocity data had better relative intrasession reliability values than did the variables calculated using displacement. Regarding the SEM values, PE produced the best values of absolute intrasession reliability, followed by MV.

The intrasession reliability of kinematic variables is shown in Tables 6 and 7. In the stable condition there are few variables that exhibit good or moderate relative intrasession reliability. Regarding traditional variables, it is not clear which variables are better. However, with reference to the nonlinear measures, DFA seemed to show the best results because it was the only variable that showed moderate relative and absolute intrasession reliability in each joint, though only on the right side of the body.

Conversely, in the unstable condition, the traditional kinematics variables showed the same trend that the results of CoP data. The MV produced the best relative intrasession reliability values in all conditions. With respect to nonlinear measures, entropy variables seemed to show the best relative intrasession reliability results, though PE and DFA produced the best absolute intrasession reliability values. Similar to the CoP variables, the measures calculated using kinematic velocity data showed the best intrasession reliability values.

Table 4. ICCs and SEM (%) for Stable condition CoP variables.

	Displacement			Velocity	
	ICC	***SEM (%)***		***ICC***	***SEM (%)***
SD$_{AP}$	.077	33.00	**MV$_{AP}$**	*.772*	14.95
SD$_{ML}$	*.334*	38.03	**MV$_{ML}$**	*.567*	21.15
BVE	.057	30.27	**MVM**	*707*	15.12
SE$_{AP}$	.211	29.20	**SE$_{AP}$**	.235	9.97
SE$_{ML}$	*.395*	23.24	**SE$_{ML}$**	.219	7.69
SE$_{Mg}$	—	—	**SE$_{Mg}$**	-.059	12.19
FE$_{AP}$	.212	32.36	**FE$_{AP}$**	*.352*	9.20
FE$_{ML}$	*.432*	22.75	**FE$_{ML}$**	*.389*	6.08
FE$_{Mg}$	—	—	**FE$_{Mg}$**	.020	10.11
PE$_{AP}$	*.591*	5.52	**PE$_{AP}$**	.212	4.12
PE$_{ML}$	*.460*	4.71	**PE$_{ML}$**	.158	3.10
PE$_{Mg}$	—	—	**PE$_{Mg}$**	*.460*	0.60
DFA$_{AP}$	*.448*	12.93	**DFA$_{AP}$**	.151	22.58
DFA$_{ML}$	*.339*	20.39	**DFA$_{ML}$**	*.361*	31.39
DFA$_{Mg}$	—	—	**DFA$_{Mg}$**	.028	16.43

AP = antero-posterio axis; ML = medio-latera axis; Mg = Magnitude
$p \leq .05$ (Values highlighted in bolded italics).

Table 5. ICCs and SEM for Unstable condition CoP variables.

	Displacement			Velocity	
	ICC	***SEM (%)***		***ICC***	***SEM (%)***
SD$_{AP}$	*.556*	22.38	**MV$_{AP}$**	*.763*	16.78
SD$_{ML}$	*.561*	20.56	**MV$_{ML}$**	*.713*	18.75
BVE	*. 568*	19.43	**MVM**	*.779*	14.24
SE$_{AP}$	*.632*	15.64	**SE$_{AP}$**	*.573*	9.64
SE$_{ML}$	*.580*	23.11	**SE$_{ML}$**	*.537*	12.24
SE$_{Mg}$	—	—	**SE$_{Mg}$**	*.352*	10.22
FE$_{AP}$	*.659*	17.47	**FE$_{AP}$**	*.689*	7.56
FE$_{ML}$	*.648*	22.74	**FE$_{ML}$**	*.753*	9.40
FE$_{Mg}$	—	—	**FE$_{Mg}$**	*.509*	8.41
PE$_{AP}$	*.603*	5.30	**PE$_{AP}$**	*.709*	2.54
PE$_{ML}$	*.870*	3.68	**PE$_{ML}$**	*.615*	2.71
PE$_{Mg}$	—	—	**PE$_{Mg}$**	*.823*	1.37
DFA$_{AP}$	*.601*	9.73	**DFA$_{AP}$**	*.581*	17.15
DFA$_{ML}$	*.727*	8.32	**DFA$_{ML}$**	*.592*	15.80
DFA$_{Mg}$	—	—	**DFA$_{Mg}$**	*.748*	10.97

AP = antero-posterio axis; ML = medio-latera axis; Mg = Magnitude
$p \leq .05$ (Values highlighted in bolded italics).

Table 6. ICCs and SEM (%) for Stable condition kinematic variables.

	Body Right side					Body Left side					
	Displacement			Velocity			Displacement			Velocity	
	ICC	*SEM(%)*		*ICC*	*SEM(%)*		*ICC*	*SEM(%)*		*ICC*	*SEM(%)*
SD_Hip$_{FLEX}$	.359	55.84	**MV_Hip**$_{FLEX}$	-.284	50.64	**SD_Hip**$_{FLEX}$	.307	65.9	**MV_Hip**$_{FLEX}$	-.019	56.08
SD_Hip$_{ADD}$	.444	17.77	**MV_Hip**$_{ADD}$	.046	33.26	**SD_Hip**$_{ADD}$	*.837*	22.97	**MV_Hip**$_{ADD}$	-.128	64.76
SD_Knee$_{FLEX}$	.325	43.37	**MV_Knee**$_{FLEX}$	.341	28.42	**SD_Knee**$_{FLEX}$	*.558*	32.6	**MV_Knee**$_{FLEX}$	.461	25.5
SD_Ankle$_{FLEX}$	.321	22.88	**MV_Ankle**$_{FLEX}$	*.772*	16.9	**SD_Ankle**$_{FLEX}$	.325	26.6	**MV_Ankle**$_{FLEX}$	.456	45.18
SD_Ankle$_{ADD}$	*.571*	34.37	**MV_Ankle**$_{ADD}$	.296	16.99	**SD_Ankle**$_{ADD}$	.229	31.51	**MV_Ankle**$_{ADD}$	.498	24.66
BVE_Hip	.482	23.52	**MVM_Hip**	-.214	39.36	**BVE_Hip**	*.654*	27.33	**MVM_Hip**	-.022	51.8
BVE_Knee	.317	35.16	**MVM_Knee**	.156	24.56	**BVE_Knee**	*.770*	17.20	**MVM_Knee**	.059	59.5
BVE_Ankle	.477	25.42	**MVM_Ankle**	.385	16.42	**BVE_Ankle**	.106	31.80	**MVM_Ankle**	.500	28.97
SE_Hip$_{FLEX}$	.503	50.73	**SE_Hip**$_{FLEX}$	.026	23.8	**SE_Hip**$_{FLEX}$	.282	75.38	**SE_Hip**$_{FLEX}$	.043	23.88
SE_Hip$_{ADD}$	.521	24.83	**SE_Hip**$_{ADD}$	-.262	17.89	**SE_Hip**$_{ADD}$	*.761*	19.24	**SE_Hip**$_{ADD}$	.103	18.57
SE_Knee$_{FLEX}$	.353	46.46	**SE_Knee**$_{FLEX}$	-.007	13.32	**SE_Knee**$_{FLEX}$	.174	65.98	**SE_Knee**$_{FLEX}$	-.284	14.02
SE_Ankle$_{FLEX}$	.084	41.65	**SE_Ankle**$_{FLEX}$	-.227	8.41	**SE_Ankle**$_{FLEX}$	.238	40.13	**SE_Ankle**$_{FLEX}$	-.093	11.56
SE_Ankle$_{ADD}$	*.599*	22.28	**SE_Ankle**$_{ADD}$	-.167	10.99	**SE_Ankle**$_{ADD}$	.430	18.23	**SE_Ankle**$_{ADD}$	.087	12.84
FE_Hip$_{FLEX}$	*.564*	43.59	**FE_Hip**$_{FLEX}$	.025	21.98	**FE_Hip**$_{FLEX}$	.303	68.77	**FE_Hip**$_{FLEX}$	.101	21.5
FE_Hip$_{ADD}$	*.525*	25.49	**FE_Hip**$_{ADD}$	-.282	16.71	**FE_Hip**$_{ADD}$	*.707*	20.08	**FE_Hip**$_{ADD}$	-.072	17.36
FE_Knee$_{FLEX}$	.371	44.58	**FE_Knee**$_{FLEX}$	-.178	11.05	**FE_Knee**$_{FLEX}$	.104	62.7	**FE_Knee**$_{FLEX}$	-.266	12.8
FE_Ankle$_{FLEX}$	.187	39.51	**FE_Ankle**$_{FLEX}$	-.363	7.33	**FE_Ankle**$_{FLEX}$	.247	42.42	**FE_Ankle**$_{FLEX}$	-.179	8.34
FE_Ankle$_{ADD}$	*.571*	21.77	**FE_Ankle**$_{ADD}$	-.227	8.99	**FE_Ankle**$_{ADD}$	.433	20.3	**FE_Ankle**$_{ADD}$	.071	10.43
PE_Hip$_{FLEX}$	*.823*	1.47	**PE_Hip**$_{FLEX}$	.102	0.52	**PE_Hip**$_{FLEX}$	*.793*	1.68	**PE_Hip**$_{FLEX}$	.449	0.22
PE_Hip$_{ADD}$	.251	1.35	**PE_Hip**$_{ADD}$	-.191	0.86	**PE_Hip**$_{ADD}$	*.735*	0.85	**PE_Hip**$_{ADD}$	.385	0.93
PE_Knee$_{FLEX}$	.191	2.34	**PE_Knee**$_{FLEX}$	.351	0.98	**PE_Knee**$_{FLEX}$	-.090	2.82	**PE_Knee**$_{FLEX}$	*.904*	0.37
PE_Ankle$_{FLEX}$	-.209	3.28	**PE_Ankle**$_{FLEX}$	.134	0.49	**PE_Ankle**$_{FLEX}$	.472	3.01	**PE_Ankle**$_{FLEX}$	.115	0.63
PE_Ankle$_{ADD}$	.142	1.49	**PE_Ankle**$_{ADD}$	.105	0.48	**PE_Ankle**$_{ADD}$	.492	1.08	**PE_Ankle**$_{ADD}$	.118	0.34
DFA_Hip$_{FLEX}$	.203	10.3	**DFA_Hip**$_{FLEX}$	*.603*	19.41	**DFA_Hip**$_{FLEX}$	*.538*	11.51	**DFA_Hip**$_{FLEX}$	.325	20.17
DFA_Hip$_{ADD}$	*.674*	9.49	**DFA_Hip**$_{ADD}$	*.627*	26.58	**DFA_Hip**$_{ADD}$	-.102	17.1	**DFA_Hip**$_{ADD}$	.429	35.38
DFA_Knee$_{FLEX}$	*.627*	9.02	**DFA_Knee**$_{FLEX}$	-.338	46.01	**DFA_Knee**$_{FLEX}$	.083	13.99	**DFA_Knee**$_{FLEX}$	-.343	25.99
DFA_Ankle$_{FLEX}$	.024	13.26	**DFA_Ankle**$_{FLEX}$	.308	20.20	**DFA_Ankle**$_{FLEX}$	.116	18.85	**DFA_Ankle**$_{FLEX}$	.231	21.23
DFA_Ankle$_{ADD}$	*.561*	10.29	**DFA_Ankle**$_{ADD}$	-.313	39.29	**DFA_Ankle**$_{ADD}$	-.409	17.15	**DFA_Ankle**$_{ADD}$	.360	26.98

FLEX = flexion; ADD = adduction;
$p \leq .05$ (Values highlighted in bolded italics).

Table 7. ICCs and SEM for Unstable condition kinematic variables.

	Body Right side					Body Left side					
	Displacement			Velocity			Displacement			Velocity	
	ICC	*SEM(%)*		*ICC*	*SEM(%)*		*ICC*	*SEM(%)*		*ICC*	*SEM(%)*
SD_Hip$_{FLEX}$	*.930*	23.82	**MV_Hip$_{FLEX}$**	*.897*	23.82	**SD_Hip$_{FLEX}$**	*.802*	41.79	**MV_Hip$_{FLEX}$**	*.860*	41.79
SD_Hip$_{ADD}$	*.631*	22.68	**MV_Hip$_{ADD}$**	*.918*	18.21	**SD_Hip$_{ADD}$**	*.675*	26.67	**MV_Hip$_{ADD}$**	*.953*	14.79
SD_Knee$_{FLEX}$	*.617*	53.83	**MV_Knee$_{FLEX}$**	*.885*	16.003	**SD_Knee$_{FLEX}$**	.303	56.56	**MV_Knee$_{FLEX}$**	*.926*	12.29
SD_Ankle$_{FLEX}$	*.319*	40.83	**MV_Ankle$_{FLEX}$**	*.921*	17.81	**SD_Ankle$_{FLEX}$**	.476	22.16	**MV_Ankle$_{FLEX}$**	*.934*	15.17
SD_Ankle$_{ADD}$	*.635*	41.01	**MV_Ankle$_{ADD}$**	*.932*	13.82	**SD_Ankle$_{ADD}$**	*.746*	23.49	**MV_Ankle$_{ADD}$**	*.972*	11.6
BVE_Hip	*.909*	12.28	**MVM_Hip**	*.905*	16.26	**BVE_Hip**	*.789*	20.54	**MVM_Hip**	*.940*	12.19
BVE_Knee	*.711*	42.60	**MVM_Knee**	*.895*	14.92	**BVE_Knee**	.450	40.16	**MVM_Knee**	.175	75.94
BVE_Ankle	.425	35.82	**MVM_Ankle**	*.927*	14.93	**BVE_Ankle**	*.700*	14.87	**MVM_Ankle**	*.964*	11.41
SE_Hip$_{FLEX}$	*.727*	33.46	**SE_Hip$_{FLEX}$**	-.084	11.15	**SE_Hip$_{FLEX}$**	*.844*	18.57	**SE_Hip$_{FLEX}$**	.013	11.02
SE_Hip$_{ADD}$	*.672*	23.37	**SE_Hip$_{ADD}$**	*.754*	4.49	**SE_Hip$_{ADD}$**	*.820*	17.09	**SE_Hip$_{ADD}$**	.123	7.78
SE_Knee$_{FLEX}$	*.753*	36.5	**SE_Knee$_{FLEX}$**	.098	9.07	**SE_Knee$_{FLEX}$**	*.735*	25.57	**SE_Knee$_{FLEX}$**	.004	11.73
SE_Ankle$_{FLEX}$	.472	20.6	**SE_Ankle$_{FLEX}$**	.484	10.14	**SE_Ankle$_{FLEX}$**	*.703*	23.86	**SE_Ankle$_{FLEX}$**	*.601*	11.51
SE_Ankle$_{ADD}$	*.820*	16.17	**SE_Ankle$_{ADD}$**	-.272	5.63	**SE_Ankle$_{ADD}$**	*.874*	17.8	**SE_Ankle$_{ADD}$**	.472	6.5
FE_Hip$_{FLEX}$	*.784*	29.64	**FE_Hip$_{FLEX}$**	.422	8.14	**FE_Hip$_{FLEX}$**	*.787*	20.48	**FE_Hip$_{FLEX}$**	*.605*	6.34
FE_Hip$_{ADD}$	*.737*	22.93	**FE_Hip$_{ADD}$**	*.844*	1.92	**FE_Hip$_{ADD}$**	*.761*	22.3	**FE_Hip$_{ADD}$**	*.870*	2.4
FE_Knee$_{FLEX}$	*.771*	35.35	**FE_Knee$_{FLEX}$**	.207	7.43	**FE_Knee$_{FLEX}$**	*.712*	24.27	**FE_Knee$_{FLEX}$**	*.616*	7.12
FE_Ankle$_{FLEX}$	.410	23.62	**FE_Ankle$_{FLEX}$**	*.659*	6.5	**FE_Ankle$_{FLEX}$**	*.685*	25.94	**FE_Ankle$_{FLEX}$**	*.773*	7.56
FE_Ankle$_{ADD}$	*.833*	15.56	**FE_Ankle$_{ADD}$**	*.704*	3.68	**FE_Ankle$_{ADD}$**	*.896*	16.66	**FE_Ankle$_{ADD}$**	*.790*	4.03
PE_Hip$_{FLEX}$	.432	4.79	**PE_Hip$_{FLEX}$**	.434	1.44	**PE_Hip$_{FLEX}$**	*.614*	3.54	**PE_Hip$_{FLEX}$**	*.664*	1.37
PE_Hip$_{ADD}$	.414	2.29	**PE_Hip$_{ADD}$**	*.586*	0.85	**PE_Hip$_{ADD}$**	.390	2.13	**PE_Hip$_{ADD}$**	*.834*	0.604
PE_Knee$_{FLEX}$	.409	3.42	**PE_Knee$_{FLEX}$**	*.546*	1.12	**PE_Knee$_{FLEX}$**	.507	3.96	**PE_Knee$_{FLEX}$**	.058	1.98
PE_Ankle$_{FLEX}$	*.701*	5.08	**PE_Ankle$_{FLEX}$**	*.662*	1.59	**PE_Ankle$_{FLEX}$**	*.743*	5.42	**PE_Ankle$_{FLEX}$**	*.766*	1.67
PE_Ankle$_{ADD}$	.432	3.48	**PE_Ankle$_{ADD}$**	*.780*	0.55	**PE_Ankle$_{ADD}$**	*.829*	1.55	**PE_Ankle$_{ADD}$**	*.693*	0.79
DFA_Hip$_{FLEX}$	.512	16.76	**DFA_Hip$_{FLEX}$**	*.586*	18	**DFA_Hip$_{FLEX}$**	.280	16.75	**DFA_Hip$_{FLEX}$**	*.907*	10.22
DFA_Hip$_{ADD}$	*.872*	6.38	**DFA_Hip$_{ADD}$**	*.591*	14.24	**DFA_Hip$_{ADD}$**	*.701*	9.31	**DFA_Hip$_{ADD}$**	*.759*	21.55
DFA_Knee$_{FLEX}$	.325	13.38	**DFA_Knee$_{FLEX}$**	*.820*	20.43	**DFA_Knee$_{FLEX}$**	.264	12.63	**DFA_Knee$_{FLEX}$**	*.857*	22.3
DFA_Ankle$_{FLEX}$	*.774*	8.45	**DFA_Ankle$_{FLEX}$**	*.815*	13.53	**DFA_Ankle$_{FLEX}$**	*.679*	12.99	**DFA_Ankle$_{FLEX}$**	*.896*	11.72
DFA_Ankle$_{ADD}$	.250	12.5	**DFA_Ankle$_{ADD}$**	*.824*	11.35	**DFA_Ankle$_{ADD}$**	.469	11.42	**DFA_Ankle$_{ADD}$**	*.588*	15.36

FLEX = flexion; ADD = adduction;
$p \leq .05$ (Values highlighted in bolded italics).

3.5. Discussion.

Several studies have characterized the postural sway in balance tasks by analyzing the CoP dynamic using traditional and nonlinear parameters. Nevertheless, the reliability of traditional linear parameters of CoP has been frequently disputed (Ruhe et al., 2010) and there are few conclusive results about the reliability of nonlinear CoP measurements (Kyvelidou et al., 2009). Furthermore, some authors have suggested that the CoP parameters can be limited in their ability to discern different postural strategies and movement patterns (Kuo et al., 1998) and that it would be convenient to use additional kinematic measures. In this study, we have assessed the intrasession reliability of CoP and kinematic parameters that characterize the postural sway in a simplified protocol of a balance task in stable and unstable conditions. Thus, we can determine which variables allow for the characterization and classification of motor balance behavior.

The mean values obtained from the CoP variables in the study under both conditions, stable and unstable, were close to others studies, both about linear variables (R. J. Doyle et al., 2007; Harringe, Halvorsen, Renstrom, and Werner, 2008; Lin et al., 2008; Salavati et al., 2009; Santos et al., 2008) and nonlinear variables (Amoud et al., 2007; S. F. Donker et al., 2007; T. L. Doyle et al., 2005; Harbourne and Stergiou, 2003; Lin et al., 2008).

In stable and unstable conditions, MV showed good results in relative intrasession reliability and is the traditional measure that best ranks individuals in balance tasks. Therefore, this variable seems to be the largest contributor in terms of consistency of the position or rank of individuals in the group relative to others to categorize participants (Weir, 2005). In addition, MV had higher consistency between trials (lower results in SEM) compared to SD and BVE. Consequently, MV seems to be a more consistent variable to detect changes in performance than SD and BVE (Raymakers, Samson, and Verhaar, 2005). SD and BVE showed poorer intrasession reliability scores in stable situations and good scores under unstable situations, but their results were lower than MV. Our outcomes are similar to those obtained by Lafond et al. (2004) and Lin et al. (2008), but in those studies, the protocols included more trials and a longer sample duration. We found that MV is reliable despite the short time series used. In the present study, MV has showed good intrasession reliability in a protocol that used sample durations of only 30 s (Le Clair and Riach, 1996; Schmid et al., 2002). Furthermore, this variable produced very good values of intrasession reliability despite the experimental conditions. These results agree with those obtained by Salavati et al. (2009). In their study, they assessed the postural stability during quiet standing in a group with musculoskeletal disorders consisting of low back pain, anterior cruciate ligament injury and functional ankle instability, and the mean total velocity in all conditions of postural difficulty showed high to very high reliability. Though Ruhe et al. (2010) noted that data from a firm stable surface tends to be more reliable, in our study the scattering measures did not produce good intrasession reliability values under stable conditions but in unstable conditions, its intrasession reliability was acceptable. According to Lee and Granata (2008) these findings may be due to the sway variance increasing with the task difficulty. This high variance may reduce the time duration needed to achieve a stationary time series. In the stable condition, different locations of the CoG in the surface of support allow a person to maintain stability (Caballero et al., 2013); different stability locations can help achieve good performance. However, more difficult conditions limit the region of stability (Lee and Granata, 2008). Thus, measures of the dispersion of the data relative to a midpoint, such as SD or BVE, are used as an indicator of postural control, but they may be affected by the non-stationarity of this data (Caballero et al., 2013). Therefore, scattering variables appear to be unreliable indexes of balance performance in stable conditions. However, in unstable situations, the increased difficulty implies that continuous adjustments are required to prevent the CoG from moving out of the surface of support. The amount of the CoP fluctuations could reflect the ability of the individual to maintain the stability, and the scattering measures in unstable condition could be a better index of the postural control.

Regarding nonlinear measures, SE and FE showed a moderate ability to rank individuals and good consistency in the stable condition, but FE showed slightly better results than did SE. In the unstable condition, the intrasession reliability values were better than those in the stable condition, and FE again showed better results than did SE. W. Chen et al. (2007) proposed FE as a more reliable measure of regularity compared with the previous measures because of its stronger relative consistency and robustness to noise. Nevertheless, both measures of CoP regularity have shown better results in this study in the unstable condition compared with in the stable condition, similar to the traditional measures. CoP is a non-stationary signal (Newell, Slobounov, Slobounova, and Molenaar, 1997; Schumann, Redfern, Furman, El-Jaroudi, and Chaparro, 1995) because of constant adjustments of CoP that are required to maintain the CoG within the stability boundary on the surface of support. More difficult conditions, such as the unstable condition of the experiment, required tighter neuromuscular control. This can result in less day-to-day variability and provide results with greater repeatability and lower SEM or absolute reliability values (Lee and Granata, 2008). In the stable condition, as indicated previously, the lower motion of the CoP allows different places of the CoG within the surface of support to maintain stability. Non-stationarity caused in the stable condition produces lower reliability values because stationarity is a basic requirement of entropy measures derived from ApEn (Costa, Goldberger, and Peng, 2005).

The results in this study indicate that PE was the nonlinear measure that had superior results in its ability to rank individuals in the balance task and better consistency than the other regularity measures. This result could be due to its robustness with respect to some noise, which may have corrupted the PE results (Bandt and Pompe, 2002). PE has also shown stronger consistency in both stable and unstable conditions, so it is less affected by the non-stationarity of the time series.

DFA is another nonlinear measure frequently used to assess the complexity of the CoP by analyzing the long-range auto-correlation of the signal. Van Dieën et al. (2010) assessed the reliability of several nonlinear tools and DFA and found that the entropy measures showed similar values in the sitting balance task. Amoud et al. (2007) analyzed the reliability of DFA assessing the postural stability in elderly people and control subjects and the effect of the recording duration. In the present study, DFA of the CoP produced good intrasession reliability values in both stable and unstable conditions. These results agree with those obtained by Amoud et al. (2007), but the DFA intrasession reliability was not as good as that of PE under unstable condition. In our study, PE was better able to rank individuals and exhibited better consistency than did DFA, but DFA had better intrasession reliability than did the other entropy measures, similar to the study of van Dieën et al. (2010). Because PE and DFA measure different characteristics of the time series, it could be best to use both nonlinear variables to obtain complementary information about the complexity of the postural sway.

It should be noted that in the unstable condition, the results obtained using the velocity data of the CoP were more reliable than those obtained using CoP displacement. This finding could be related to the stationarity of the signal. Non-stationarities may lead to a spurious increase in the apparent degree of irregularity of a time series for the shortest scales (Costa et al., 2007). To avoid this increase, Costa et al. applied some methods to detrend the data. However, they suggested that the derivative time series are much more persistent than the original time series and that there is no need to detrend the velocity time series. Therefore, when SE and FE are used, it is recommended that one use a velocity time series or apply methods to detrend the data before assessing the complexity of CoP.

The kinematic variables show similar results to those obtained using CoP variables, particularly on traditional measures. SD, BVE and MV produced poorer intrasession reliability, both in their ability to rank and in their consistency, in the stable condition. Good intrasession reliability results can be found in the unstable condition, and MV again showed better intrasession reliability values.

Under the stable condition, no kinematic nonlinear variable has clearly shown good results in its ability to rank individuals. However, referring to the consistency values, PE showed excellent results for both angular displacement and angular velocity data. FE produced good SEM values using the derived data, and SE produced the same trend as FE, but with poorer SEM values. As indicated above, the differences between angular displacement and angular velocity data could occur because the derived signal (i.e., the angular velocity data) is much more persistent (Costa et al., 2007), and this stationarity affects entropy measures, except PE, according to the results found for the CoP signal.

In the unstable condition, PE showed a good or moderate ability to rank individuals in the angular velocity data. In addition, this measure produced the best SEM values for both the angular displacement and angular velocity data, but the angular velocity data were slightly better than angular displacement data. However, SE and FE both showed inconsistent results. These entropy measures produced good or moderate values ranking individuals, presenting better values for angular displacement than for angular velocity data. However, regarding the consistency values, these measures showed better results in the derived signal. Therefore, there is no situation in which these measures have shown good ICC values and SEM values simultaneously. DFA showed good ICC values in the derived data that were better than those obtained for the angular displacement data. The values of SEM indicate the good consistency of DFA, with no clear differences between derived and nonderived data. Generally, the kinematic variables produced lower values of intrasession reliability than did the CoP variables. The kinematic analysis overlooks the control forces involved in motor control, and these signals represent the integral of those forces, acting as a mechanical low-pass filter (Moorhouse and Granata, 2005). This filtering behavior can limit the performance of nonlinear analyses, as noted by the poorer reliability limit the performance of nonlinear analyses, as noted by the poorer reliability of nonlinear stability. For this reason, kinematic signals take longer to achieve stationarity (Lee and Granata, 2008). This finding does not mean that the measured data are not an adequate representation of the stabilizing control of this dynamic system. It would be necessary to use additional measures that are more consistent to subtle changes in movement throughout the body. The information that the kinematic variables provide is very important to determine any changes in movement throughout the body (Kuo et al., 1998; Madigan et al., 2006), but more recording time is required to achieve good reliability values. In this sense, CoP would be a better index than kinematics in a simplified balance task protocol.

3.6. Conclusions.

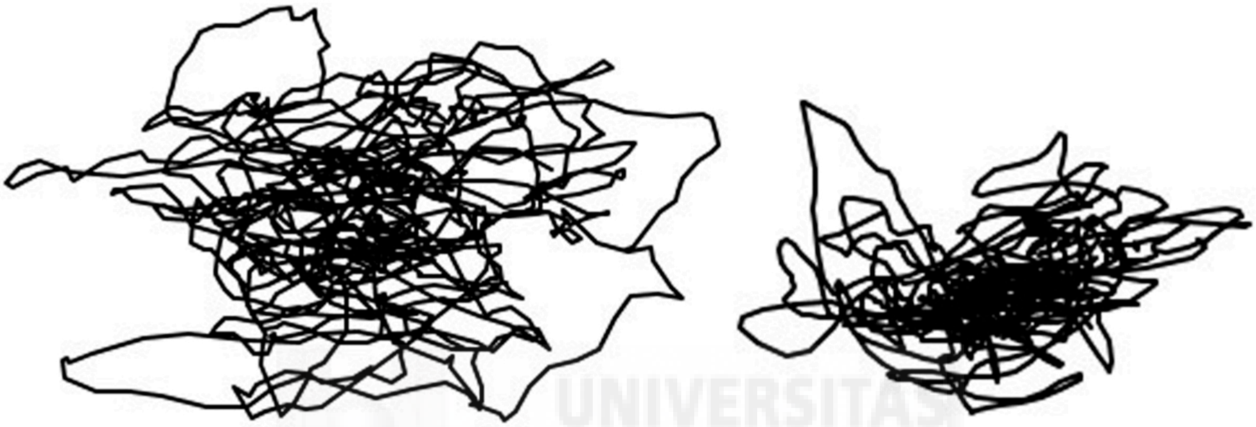
In the CoP signal, MV was the best measure for ranking individuals in a motor balance task among the traditional measures. Furthermore, MV showed higher consistency between trials in a simplified balance task.

PE was the best measure for ranking individuals and produced higher consistency values than did the other nonlinear tools. DFA showed good values for ICC and SEM. The use of both PE and DFA should be recommended in a simplified protocol because these tools measure different characteristics of the time series and they can provide complementary information about the complexity of the postural sway.

The stationarity of the signal affects the intrasession reliability of the measures. This must considered when designing a simplified protocol with a short time series. The type of signal affects the required length of the time series. Kinematic signals need more recording time to achieve good intrasession reliability values than do CoP signals. In addition, when using entropy measures such as SE or FE, it is recommended to use velocity time series or apply methods to detrend the time series. Finally, unstable balance tasks require less recording time to achieve stationarity than do stable balance tasks.

The measures of CoP seemed to have more ability to rank individuals in balance tasks and showed higher consistency between trials in a simplified protocol than did kinematics, although both CoP and kinematics should be used as complementary signals to better characterize balance behavior.

In summary, to achieve a good analysis of postural control, it is very important to consider that the reliability of the different variables appears to be dependent on the conditions measured and the signals analyzed.



4. Study II

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VARIATIONS IN TASK CONSTRAINTS SHAPE EMERGENT PERFORMANCE OUTCOMES AND COMPLEXITY LEVELS IN BALANCING

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4.1. Abstract.

This study investigated the extent to which specific interacting constraints of performance might increase or decrease the emergent complexity in a movement system, and whether this could affect the relationship between observed movement variability and the CNS's capacity to adapt to perturbations during balancing. Fifty-two healthy volunteers performed eight trials where different performance constraints were manipulated: task difficulty (three levels) and visual biofeedback conditions (with and without the CoP displacement and a target displayed). Balance performance was assessed using CoP-based measures: MVM and BVE. To assess the complexity of CoP, FE and DFA were computed. ANOVAs showed that MVM and BVE increased when task difficulty increased. During biofeedback conditions, individuals showed higher MVM but lower BVE at the easiest level of task difficulty. Overall, higher FE and lower DFA values were observed when biofeedback was available. On the other hand, FE reduced and DFA increased as difficulty level increased, in the presence of biofeedback. However, when biofeedback was not available, the opposite trend in FE and DFA values was observed. Regardless of changes to task constraints and the variable investigated, balance performance was positively related to complexity in every condition. Data revealed how specificity of task constraints can result in an increase or decrease in complexity emerging in a neurobiological system during balance performance.

Keywords: postural control, nonlinear analyses, task constraints, biofeedback, center of pressure, movement variability.

4.2. Introduction.

In humans, conceptualized as complex adaptive systems (Riley, Shockley, and Van Orden, 2012), movement variability is omnipresent due to the distinct constraints that shape each individual's goal-directed behaviors (Davids et al., 2003). Movement variability has been studied as the natural variations that occur in motor performance across multiple repetitions of a task, reflecting changes in both space and time (Newell and Slifkin, 1998; Stergiou et al., 2006).

In dynamical system theory, these variations have a functional role to drive adaptive behaviors in movement systems, allowing the CNS to exploit the high dimensionality offered by the abundance of motor system DOF (Davids et al., 2003). Adaptive behavior refers to a form of learning characterized by gradual improvement in performance in response to altered conditions (Krakauer and Mazzoni, 2011). The relationship between variability and adaptive behavior will change depending on task constraints faced by each individual. Several studies have related movement variability to the capacity of the CNS to adapt behaviors to environmental changes (Davids et al., 2006; Davids et al., 2003; Renart and Machens, 2014; Riley and Turvey, 2002).

In order to observe motor behavior changes during adaptation, several studies have examined changes in the neuromuscular system analyzing postural control dynamics and their relationship with physiological complexity (Manor et al., 2010; Manor and Lipsitz, 2013). This is because during postural control, the CNS regulates the activities of many neuromuscular components acting together in a complementary manner (Manor et al., 2010; Riley and Turvey, 2002).

Previous analyses of the relationship between postural control and variability in movement coordination have examined two different global dimensions: the amount of observed variability and the structural dynamics of variability, addressed by analyzing its complexity (Stergiou et al., 2006).

Complexity has been defined as the number of system components and coupling interactions among them (Newell and Vaillancourt, 2001). Some researchers have indicated that complexity in different physiological processes can be observed through nonrandom fluctuations on multiple time scales in physiological dynamics (Costa et al., 2002; Lipsitz and Goldberger, 1992; Manor et al., 2010). This second dimension provides additional information about properties of the dynamics of observed variability on multiples scales, which reveals important information on strategies used by the CNS during task performance (Caballero et al., 2014).

The complexity of CoP has been a prominent measure used for assessing the relationship between the complexity shown in a biological signal, and a neurobiological system's capacity to adapt to perturbations in motor tasks like postural control and balance (Decker et al., 2010; Goldberger, Peng, et al., 2002; Menayo, Encarnación, Gea and Marcos, 2014). This methodological prominence has emerged because it has been considered a collective variable, responsible for capturing postural organization and balance in individuals (Riley and Turvey, 2002).

Data on balance performance have suggested that complexity in a biological signal may be related to the CNS's capacity to re-organize DOF to adapt to perturbations (Barbado et al., 2012; Goldberger, Peng, et al., 2002). Adaptive movement responses have also been considered to exemplify functional exploratory behaviors, which reveal useful sources of information to perform and learn new skills (Stergiou et al., 2006). In this regard, less complexity in CoP dynamics has been associated with less capacity to adapt (Barbado et al., 2012; Manor et al., 2010). Moreover, in some cases, the loss of complexity in CoP dynamics has been related to disorders in the CNS (Cattaneo et al., 2015; Schmit et al., 2006).

However, the direction of this relationship remains somewhat unclear. Other studies of performance in balance tasks have reported data which do not support the aforementioned relationship, reporting greater complexity in fluctuations of CoP associated with worse task performance (Duarte and

Sternad, 2008; Vaillancourt and Newell, 2002). For example, in Duarte and Sternad's (2008) study comparing young and elderly people, they found a higher degree of complexity in older people over an extended time (30 min) during performance in a standing balance task. This finding indicates that high levels of complexity could reflect a decreased adaptive capacity of CNS over longer time scales. Vaillancourt and Newell (2002, 2003) suggested that increases or decreases in the complexity of CNS behaviors can be functional, but may be dependent on the nature of both the intrinsic dynamics of the system and the task constraints that need to be satisfied. Due to specific performance constraints encountered, there may be a reduction in the number of configurations available to a dynamical system through a re-structuring of the state space of all possible configurations available (Davids et al., 2003; Newell and Vaillancourt, 2001). Here, we sought to understand the extent to which specific interacting constraints of performance might lead to an increase or decrease of emergent complexity in a movement system, during task performance.

Another important question concerns whether the 'controversy' surrounding the relationship between observed movement variability and the capacity to adapt to unexpected perturbations may actually be due to the specific experimental procedures of analysis selected to address complexity (Goldberger, Peng, et al., 2002; Stergiou et al., 2006). For instance, it has been suggested that entropy measures which analyze the regularity of a signal do not measure the complexity of system dynamics (Goldberger, Peng, et al., 2002). These studies did not consider whether signal regularity was clearly related to the complexity of system dynamics. Instead, it may be more appropriate to use fractal measures or long-range auto-correlation analysis, such as DFA, to investigate complexity in complex adaptive systems. Regardless, several studies have shown the utility of entropy measures in interpreting the randomness in experimental data from physiological systems in relation to postural control (Barbado et al., 2012; S. F. Donker et al., 2007; Menayo et al., 2014), heart rate (Lake et al., 2002; Wilkins et al., 2009), neuromotor control of movements early in life (B. A. Smith, Teulier, Sansom, Stergiou, and Ulrich, 2011), mental fatigue (Liu, Zhang, and Zheng, 2010), intracranial pressure (Hornero, Aboy, Abásolo, McNames, and Goldstein, 2005) or local muscle fatigue (Xie, Guo, and Zheng, 2010).

Up to now, the literature seems to support the view that motor variability is related to adaptive capacity, but the direction of the relationship seems to be unclear, possibly for different reasons, including: 1) the role that specific task constraints may play in shaping emergent behaviors; and 2), the difficulty in choosing the most appropriate tool to measure and address complexity in motor behavior. Addressing possible reasons for this methodological controversy behind the relationship between movement variability and adaptive capacity, we sought to understand whether manipulation of task constraints would result in a modification of participant performance strategies, due to the emergence of novel exploratory behaviors captured by the re-organization of motor system DOF to adapt to challenging performance situations. In this regard, we analyzed emergent movement adaptations under varying task constraints. We also used different nonlinear tools to measure the complexity of observed system variability. We hypothesized that increases or decreases in the complexity of a behavior depends on the nature of the task constraints to be satisfied. In particular, we expected that increasing difficulty and availability of biofeedback would lead to a reduction in the number of configurations available in the motor system, causing a loss of complexity and performance decrements.

4.3. Methods.

4.3.1. Participants.

Fifty-two healthy volunteers (13 women) took part in this study (age = 25.5 ± 6.01 years, height = 1.70 ± 0.25 m, mass = 70.66 ± 10.33 kg).They had no previous experience in the balance task used in this study.

Written informed consent was obtained from each participant prior to testing. The experimental procedures used in this study were in accordance with the Declaration of Helsinki and were approved by a University Office for Research Ethics.

4.3.2. Experimental Procedure and Data Collection.

To assess CoP fluctuation, ground reaction forces were recorded at 1000 Hz on a Kistler 9287BA force platform.

The task required the participants to stand on a wooden platform (0.50 m x 0.50 m) and perform eight trials of 70 s each, with 1 min rest periods between trials. Standing stability and availability of visual biofeedback were manipulated. The decision to manipulate these two different task constraints was taken because both are heavily used in the literature to analyze and train postural control. In particular, the use of biofeedback was chosen to control "error sensitivity". According to Herzfeld and Shadmehr (2014, pp. 149) "when we make a movement and experience an error, on the next attempt our brain updates motor commands to compensate for some fraction of the error", and this error sensitivity term varies substantially from individual to individual and from task to task. Thus, error sensitivity remains constant for all participants. Two of the eight trials were performed on a solid floor (stable condition or SC). The other six were performed on an unstable platform (unstable condition or UC). All trials were performed under four different levels of difficulty, defined by the stability of the base of support. To achieve this aim, a wooden platform (0.02 m thick) was affixed to the flat surface of three polyester resin hemispheres with the same height (0.1 m) and different diameters: UC1 = 0.50 m of diameter; UC2 = 0.40 m of diameter and UC3 = 0.30 m of diameter (Figure 7). Each condition was experienced under two different visual biofeedback conditions: A) without visual biofeedback, where the representation of CoP displacement was not displayed. Here, the instruction to participants was to stay "as still as possible" (Duarte and Sternad, 2008); and B) with visual biofeedback, where CoP displacement, beside a static center target (0.003 m of diameter on the base of support and 0.05 m projected on the wall in front of the participant; scale displays: 16.6 to 1), was displayed in real-time. Participants were instructed to keep their CoP on the target (Figure 7).

4.3.3. Data Analysis and Reduction.

An application under Labview 2009 (Mathworks, Natick MA, USA), developed in our laboratory, was used to perform the data analysis. CoP time series were previously down sampled from 1000 Hz to 20 Hz due to: 1) there being little of physiological significance above 10 Hz in the CoP signal (Borg and Laxåback, 2010), and suggestions to use sampling frequencies close to CoP dynamics (Caballero et al., 2013); 2) signal oversampling possibly leading to artificial co-linearities, affecting the variability data (Rhea et al., 2011). The first and last 5 s of each trial were discarded to avoid non-stationarity related to trial initiation (van Dieën et al., 2010). Time series length was 1200 data points. It has to be taking in account that one time series were shorter than 1200 data points (590 data points) due to the fact that two participants were unbalanced before 70 s. We computed the time series data before these failures. That result were included in the analysis because it did not show outlier values in any of the assessed variables. Two filtering processes were used to analyze different postural control behaviors that are related to two different components of CoP displacement: *rambling* and *trembling* (Zatsiorsky and Duarte, 1999). The first is defined as the motion of a moving reference point with respect to which the body´s equilibrium is instantly maintained and characterized by large amplitudes at low frequencies. This component could be related to central control (Tahayori, Riley, Mahmoudian, Koceja, and Hong, 2012). Thus, we used a low-pass filter (4th order, zero-phase-lag, Butterworth, 5 Hz cut-off frequency) (Lin et al., 2008) to assess it. The *trembling* component is defined as the oscillation of CoP around a reference point trajectory, being characterized by short amplitudes at high frequencies (Zatsiorsky and Duarte, 1999). This component could be related to peripheral control (Tahayori et al., 2012). Hence, we used a high-pass filter (4th order, zero-phase-lag, Butterworth, 10 Hz cut-off frequency), similar to that used by Manor et al. (2010).

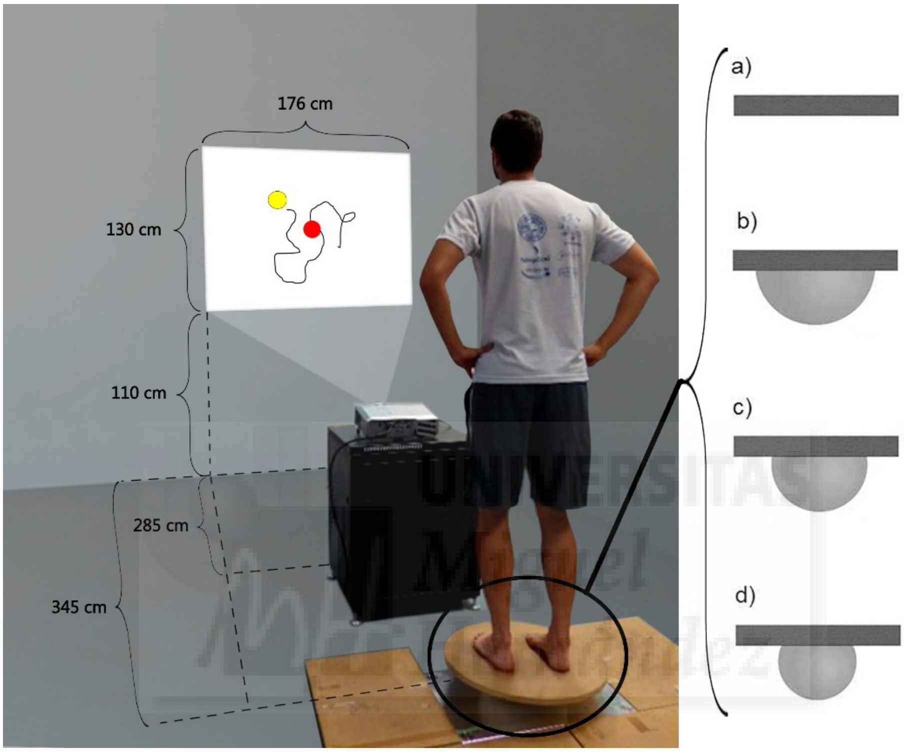


Figure 7. Schematic illustration of the protocol distribution and the different surfaces used: a) stable platform; b) UC1: unstable platform with 50 cm of diameter; c) UC2: unstable platform with 40 cm of diameter; d) UC3: unstable platform with 30 cm of diameter.

Postural sway was assessed using traditional bivariate CoP-based measures combining the AP and ML displacement trajectories: BVE and MVM. These variables were used to assess task performance and were calculated over the signal, filtered using a low-pass filter. We used just the filtered signal using a low-pass filter because static balance is characterized by small amounts of postural sway which is analyzed at low frequencies.

BVE was measured as the average value of the absolute distance to each participant's own midpoint (Equation 1) (Hancock et al., 1995; Prieto et al., 1996)

$$BVE = \frac{1}{N}\sum_{i=1}^{N}\sqrt{((X_i - \bar{X})^2 + (Y_i - \bar{Y})^2)} \tag{1}$$

where *N* is the number of data points in the CoP displacement time series and *i* is each successive data point.

MVM was measured as the average velocity of CoP (Equation 2) (Prieto et al. 1996)

$$MVM = \frac{1}{T}\sum_{i=1}^{N-1}\sqrt{\left(\left((X_{i+1} - X_i)\right)^2 + \left((Y_{i+1} - Y_i)\right)^2\right)} \tag{2}$$

where *T* is the trial duration (60 s).

The variables used to assess the complexity of CoP were FE and DFA. These variables were calculated after both were filtered and processed (low-pass and high-pass filters). The variables were calculated over the RD CoP time series (Figure 8), instead of the AP and ML time series, due to the fact that the orientation of the base-of support is only approximately aligned with the axes of the force platform, especially in unstable situations (Prieto et al., 1996). Thus, measures based on the AP time series probably reflect some ML movements of the participant, and vice versa, while the RD vector is not sensitive to theorientation of the base of support with respect to the force platform (Prieto et al., 1996; Roerdink et al., 2011). RD is the vector distance from the center of the posturogram to each pair of points in the AP and ML time series (Equation 3).

$$RD\ time\ series_{i=1} = \sum_{i=1}^{N} \sqrt{((X_i - \bar{X})^2 + (Y_i - \bar{Y})^2)} \tag{3}$$

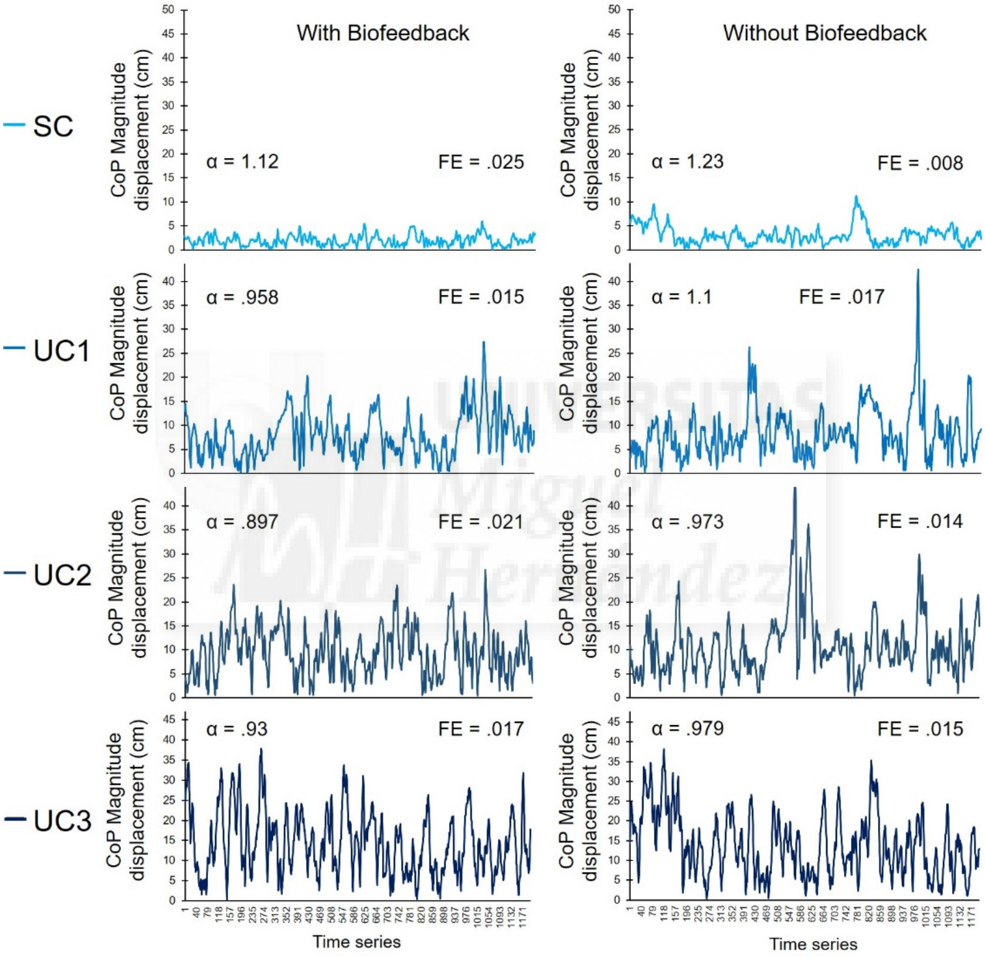


Figure 8. An example of the CoP resultant magnitude time series over 60 s for a participant. SC = stable condition; UC1: unstable platform with 50 cm of diameter; UC2: unstable platform with 40 cm of diameter; UC3: unstable platform with 30 cm of diameter; *α* = auto-correlation values obtained by DFA.

FE typically returns values that indicate the degree of irregularity in the signal. This measure computes the repeatability of vectors of length m and *m + 1* that repeat within a tolerance range of *r* of the standard deviation of the time-series. Higher values of FE thus represent lower repeatability of vectors of length m to that of *m + 1*, marking a greater irregularity in the time domain of the signal. Lower values represent a greater repeatability of vectors of length *m + 1*, and are, thus, a marker of lower irregularity in signal output. To calculate this measure we used the following parameter values: vector length, *m* = 2; tolerance window, *r* = 0.2*SD; and gradient, *n*=2. In previous research these parameter values have shown high levels of consistency, which underlies their frequent use (W. Chen et al., 2007). FE was calculated according to the procedures of W. Chen et al. (2007). We also conducted analyses of other related complexity measures, such as SE[1]. However, we chose FE because it displays some advantages, such as a stronger relative consistency, less dependency on data length, free parameter selection and more robustness to noise (W. Chen et al., 2009; Xie et al., 2010).

DFA represents a modification of classic root mean square analysis with random walk to evaluate the presence of long-term correlations within a time series using a parameter referred to as the scaling index α (Bashan et al., 2008; Peng et al. 1995). The scaling index α corresponds to a statistical dependence between fluctuations at one time scale and those over multiple time scales (Decker et al., 2010). This procedure estimates the fractal scaling properties of a time series (Duarte and Sternad, 2008) and has also been used to describe the complexity of a process (Goldberger, Amaral, et al., 2002). This measure was computed according to the procedures of Peng et al. (1995). In this study, the slope α was obtained from the window range $4 \leq n \leq N/10$ to maximize the long-range correlations and reduce errors incurred

[1] Sample Entropy was also calculated as another entropy measure to assess the degree of irregularity of CoP values. To calculate this measure we used the following parameter values: vector length, m = 2; tolerance window, r = 0.2*SD (Pincus, 1991). The results were very similar to the FE results, both in the effect of the different constraints and the correlation between performance and complexity.

by estimating *α* (Z. Chen et al., 2002). Different values of *α* indicate the following: *α* > 0.5 implies persistence in position (the trajectory tends to remain in its current direction); *α* < 0.5 implies anti-persistence in position (the trajectory tends to return from where it came) (Roerdink et al., 2006).

4.3.4. Statistical Analysis.

Normality of the variables was evaluated using the Kolmogorov-Smirnov test with the Lilliefors correction. Mixed repeated measures ANOVA with two intra-individual factors, task difficulty level and biofeedback availability, was used to assess effects of both factors on performance outcome measures and complexity variables. Outcomes of the ANOVAs were considered to be statistical significant when there was a <5% chance of making a type I error ($p < 0.05$). Bonferroni adjustment for multiple comparisons was performed to ascertain differences between task performance under different constraints according to each intra-individual factor. Partial eta squared (η_p^2) was calculated as a measure of effect size and to provide a proportion of the overall variance that is attributable to the factor. Values of effect size ≥0.64 were considered strong, around 0.25 were considered moderate and ≤ 0.04 were considered small (Ferguson, 2009). Finally, Pearson product moment correlation coefficients were calculated to assess relationships between performance variables (BVE and VMM) and complexity measures (FE and DFA).

4.4. Results.

Mean values obtained under each balance condition and pairwise comparisons between difficulty conditions and biofeedback conditions are displayed in Table 8.

MVM showed higher values in biofeedback condition ($F_{1,51} = 74.88$; $p<.001$; $\eta_p^2 = .595$). In contrast, despite BVE not revealing overall differences between biofeedback availability conditions ($F_{1,51} = 2.64$; $p = .111$; $\eta_p^2 = .049$), at lower levels of difficulty, lower values of BVE were observed in the biofeedback condition (Figure 9). BVE differences observed between biofeedback conditions did decrease as task difficulty level increased, and even disappeared at the most difficult performance levels. Additionally, both performance variables displayed higher values when task difficulty increased, being significantly different between conditions (BVE: $F_{1.83,93.36} = 374.31$; $p < .001$; $\eta_p^2 = .880$; MVM: $F_{1.89,96.6} = 491.24$; $p < .001$; $\eta_p^2 = .906$) (Figure 9).

With regard to complexity variables, in the low-pass filtered signal, higher FE ($F_{1,51} = 77.66$; $p < .001$; $\eta_p^2 = .604$) and lower DFA values ($F_{1,51} = 65.39$; $p < .001$; $\eta_p^2 = .562$) were observed when biofeedback was available. However, differences in these dependent measures decreased as task difficult level were increased (Figure 10). Regarding the high-pass filtered signal, the presence of biofeedback did not display effects on any complexity variable (FE: $F_{1,51} = 3.949$; $p = .052$; $\eta_p^2 = .072$; DFA: $F_{1,51} = 1.744$; $p = .192$; $\eta_p^2 = .033$).

Complexity values at different task difficulty levels varied according to the filter used, the biofeedback condition and the variable recorded (Figure 10). When variables were calculated over the low-pass filtered signal, in the presence of biofeedback, FE values were significantly different between SC and UC3 and between UC3 and UC1, decreasing as difficulty increased. However, without biofeedback, FE increased with task difficulty, displaying significant differences in the value between SC and every UC condition. Regarding DFA in the conditions with biofeedback, significant differences were observed between UC1 and UC3 and between UC2 and UC3, reaching the highest values at the most difficult task level. Without biofeedback, DFA values decreased from SC to UC2 and UC3, and from UC1 to UC2, attaining the highest values at the least difficult task level.

On the other hand, when complexity variables were calculated with the high-pass filtered signal, FE decreased and DFA increased as task difficulty increased regardless of the availability of biofeedback. So, in most of the conditions, dependent variables showed significant differences between levels of task difficulty, but differences between biofeedback conditions were only found with low-pass filtered signals.

Table 8. Average values (mean ± SD) in each balance condition of every variable calculated in the study.

	SC	UC1	UC2	UC3
BVE	3.67 ± 1.29	10.76 ± 3.09	12.58 ± 3.48	16.6 ± 6.01
BVE_FB	2.54 ± .829	9.69 ± 1.83	12.02 ± 3.48	17.31 ± 3.77
MVM	6.23 ± 2.01	24.92 ± 7.38	31.71 ± 9.52	41.25 ± 12.79
MVM_FB	8.66 ± 2.98	30.09 ± 7.29	37.02 ± 9.26	48.39 ± 11.11
Low-pass filter				
FE	.356 ± .126	.456 ± .120	.496 ± .144	.503 ± .166
FE_FB	.555 ± .125	.580 ± .105	.564 ± .111	.530 ± .137
DFA	1.13 ± .116	1.07 ± .133	1.01 ± .131	1.04 ± .143
DFA_FB	.956 ± .115	.931 ± .107	.945 ± .102	.997 ± .120
High-pass filter				
FE	2.05±.104	1.95±.151	1.91±.176	1.76±.290
FE_FB	2.03±.094	1.94±.151	1.88±.165	1.73±.244
DFA	.565±.102	.666±.126	.695±.127	.744±.119
DFA_FB	.565±.100	.661±.124	.721±.124	.769±.117

Units of CoP measures are as follows: mm (BVE); mm/s (MVM). FB = with biofeedback; SC = Stable condition; UC1 = Unstable condition difficulty level 1; UC2 = Unstable condition difficulty level 2; UC3 = Unstable condition difficulty level 3.

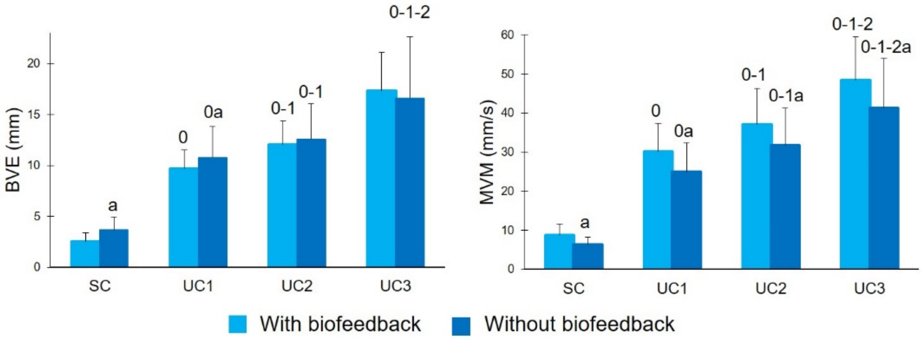


Figure 9. Pairwise Comparisons between difficulty levels and biofeedback conditions in performance variables. *a* = significant differences between biofeedback conditions; 0 = significant differences according to SC; 1 = significant differences according to UC1; 2 = significant differences according to UC2; 3 = significant differences according to UC3.

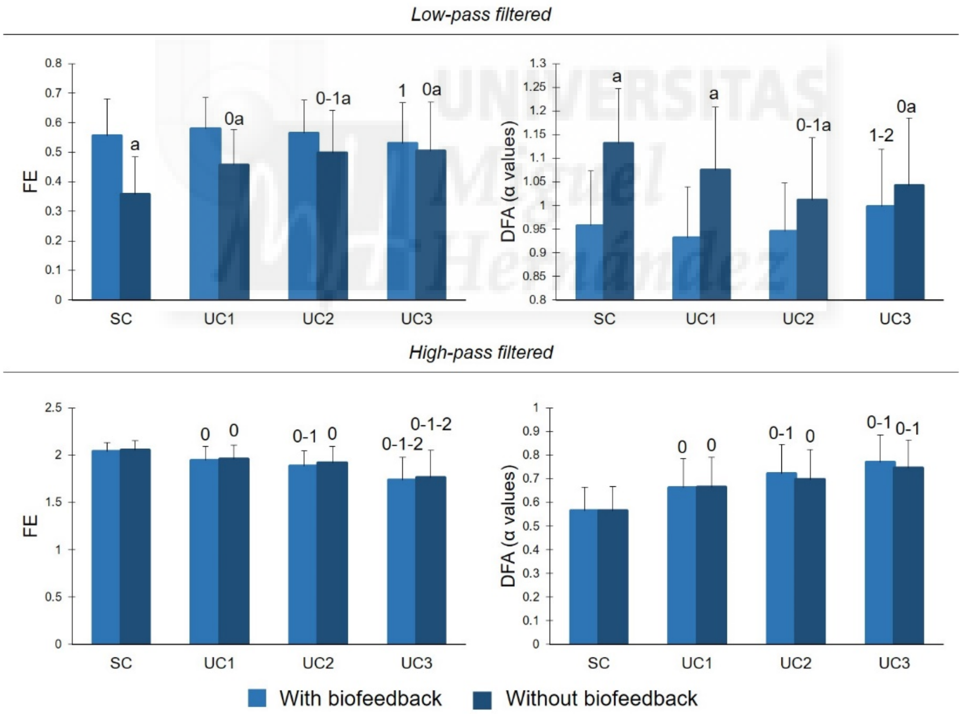


Figure 10. Pairwise Comparisons between difficulty levels and biofeedback conditions in complexity variables. *a* = significant differences between biofeedback conditions; 0 = significant differences according to SC; 1 = significant differences according to UC1; 2 = significant differences according to UC2; 3 = significant differences according to UC3.

Performance variables (BVE and MVM) were positively correlated, but showed an inverse correlation with complexity variables. Furthermore, the degree of dependence between them varied according to the filter used and biofeedback availability. When the low-pass filtered signal was used (Table 9), and in conditions without biofeedback, BVE was negatively correlated with FE and positively correlated with DFA. Nevertheless, in conditions with biofeedback, this correlation was only found at the highest task difficulty level. MVM showed positively correlation with FE and negatively correlation with DFA despite the availability of biofeedback. Additionally, FE and DFA variables displayed an inverse relationship in every condition.

When the high-pass filter was used (Table 10) BVE was negatively correlated with FE, only in the most difficult task condition regardless of the availability of biofeedback. A positive correlation between BVE and DFA was found when biofeedback was available, only at the lowest and highest task difficulty levels, but no correlation between them was found in conditions without biofeedback. With regard to MVM, this variable was negatively correlated with FE in all of the unstable conditions (with or without biofeedback). MVM was positively correlated with DFA only in the stable condition when the biofeedback was available. In the condition without biofeedback, this correlation was observed in UC1 and UC2.

Table 9. Pearson product moment correlation coefficient calculated between performance variables and complexity variables, using a *low-pass filter*, in each balance condition.

	With biofeedback			Without biofeedback		
SC						
	MVM	**FE**	**DFA**	**MVM**	**FE**	**DFA**
BVE	.834**	-.366**	.166	.392**	-.500**	.378**
MVM		.129*	-.161		.436**	-.337*
FE			-.631**			-.754**
UC1						
	MVM	**FE**	**DFA**	**MVM**	**FE**	**DFA**
BVE	.613**	-.143	-.092	.333*	-.361*	.319*
MVM		.598**	-.421**		.662**	-.570**
FE			-.577**			-.830**
UC2						
	MVM	**FE**	**DFA**	**MVM**	**FE**	**DFA**
BVE	.615**	-.263	.084	.336*	-.430**	.344*
MVM		.522**	-.315*		.605**	-.384**
FE			-.521**			-.623**
UC3						
	MVM	**FE**	**DFA**	**MVM**	**FE**	**DFA**
BVE	.425**	-.485**	.471**	.571**	-.432**	.466**
MVM		.477**	-.319*		.416**	-.211
FE			-.800**			-.736**

SC = Stable condition; UC1 = Unstable condition difficulty level 1; UC2 = Unstable condition difficulty level 2; UC3 = Unstable condition difficulty level 3.
** Correlation is significant at the 0.05 level (2-tailed).
* Correlation is significant at the 0.01 level (2-tailed).

Table 10. Pearson product moment correlation coefficients calculated between performance variables and complexity variables, using a *high-pass filter*, in each balance condition.

	With biofeedback			Without biofeedback		
			SC			
	MVM	**FE**	**DFA**	**MVM**	**FE**	**DFA**
BVE	.834**	-.176	.208*	.392**	.060	-.034
MVM		-.264	.328*		-.017	-.009
FE			-.513**			-.291*
			UC1			
	MVM	**FE**	**DFA**	**MVM**	**FE**	**DFA**
BVE	.613**	.042	-.039	.333*	-.111	.183
MVM		-.305*	.204		-.552**	.326*
FE			-.639**			-.681**
			UC2			
	MVM	**FE**	**DFA**	**MVM**	**FE**	**DFA**
BVE	.615**	-.138	.027	.336*	.075	-.006
MVM		-.474**	.101		-.389**	.288*
FE			-.476**			-.747**
			UC3			
	MVM	**FE**	**DFA**	**MVM**	**FE**	**DFA**
BVE	.425**	-.369**	.396**	.571**	-.382**	.071
MVM		-.438**	.164		-.528**	-.015
FE			-.594*			-.281*

SC = Stable condition; UC1 = Unstable condition difficulty level 1; UC2 = Unstable condition difficulty level 2; UC3 = Unstable condition difficulty level 3.
∗∗ Correlation is significant at the 0.05 level (2-tailed).
∗ Correlation is significant at the 0.01 level (2-tailed).

4.5. Discussion.

Recently it has been argued that an increase or decrease in the complexity of a behavioral or physiological system depends on interactions between system intrinsic dynamics and performance task constraints (Vaillancourt and Newell, 2002, 2003). In this experiment we investigated the complexity of movement system variability during performance of different balance tasks, observing that participants modified their postural control dynamics according to task difficulty and availability of biofeedback. In addition, regardless of these changes to task constraints, performance was positively related to complexity.

Performance decreased when balance task difficulty was increased as reported in previous research (Barbado et al., 2012; Borg and Laxåback, 2010). Values in performance measures, both in BVE and MVM, increased as task difficulty level increased (Figure 9). However, availability of biofeedback had different effects on BVE and MVM values. With biofeedback, BVE values decreased significantly, but only at lower task difficulty levels. However, as difficulty level was increased, biofeedback availability did not influence the amount of variability observed in CoP measures. In stable or less challenging unstable task conditions, different locations of the CoP on the surface of support allowed a participant to maintain stability (Caballero et al., 2014). However, increasing task difficulty limited the region of stability, signifying that in the difficult balancing conditions, there were a limited number of CoP locations where system stability could be maintained (Lee and Granata, 2008). Under more stable balancing conditions visual biofeedback was used to maintain CoP location on the target. Under more challenging postural control conditions, visual biofeedback information might have been redundant, because participants did not have many CoP locations where they could maintain system stability. They only had possible outcome solution: the same as displayed by the available biofeedback signal. From a dynamical systems viewpoint, differences between biofeedback conditions could be interpreted as the existence of different types of attractors in a performance landscape. It seems that participants used a behavior similar to a fixed-point attractor when biofeedback was available, characterized by a fixed point in state space where no movement is observed (van Emmerik and van Wegen, 2000). Nevertheless, participants explored the oscillatory CoP dynamics (Vaillancourt and Newell, 2003) without biofeedback in the least challenging conditions. Availability of biofeedback seemed to change postural control strategies by decreasing the number of configurations available to a dynamical movement system (Davids et al., 2003). In this regard, available information seemed to constrain the system to one area of the attractor landscape in this task.

On the other hand, MVM values displayed an increase in biofeedback conditions compared to when biofeedback was not available. Although there are a greater number CoP locations where stability can be maintained, this increase in MVM could be due to the fact that under the less challenging task constraints, visual biofeedback drives the system to one specific location. Without biofeedback, participants focused on avoiding falling. In the conditions with biofeedback they tried to adjust their CoP to the target, performing a greater number of adjustments. The increased values of MVM in biofeedback situations can also be related to an increased error sensitivity of the individuals regulated by the CNS (Herzfeld and Shadmehr, 2014). In this sense, MVM could be an index of the amount of corrections needed to adjust the CoP location, increasing neuromuscular effort and resulting from participant exploratory behaviors. Higher CoP velocity would be an index of exploratory behaviors in discovering stable performance solutions under relatively novel task constraints (Davids, Kingsbury, George, O'Connell, and Stock, 1999).

According to previous studies, CoP analysis has revealed two different postural control mechanisms: *rambling* and *trembling* (Mochizuki, Duarte, Amadio, Zatsiorsky, and Latash, 2006; Tahayori et al., 2012). These two processes may reflect changes in the body reference configuration and changes in the properties of the mechanical and neural structures implementing the supraspinal control signals (Danna-Dos-Santos, Degani, Zatsiorsky, and Latash, 2008). Observed variability of low-pass filtered CoP, related to volitional control (*rambling* component), showed a higher degree of irregularity and less long-range auto-correlation when biofeedback was available. The changes in these variables, influenced by biofeedback, might indicate that the existence or not of this task constraint drives the system to different kinds of behaviors. The system would transit to a state space, displaying lower values of complexity without biofeedback (similar to oscillatory dynamic), and a behavior related to a fixed-point attractor in conditions with feedback, revealing more complexity in CoP behaviors (van Emmerik and van Wegen, 2000). Taking into account the effect of difficulty level, when biofeedback was available, the degree of irregularity of low-pass filtered CoP decreased as task difficulty increased, whereas the long-range auto-correlation values increased. However, under task constraints when biofeedback was not available, the trend for FE and DFA values was inverted. Moreover, as task difficulty levels increased, clearly the difference between biofeedback conditions was reduced. This finding reflects again the redundancy of biofeedback in these more challenging conditions, where CoP locations compatible with maintaining system stability are reduced. Unlike the findings of Manor et al. (2010) which support the role of complexity of fluctuations related to peripheral adjustments in postural control when standing, our results seem to indicate that complexity is more related to volitional changes in CoP dynamics, reflecting a search strategy in participants to cope with task constraints which do not necessarily require an involvement of a greater number of DOF. According to Danna-Dos-Santos et al. (2008), this search strategy could be reflected by the *rambling* component. These findings are supported by Newell and Vaillancourt (2001) who suggested that the increase or the decrease of complexity can be independent of the number of component mechanical DOF being harnessed as a system, but the direction of the changes in complexity is driven by task constraints.

These contrasting results could have emerged for different reasons. First, it is possible that the balance task constraints used in both studies were different. Thus, the type of control requirements for keeping balance could have differed. Another reason could be due the populations studied. Manor et al., (2010) studied CoP complexity in people with risk factors for falls for whom peripheral control could be a key factor in avoiding falls, whilst the participants of our study were healthy people with little risk of falling. Nevertheless, it is difficult to compare the results of the two studies because Manor et al. (2010) did not analyze low-pass CoP signals. In future studies, it would be interesting to assess both kind of components of CoP displacement and changes in CoP complexity in relation to distinct task constraints and with different populations.

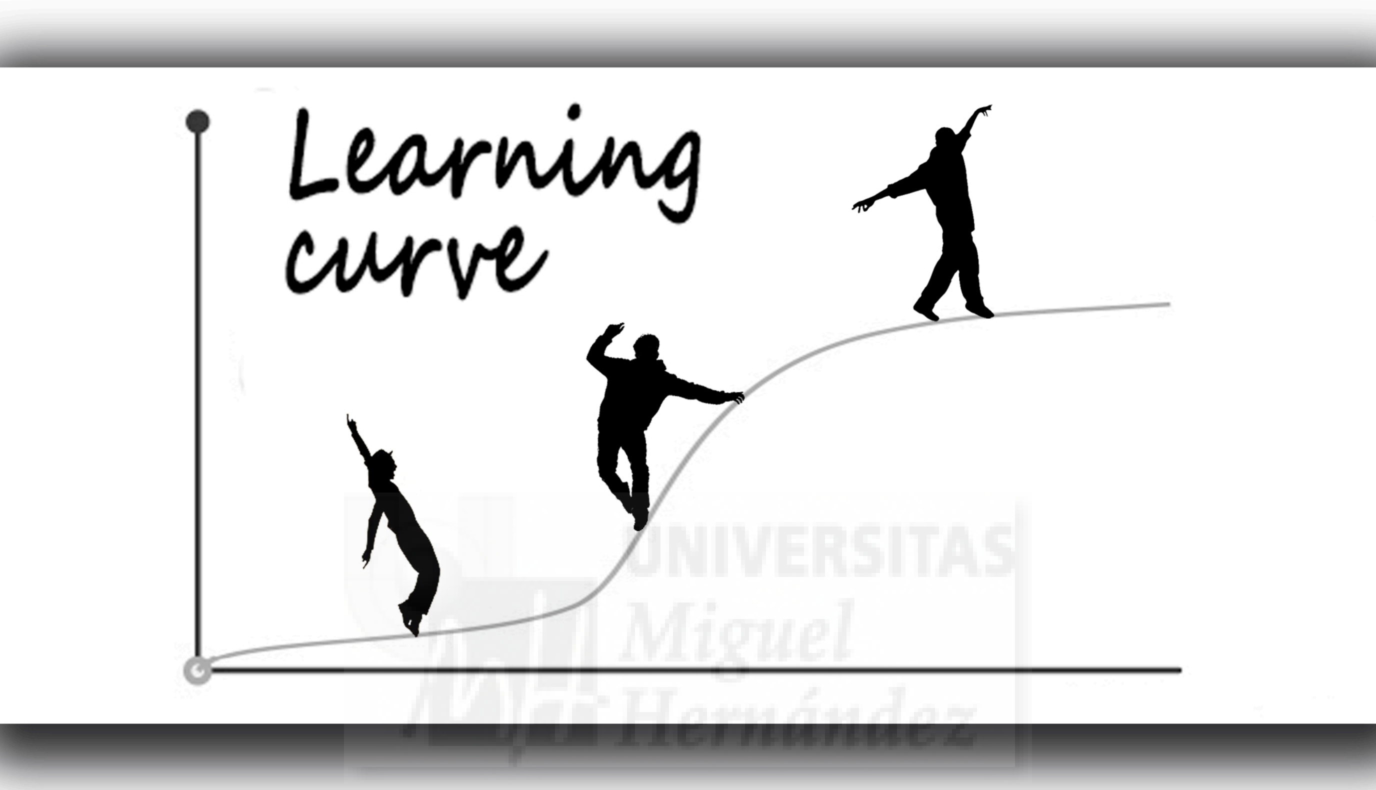
Regarding the high-pass filtered CoP signal, the availability of biofeedback did not affect system complexity, but task difficulty did, showing a decrease of irregularity and an increase in long-range auto-correlation as task difficulty increased. Taking into account that this filter procedure could reflect peripheral postural control (*trembling* component), this lack of effect of the biofeedback condition could be due to the fact that the fluctuations of the *trembling* component represent an involuntary adjustment of CoP (Danna-Dos-Santos et al., 2008; Tahayori et al., 2012). On the other hand, the fact that the most difficult conditions revealed less irregularity and greater long-range auto-correlation of the CoP signal could indicate that, in these situations, individuals reduced the number of involuntary adjustments due to the difficulty in correcting CoP displacement because of the increase in inertia.

Regarding correlational analysis, a direct relationship between BVE and complexity was found in both low-pass and (to lesser extent) high-pass filtered CoP signals. These results seem to indicate that participants who showed lower balance performance exhibit a lower number of postural adjustments. Conversely, MVM was directly related to complexity in the low-pass filtered CoP signal and, inversely, to complexity in the high-pass filtered CoP signal. This finding could mean that individuals who displayed low CoP velocities showed a higher number of peripheral postural adjustments and a low number of volitional corrections. Additionally, when participants showed higher CoP velocities, it could mean that the peripheral system could not control stability and more volitional postural corrections were needed to maintain balance.

The fact that the relationships between balance performance variables and complexity were stronger in the low-pass filtered CoP, revealed the prevalence of volitional adjustments in postural control to maintain balance. Peripheral adjustments played a less relevant role in the postural control strategy during the balance tasks analyzed in this study.

Our results indicated that a specific relationship that emerges between system complexity and performance is dependent on task constraints (Newell and Vaillancourt, 2001; Vaillancourt and Newell, 2002, 2003; Vaillancourt, Sosnoff, and Newell, 2004). It seems that each performance variable varied according to different task constraints encountered by participants, revealing different trends. These findings signified that when researchers wish to assess the relationship between an individual's capacity to adapt and system complexity when learning or under different performance constraints, contradictory results may be observed due to the influence of distinct task constraints designed into experiments. Furthermore, this is a very important point to take into account when the system complexity is related to system constraints of ageing, illness or damage.

To conclude, in this study we provided some support for the idea that specific task constraints can lead to an increase or decrease in complexity emerging in a neurobiological system during performance. Informational constraints, such as availability of biofeedback and level of task difficulty, shaped emergent strategies of movement coordination, due to participants searching for different attractors to functionally regulate their behaviors.



5. Study III

SUBMITTED AS:

Barbado, D., Caballero, C., Moreside, J.M., Vera-García, F.J., Moreno, F.J. Can the Structure of Motor Variability Predict Learning Rate?

CAN THE STRUCTURE OF MOTOR VARIABILITY PREDICT LEARNING RATE?

David Barbado, Carla Caballero, Janice M. Moreside, Francisco J. Vera-Garcia and Francisco J. Moreno

5.1 Abstract.

Recent studies show that motor variability is actively regulated as an exploration tool to promote learning in reward-based tasks. However, its role in learning processes during error-based tasks, when a reduction of the motor variability is required to achieve good performance, is still unclear. In this study, we hypothesized that error-based learning not only depends on exploration but also on the individuals' ability to measure and predict the motor error. Previous studies identified a less auto-correlated motor variability as a higher ability to perform motion adjustments (Amoud et al., 2007; Wang and Yang, 2012). Two experiments investigated the relationship between motor learning and variability, analyzing the long-range auto-correlation of the CoP fluctuations through the *α* score of a DFA in balance tasks. In experiment 1, we assessed the relationship between variability and learning rate using a standing balance task. Based on the results of this experiment, and to maximize learning, we performed a second experiment with a more difficult sitting balance task and increased practice. The learning rate of the two groups with similar balance performances but different *α* scores was compared. Individuals with a lower *α* score showed a higher learning rate. Because the *α* scores reveal how the motor output changes over time, instead of the magnitude of those changes, the higher learning rate is mainly linked to the higher error sensitivity rather than the exploration strategies. The results of this study highlight the relevance of the structure of output motor variability as a predictor of learning rate in error-based tasks.

Keywords: variability, learning rate, balance.

5.2. Introduction.

Motor variability is described as the “noise” caused by stochastic neuromuscular function that must be minimized to increase task performance (Churchland, Afshar, and Shenoy, 2006; Harris and Wolpert, 1998; Osborne, Lisberger, and Bialek, 2005; Schmidt et al., 1979; Shmuelof, Krakauer, and Mazzoni, 2012). While learning any motor skill, the magnitude of motor variability progressively decreases as movement execution improves (Caballero et al., 2014; Stein et al., 2005). However, others approaches indicate that variability plays a functional role, allowing individuals to generate more adaptive responses to stressors (Goldberger, 1996; Goldberger, Peng, et al., 2002). Motor variability reflects the motor system’s ability to explore different motor configurations, looking for an optimal solution facilitating adaptive (Barbado et al., 2012; Manor et al., 2010; Zhou et al., 2013) and/or learning processes (Tumer and Brainard, 2007; Wu et al., 2014). However, although some studies have found that high motor variability predicted faster reward-based learning of different reaching tasks (Pekny, Izawa, and Shadmehr, 2015; Wu et al., 2014), there is limited evidence about motor variability playing a similar role during error-based learning (Wu et al., 2014).

Functional perspectives of motor variability are not in opposition to the traditional view. Variability seems to be a multidimensional feature of the motor system (Stergiou and Decker, 2011). Previous findings include the need for high-variability when exploration is required to learn a novel task, but low-variability improves accuracy, exploiting a viable solution (Woolley and Doupe, 2008; Wu et al., 2014). Nevertheless, when motor variability during a novel task is analyzed, it is difficult to estimate the extent to which motor variability is a consequence of stochastic neuromuscular noise, which must be reduced to improve motor performance, or whether it is being actively regulated to promote learning. Novices usually show higher motor variability but exhibit a higher learning-rate than experts. Therefore, how can we measure motor variability to reveal the system functional properties during learning when a low magnitude of variability is required to perform the task properly?

Some mathematical tools allow for the discrimination between both concepts of variability. Scattering variables have been used to describe the magnitude of the variability (Stergiou and Decker, 2011), suggesting that the mean is the ultimate performance goal and diversion from the mean is the error. Nonlinear mathematical tools have been used to analyze the temporal organization of variability. For example, the analysis of long-range auto-correlation (Amoud et al., 2007; Peng et al., 1995) and the regularity (Barbado et al., 2012; Rhea et al., 2011) of the time series were used to assess the extent to which further motor behavior is dependent on previous fluctuations. Less dependence on previous behavior (lower long-range auto-correlation or regularity) was interpreted as a higher flexibility to perform motion adjustments (Amoud et al., 2007; Wang and Yang, 2012). Studies on balance tasks in older (Manor et al., 2010; Zhou et al., 2013) and young individuals (Barbado et al., 2012) revealed that individuals who showed lower long-range auto-correlation and less regularity of CoP fluctuations while standing on a stable surface demonstrated better performance with more difficult balance tasks. Therefore, an important question is how the structure of motor variability, demonstrated during the early stages, relates to learning rate during an error-based task and what it means.

To answer these questions, two experimental setups were carried out to analyze the relationship between motor variability and learning rate in balance tasks where the performance criterion was the reduction in the amount of variability. In experiment 1, the learning rate in a standing balance task was assessed within-session. Based on the results of experiment 1 and its limitations, a second experiment was performed using a less common and more difficult sitting balance task with longer trial times and an increased practice period. In both experiments, the learning rate was compared between the two groups and showed similar balance performance (magnitude of variability) but a different long-range auto-correlation of the postural sway fluctuations (structure of variability).

5.3. Experiment 1: Standing protocol.

5.3.1 Method.

5.3.1.1. Participants.

Thirty volunteers took part in experiment 1 (age = 24.2 ± 4.6 years; height = 1.72 ± 0.09 m; mass = 69.0 ± 10.7 kg), 11 women (age = 23.4 ± 3.4 years; height = 1.64 ± 0.06 m; mass = 59.5 ± 5.0 kg) and 19 men (age = 24.6 ± 5.2 years; height = 1.77 ± 0.07 m; mass = 74.5 ± 9.2 kg).

All of the participants were healthy and without current knee or ankle injury or past pathology in these regions. All of the subjects participants reported having no neurological or musculoskeletal problems. No participant had previous experience in the balance task used in this study. Written informed consent was obtained from each participant prior to testing. The experimental procedures used in this study were in accordance with the Declaration of Helsinki and were approved by the University Office for Research Ethics.

5.3.1.2. Experimental Procedure and Data Collection.

The participants were asked to “stand as still as possible” (Cavanaugh et al., 2007; Duarte and Sternad, 2008) on a BOSU® balance trainer (BOSU®, Ashland, OH, USA) (diameter: 65 cm; height: 23 cm) with their feet placed 30 cm apart and their hands resting on their hips (Figure 11). The BOSU pressure was constant between the participants (0.3 bar) and was checked before and after each participant’s testing. To assess postural stability, this study used a force plate (Kistler, Switzerland, Mode 9287BA). The feet were positioned such that the line between their heels coincided with the medial-lateral axis of the platform. Trials were performed barefoot in front of a clear white wall with no visual reference. Although a safety rail was placed in front of the participant providing a secure bar to grasp if participants perceived they were unable to control their balance, all participants were able to maintain the standing posture, without grasping a support rail or stepping in any direction during the trials. The ground reaction forces were recorded at 1000 sample/s and were calibrated at the beginning of each participant's collection. The participants performed a 30 s pre-test trial. After that, to analyze the effect of practice, the participants had 10 practice trials on a single day. Each practice trial lasted 15 s, with a 45 s rest period between trials. Then, they performed a 30 s post-test under the same conditions as the pre-test. Each data collection began when participants were relatively stable.

5.3.1.3. Data Analysis and Reduction.

A custom software program in Labview 2009 (National Instruments, Texas, USA) was used for data analysis. There is little physiological significance to the CoP signal frequencies above 10 Hz (Borg and Laxåback, 2010), and thus, the CoP time series were subsampled at 20 Hz. This also removed the artificial co-linearities that could affect the variability analysis (Barahona and Poon, 1996; Rhea et al., 2011). The first and the last 5 s of each trial were discarded to avoid non-stationarity related to the beginning and end of the trial (van Dieen et al., 2010). Finally, a low-pass filter (4^{th}-order, zero-phase-lag, Butterworth, 5 Hz cut-off frequency) was performed, according to Lin et al. (2008).

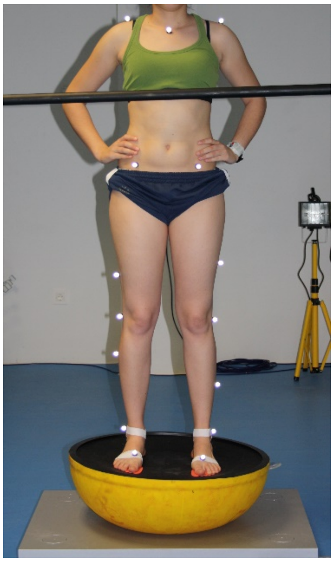


Figure 11. Participant performing a standing stability task on a BOSU surface.

Because the orientation of the participant was only approximately aligned with the axes of the force platform, the resultant distance (RD) was used as a global measure to quantify the performance during the balance trials (Prieto et al., 1996). RD was calculated as the average of the vector distance magnitude (mm) of the CoP from the participant's own mean CoP position. The absolute learning rate (ALR) and relative learning rate (RLR) were calculated as follows: the ALR was the RD differences between the pre-test (RD_{PRE}) and post-test (RD_{POST}), while the RLR was calculated relative to the initial performance of each individual [$100*(RD_{PRE} - RD_{POST}) / RD_{PRE}$].

To assess the structure of the variability we used DFA. DFA is a method based on the random walk theory, representing a modification of a classic root mean square analysis of the random walk, which evaluates the presence of long-term correlations within the time series by a parameter referred to as the scaling index α (Peng et al., 1994; Peng et al., 1995; Roerdink et al., 2006). Different values of α indicate the following: $\alpha > 0.5$ implies persistence (i.e., the trajectory tends to continue in its current direction); $\alpha < 0.5$ implies anti-persistence (i.e., the trajectory tends to return to where it came from);

and α = 0.5 implies uncorrelated signal (Roerdink et al., 2006). Therefore, α identifies the extent to which further data are dependent on the previous (Jordan and Newell, 2008). Typically, CoP displacement exhibits α values ranging from 0.5 to 1.5. α CoP data have been used to assess human adaptability to postural or motion adjustments (Amoud et al., 2007; Wang and Yang, 2012).

To maximize the long-range correlations and to reduce the estimation error of α, long-term correlation was characterized by the slope α obtained from the range of $4 \leq n \leq N/10$, where N is the data length (Z. Chen et al., 2002). The participants were only approximately aligned with the axes of the force platform, and the α of each participant was calculated as the average α obtained from both axes.

5.3.1.4. Statistical Analysis.

Normality of the variables was evaluated through the Kolmogorov-Smirnov test with Lilliefors correction. First, a Pearson's correlation was performed between RD_{PRE}, α_{PRE}, ALR and RLR to assess the initial performance and variability influence on learning rate (Table 10). Second, to avoid the initial performance bias on learning rate, participants were grouped using a linear regression method (Figure 12). Specifically, participants were classified into three groups, according to their RD_{PRE}. Then, we performed a linear regression between RD_{PRE} and α_{PRE} in each performance group. Finally, participants were grouped according their residual scores. The higher residual scores in each group were included in the "High auto-correlated variability" (HAV) group. The lower residual scores in each group were included in the "Low auto-correlated variability" (LAV) group (Figure 12). One-way ANOVA for independent measures was performed to assess the ALR and RLR differences between groups, with the initial structure of variability as an inter-subject factor (HAV and LAV groups) (Tables 2). A mixed-way ANOVA was performed with RD as a within-subject factor (PRE and POST) and with the initial structure of variability as an inter-subject factor (HAV and

LAV groups) (Figure 13). The partial eta squared (η_p^2) was calculated as a measure of effect size. The values of an effect size ≥ 0.64 were considered strong, between 0.64 and 0.25 were considered moderate, and ≤ 0.25 were considered small (Ferguson, 2009).

Finally, to check the results obtained with the linear regression method, we performed a Principal Component Analysis (PCA) (Table 13 and Figure 14) on the initial structure of the variability (α_{PRE}), the initial performance (RD_{PRE}) and the relative learning rate (RLR). This method reduces the dimensionality of interrelated measures (Jolliffe, 2002) and facilitates the interpretation of the results as it extracts features that are directly related to the original data set (Rocchi, Chiari, and Cappello, 2004).

5.3.2. Results.

Participants improved their performance, reducing their RD significantly after practice trials (RD_{PRE} = 14.5 ± 5.0 mm; RD_{POS} = 12.6 ± 3.1 mm; $F_{1,29}$ = 4.57; p = 0.041; η_p^2 = 0.136). As shown in table 11, the learning rate significantly correlated with the initial performance, while no significant correlations were found between the learning rate and the initial structure of variability. These results indicate that the learning rate is highly determined by the initial performance, while the initial structure of variability does not seem to influence it. That is, less skillful individuals have a higher room for improvement than more skillful ones. However, although no significant relationship was found between RD_{PRE} and α_{PRE}, it was close to being significant (r = 0.319; p = 0.086), suggesting that initial performance could bias the relationship between the variability and learning rate. That is, less skillful individuals who tend to show higher α_{PRE} values could show higher learning rates.

Table 11. Pearson's bivariate correlations among individuals' initial balance performance (RD_{PRE}), initial structure of variability (α_{PRE}) and learning rate in absolute (ARL) and relative (RLR) values.

	α_{PRE}	**ALR**	**RLR**
RD_{PRE}	0.319 (0.086)	0.799 (<0.001)	0.596 (<0.001)
α_{PRE}		0.053 (0.782)	-0.058 (0.760)

Pearson correlation coefficient (level of significance)
α_{PRE} = long-range auto-correlation index shown in the pretest; RD_{PRE} = resultant distance shown in the pretest.

To assess the relationship between the initial structure of the variability (α_{PRE}) and the learning rate (ALR, RLR), avoiding the bias of the initial performance (RD_{PRE}), participants were grouped using a linear regression method (Figure 12). The higher residual scores (black dots in Figure 12) in each performance level were included in the HAV group, while the lower residual scores (white dots) were included in the LAV group.

Table 12 shows the values of the two groups after the distribution of the participants. The groups were quite similar in the initial performance (RD_{PRE}: $F_{1,29} = 0.01$; $p = 0.938$: $\eta_p^2 = 0.001$) but different in the structure of the variability (α_{PRE}: $F_{1,29} = 24.61$; $p < 0.001$; $\eta_p^2 = 0.468$). After analyzing the effects of practice on the performance variables, no significant differences were found between the groups in the learning rate, but the LAV group showed higher RLR values compared to the HAV group, although the differences were only close to being significant (RLR: $F_{1,29} = 3.74$; $p = 0.063$; $\eta_p^2 = 0.118$).

Based on these results, we performed a PCA to examine the underlying relationships between the initial performance, the initial structure of the variability and the learning rate. The first principal component factor (PC_1) accounted for 55.14% of the total variance and showed that a higher RLR was mainly related to a higher RD_{PRE} (worse performance) and to a lesser extent to a higher α_{PRE}, supporting the notion that the learning rate is highly determined by the initial performance (Table 13). In addition, less skillful individuals showed a high auto-correlated CoP variability. PC_2, accounting for 34.94% of the total variance, showed that a higher RLR was related to a low α_{PRE} and was unrelated to RD_{PRE} (Table 13). Figure 14 shows the relationship between these variables, indicating that individuals with low PC_2 values showed a higher learning rate (R^2 = 0.229; p = 0.007), lower auto-correlated CoP variability (R^2 = 0.817; p < 0.001) and equivalent initial performances (R^2 = 0.002; p = 0.793) compared to individuals with high PC_2 values. Nevertheless, as pairwise comparisons show (Figure 13), while the LAV group reduced the RD significantly between pre-test and post-test measures, the HAV group did not show significant changes in RD. Thus, only the LAV group showed an improved performance (Figure 13).

Table 12. Mean ± SD differences of the initial structure of variability (α_{PRE}), the initial performance (RD_{PRE}) and the absolute and relative learning rate (ALR and RLR) between individuals with high or low initial long-range auto-correlation grouped according to the residuals of the linear regression grouping method.

	LAV group (n=15)	**HAV group (n=15)**	$F_{1,29}$	***P***	η_p^2
α_{PRE}	0.96 ± 0.09	1.14 ± 0.09	24.614	<0.001	0.468
RD_{PRE} (mm)	14.41 ± 4.60	14.57 ± 5.55	0.006	0.938	0.001
ALR (mm)	3.19 ± 4.29	0.61 ± 5.30	2.183	0.151	0.072
RLR (%)	17.26 ± 26.57	-3.01 ± 30.72	3.735	0.063	0.118

One-way ANOVA for independent measures.
α_{PRE} = long-range auto-correlation index shown in the pretest.
RD_{PRE} = resultant distance shown in the pretest.
LAV group = Low auto-correlated variability group.
HAV group = High auto-correlated variability group.

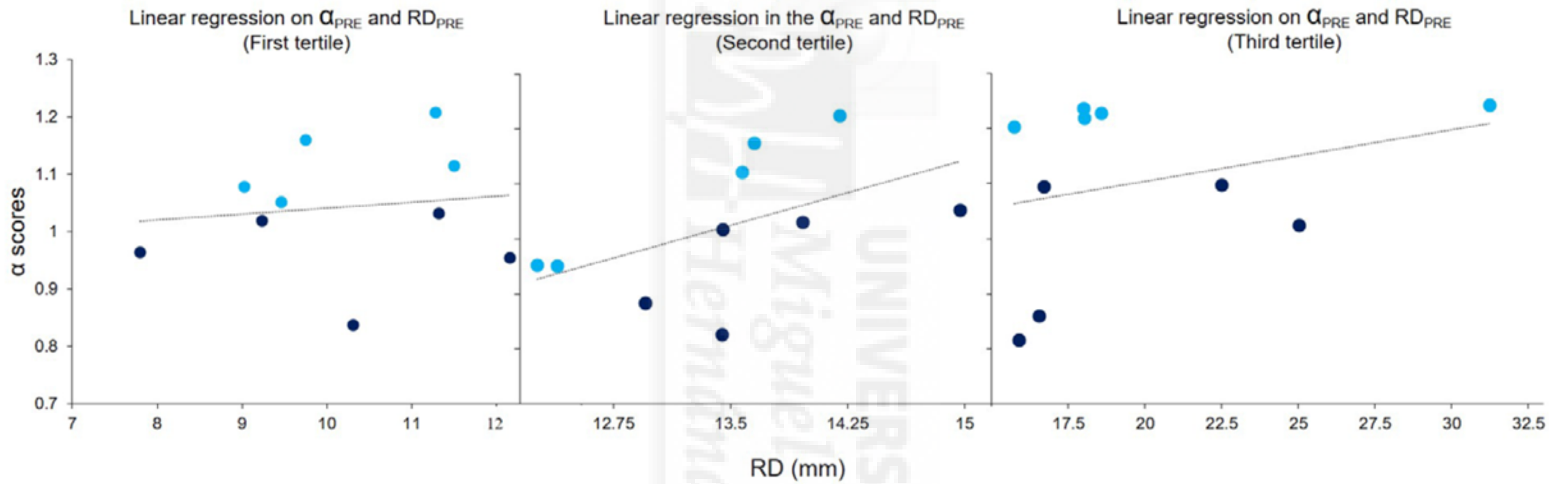


Figure 12. Linear regression of the initial structure of the variability (α_{PRE}) and the initial performance (RD_{PRE}) during a standing balance protocol in the three performance group. Light blue dots represent the participants included in the “High auto-correlated variability” group (HAV), and the navy blue dots represent the participants included in the “Low auto-correlated variability” group (LAV).

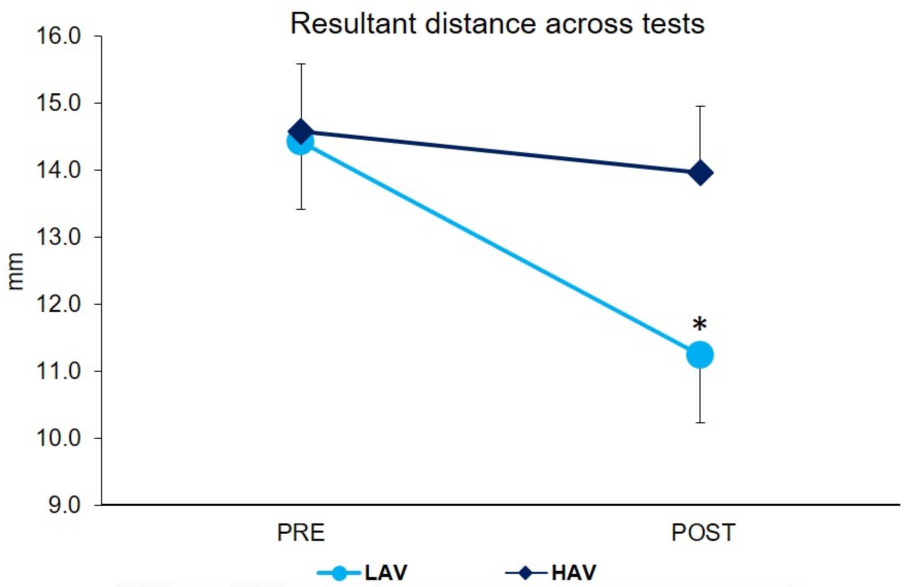


Figure 13. Pre- and post-test differences in the resultant distance (RD) between the “High auto-correlated variability” (HAV) and the “Low auto-correlated variability” (LAV) groups. Participants were grouped in the HAV or LAV groups according to the residual scores of the linear regression method between the initial performance (RD_{PRE}) and initial structure of variability (α_{PRE}). *Significant pre- and post-test differences of the LAV group.

Table 13. Principal component factors (PC) obtained from the Principal Component Analysis during the standing protocol.

Components	PC_1	PC_2	PC_3
RD_{PRE}	**0.924**	0.049	-0.378
RLR	**0.810**	**-0.479**	0.338
α_{PRE}	0.379	**0.904**	0.200

α_{PRE} = long-range auto-correlation index shown in the pretest.
RD_{PRE} = resultant distance shown in the pretest.
LAV group = Low auto-correlated variability group.
HAV group = High auto-correlated variability group.

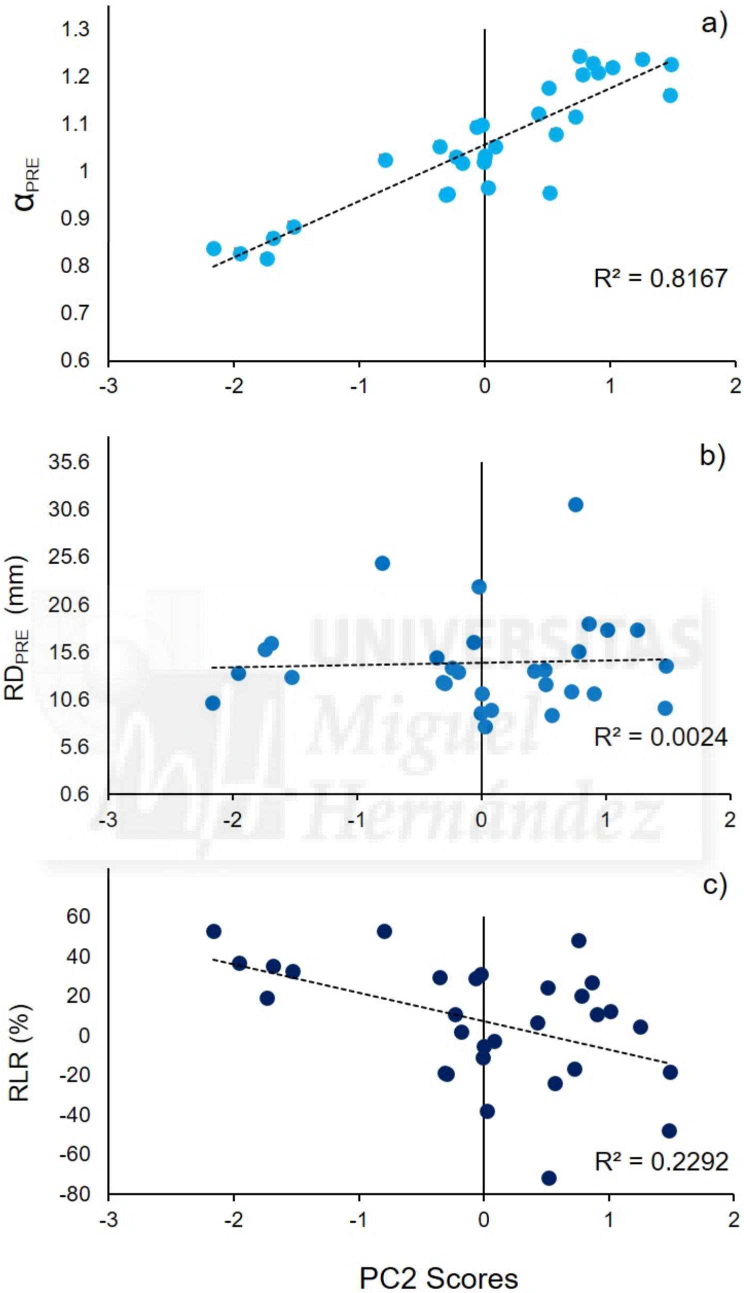


Figure 14. Relationship between PC2 scores and a) the initial performance (RD_{PRE}); b) the initial long-range auto-correlation of the CoP variability (α_{PRE}) and c) the relative learning rate (RLR) during the protocol of experiment 1.

5.3.3. Discussion.

Previous studies found a relationship between an individual's motor variability during a baseline period and learning rate in reward-based tasks, but limited evidence is available for error-based learning (Wu et al., 2014).

In this study, we found little evidence about motor variability predicting the rate of learning. However, our results suggest that this relationship is influenced by an individual's initial performance level. The correlational results and PC_1 (Tables 11 and 13) revealed that individuals with higher auto-correlated CoP variability tended to show poorer performance. Previous studies have linked higher auto-correlated motor fluctuations to lower flexibility to carry out postural adjustment and therefore poorer performance (Amoud et al., 2007; Wang and Yang, 2012; Zhou et al., 2013). In our study, the participants with higher α_{PRE}, showed a lower performance level and, consequently, had greater room for improvement, biasing the hypothetical relationship between learning and variability structure. Lower auto-correlated motor fluctuations indicate better balance performance and could be considered a sign of a later stage of learning in which individuals show more of an exploitation rather than an exploration behavior.

However, it would be reasonable to assume that individuals who display a higher ability to perform postural adjustments would also show a higher learning rate. When participants were grouped using the linear regression method and the initial performance bias was avoided, the individuals with low long-range auto-correlated CoP variability (low α_{PRE}) tended to display greater performance improvement than those with high long-range auto-correlation. PC_2 confirmed these findings, supporting the hypothesis that individuals with a higher ability to perform postural adjustment have greater improvement potential.

In terms of limitations, it could be argued that the between-group differences in the learning rate, based on the initial structure of the variability, showed a small size-effect and were only significant when the learning rate was assessed in a relative sense. These results were influenced by the small learning rate observed after practice. Even so, some individuals showed a poorer performance after practice (Figure 13), suggesting that the task was too easy or that the practice was not extensive enough to promote learning. If this were the case, there would have been no need for the motor exploration, thus decreasing the importance of the motor variability as a functional feature of learning (Woolley and Doupe, 2008; Wu et al., 2014). Another limitation could be related to the low reliability that scattering variables such as RD exhibit during the data series involving short easy tasks (Lee and Granata, 2008; van Dieën et al., 2010). If a balance task is too easy, participants might attempt to maintain balance with their center of mass at different locations relative to their support surface (Caballero, Barbado, and Moreno, 2015). In such cases, it is difficult to achieve stationarity of the time series, decreasing the reliability of the scattering variables such as RD (Caballero et al., 2015; Lee and Granata, 2008) and DFA (Caballero et al., 2015).

Taking the results and the aforementioned concerns into account, we tested the hypothesis in a second experiment using a less common and more difficult balance task with longer trial times and with an increased practice period.

5.4. Experiment 2: Sitting protocol.

5.4.1. Method.

5.4.1.1. Participants.

Twenty-two volunteers took part in experiment 2 (age = 24.6 ± 4.6 years; mass = 73.6 ± 7.5 kg, height = 1.74 ± 0.07 m; trunk moment of inertia = 5.22 ± 0.76 kg•m^2), and all were males. The inclusion criteria were the same as the previous experiment. All subjects were healthy, without current pain in the hip or back or past pathology in these regions. All of the subjects reported having no neurological or musculoskeletal problems. No participant had previous experience in the balance task used in this study. Written informed consent was obtained from each participant prior to testing. The experimental procedures were in accordance with the Declaration of Helsinki and were approved by the University Office for Research Ethics.

5.4.1.2. Experimental Procedure and Data Collection.

Participants sat upon a seat assembly consisting of a wooden platform (50 cm x 50 cm) affixed to the flat surface of a polyester resin hemisphere (diameter of hemisphere: 35 cm; height of the seat relative to the bottom of the hemisphere: 12 cm) (Figure 15). The seat was equipped with wooden leg and foot supports to prevent lower body movement relative to the platform. Foot support height was individually adjusted to create a 90º knee angle and light plantar foot support, while elastic straps secured each participant’s lower leg to the leg support. A safety rail was placed in front of the participant, thus providing a secure bar to grasp if participants perceived they were unable to control their balance, and to hold onto during rest periods (Figure 15). In addition, a wooden stabilizing device was inserted under the seat platform during the rest periods, thus stabilizing the platform from any rocking motion. In this way, fatigue was avoided and participants were unable to gain further balance practice during the rest periods.

To analyze the effect of practice, participants attended 3 testing sessions spaced 1 week apart. Five 70-s trials were collected per session (15 trials in total) with 2 min of rest between trials. The 70-s of data collection began when they were relatively stable with their hands on their lateral chest at rib level. They were instructed to maintain their balance, keeping the unstable platform “as still as possible” (Cavanaugh et al, 2008) (Figure 15).

The seat assembly was placed atop a force plate (Kistler, Switzerland, Model 9286AA), which was sampled at 1000 Hz and calibrated prior to each test. The CoP data were subsampled at 20 Hz following the same principle explained in experiment 1.

5.4.1.3. Data analysis and reduction.

While the data analysis closely followed the procedure used in the previous experiment, there were a few differences. To avoid non-stationarity related to the beginning of the trial, the first 10 s of each trial were discarded (van Dieën et al., 2010). The length of the time series analyzed was 1200 data points.

Similar to the first experiment, because the orientation of the participant was only approximately aligned with the axes of the force platform, the resultant distance (RD) was used as a global measure to quantify the performance during the balance trials (Prieto et al., 1996), and the *α* scores of each participant were calculated as the average *α* obtained from both axes.

In this experiment, the RD and *α* of each participant were averaged over the three last trials of each session. The ALR was now calculated as the RD differences between the third and second sessions relative to the first ($ALR_{1\text{-}2}$ and $ALR_{1\text{-}3}$). The RLR was similarly calculated relative to the initial performance of each individual ($RLR_{1\text{-}2}$ and $RLR_{1\text{-}3}$).

Figure 15. Participant performing the sitting stability task on the unstable seat.

5.4.1.4. Statistical Analysis.

The statistical analysis performed in experiment 2 was similar to experiment 1. The normality of the variables was evaluated through the Kolmogorov-Smirnov test with Lilliefors correction. First, a Pearson's correlation was performed between the performance (RD_1) and long-range auto-correlation

(α_1) in the first session, and the learning rate (ARL_{1-2}, ARL_{1-3}, RLR_{1-2} and RLR_{1-3}) to assess the initial performance and variability influence on the learning rate (Table 4). Second, to avoid the initial performance bias on the learning rate, participants were grouped using a linear regression method (Figure 16). Specifically, the participants were classified into three groups according to their RD_1. Then, we performed a linear regression between RD_1 and α_1 in each performance group. Similar to the first experiment, the participants were grouped according to their residual scores. Higher residual scores in each group were included in the HAV group. The lower residual scores in each group were included in the LAV group (Figure 16). One-way ANOVA for independent measures was performed to assess the learning rate (ARL_{1-2}, ARL_{1-3}, RLR_{1-2} and RLR_{1-3}) differences between the groups with the initial structure of the variability as an inter-subject factor (HAV and LAV groups) (Table 15). A mixed-way ANOVA was performed with RD as a within-subject factor (session 1, session 2 and session 3) and with the initial structure of the variability as an inter-subject factor (HAV and LAV groups) (Figure 17). The partial eta squared (η_p^2) was calculated as a measure of effect size. Values of an effect size ≥0.64 were considered strong, between 0.64 and 0.25 were considered moderate, and ≤ 0.25 were considered small (Ferguson, 2009).

Finally, we performed PCA (Table 16 and Figure 18) to check the results obtained with the linear regression method and to extract the underlying relationships between the initial structure of the variability (α_1), the initial performance (RD_1) and the relative learning rate (RLR_{1-3}).

5.4.2. Results.

All of the participants improved their performance and significantly reduced their RD between session 1 and session 3 ($RD_1 = 4.9 \pm 1.2$ mm; $RD_2 = 4.3 \pm 1.0$ mm; $RD_3 = 3.3 \pm 0.8$ mm; $F_{1,21} = 32.69$; $p < 0.001$; $\eta_p^2 = 0.598$); nevertheless, as the size effect indicated, the learning rate in experiment 2 was higher than the learning rate in experiment 1. As Table 14 shows, the learning rate significantly correlated with initial performance, while no significant correlations were found between the learning rate and the initial structure of the variability. Again, these results indicate that the learning rate is highly determined by initial performance, while the initial structure of the variability does not seem to influence it. However, a significant relationship was found between RD_1 and α_1, supporting that the initial performance biased the relationship between the variability and the learning rate. That is, less skillful individuals who show higher α_1 values have a higher learning rate.

Table 14. Pearson's bivariate correlations between the individual's initial balance performance (RD_1), initial structure of the variability (α_1) and learning rate in absolute (ALR_{1-2}, ALR_{1-3}) and relative (RLR_{1-2}, RLR_{1-3}) values.

	RD_1	**α_1**	**ALR_{1-2}**	**RLR_{1-2}**	**ALR_{1-3}**	**RLR_{1-3}**
RD_1		0.537 (0.010)	0.536 (0.010)	0.407 (0.060)	0.723 (<0.001)	0.485 (0.022)
α_1	0.537 (0.010)		0.350 (0.111)	0.332 (0.131)	0.283 (0.202)	0.161 (0.474)

Pearson correlation coefficient (level of significance)
α_1 = long-range auto-correlation index shown in the first session; RD_1 = Resultant distance shown in the first session; ALR_{1-2} = absolute learning rate between sessions 1 and 2; ALR_{1-3} = absolute learning rate between sessions 1 and 3; RLR_{1-2} = relative learning rate between sessions 1 and 2; RLR_{1-3} = relative learning rate between sessions 1 and 3.

As in experiment 1, to assess the relationship between the initial structure of the variability (α_1) and the learning rate (ALR_{1-2}, ALR_{1-3}, RLR_{1-2}, RLR_{1-3}) and avoid the bias of the initial performance (RD_1), participants were grouped using a linear regression method (Figure 16). Again, higher residual scores (black dots in Figure 16) in each performance level were included in the HAV group, while lower residual scores (white dots) were included in the LAV group.

Table 15 shows the values of the two groups after the distribution of the participants. The groups were quite similar in initial performance (RD_1: $F_{1,21}$ = 0.038; p = 0.847: η_p^2= 0.002) but different in the structure of the variability (α_1: $F_{1,21}$ = 24.61; p < 0.001; η_p^2= 0.468). After analyzing the effects of practice on the performance variables, significant differences between the groups were found in

$ALR_{1\text{-}3}$ and $RLR_{1\text{-}3}$. The LAV group showed a higher learning rate than the HAV group.

The mixed measure ANOVA showed a performance improvement after practice in both groups ($F_{1,21} = 32.69$; $p < 0.001$; $\eta_p^2 = 0.598$). However, the LAV group showed higher improvements between sessions 3 and 1 than the HAV group (Interaction $F_{1,20} = 4.39$; $p = 0.049$; $\eta_p^2 = 0.180$). The pairwise comparisons showed significant differences in RD between the groups in session 3 (Figure 17).

Table 15. Mean $\pm$ SD differences of the initial structure of the variability (α_1), the initial performance (RD_1) and the absolute and relative learning rate ($ALR_{1\text{-}2}$, $ALR_{1\text{-}3}$, $RLR_{1\text{-}2}$, $RLR_{1\text{-}3}$) between individuals with high or low initial long-range auto-correlation grouped according to the residuals of the linear regression grouping method.

	HAV group (n=11)	**LAV group (n=11)**	$F_{1,21}$	***P***	η_p^2
$\boldsymbol{\alpha_1}$	1.11 ± 0.11	1.22 ± 0.11	6.437	0.020	0.243
$\mathbf{RD_1}$	4.84 ± 1.18	4.95 ± 1.26	0.038	0.847	0.002
$\mathbf{ALR_{1\text{-}2}}$	0.86 ± 0.73	0.40 ± 0.88	1.834	0.191	0.084
$\mathbf{ALR_{1\text{-}3}}$	1.98 ± 0.83	1.15 ± 1.02	4.389	0.049	0.180
$\mathbf{RLR_{1\text{-}2}}$	16.85 ± 15.18	5.59 ± 19.54	2.277	0.147	0.102
$\mathbf{RLR_{1\text{-}3}}$	39.69 ± 10.32	20.46 ± 17.81	9.599	0.006	0.324

One-way ANOVA for independent measures.
α_1 = long-range auto-correlation index shown in the first session; RD_1 = resultant distance shown in the first session; $ALR_{1\text{-}2}$ = absolute learning rate between sessions 1 and 2; $ALR_{1\text{-}3}$ = absolute learning rate between sessions 1 and 3; $RLR_{1\text{-}2}$ = relative learning rate between sessions 1 and 2; $RLR_{1\text{-}3}$ = relative learning rate between sessions 1 and 3; LAV group = Low auto-correlated variability group; HAV group = High auto-correlated variability group.

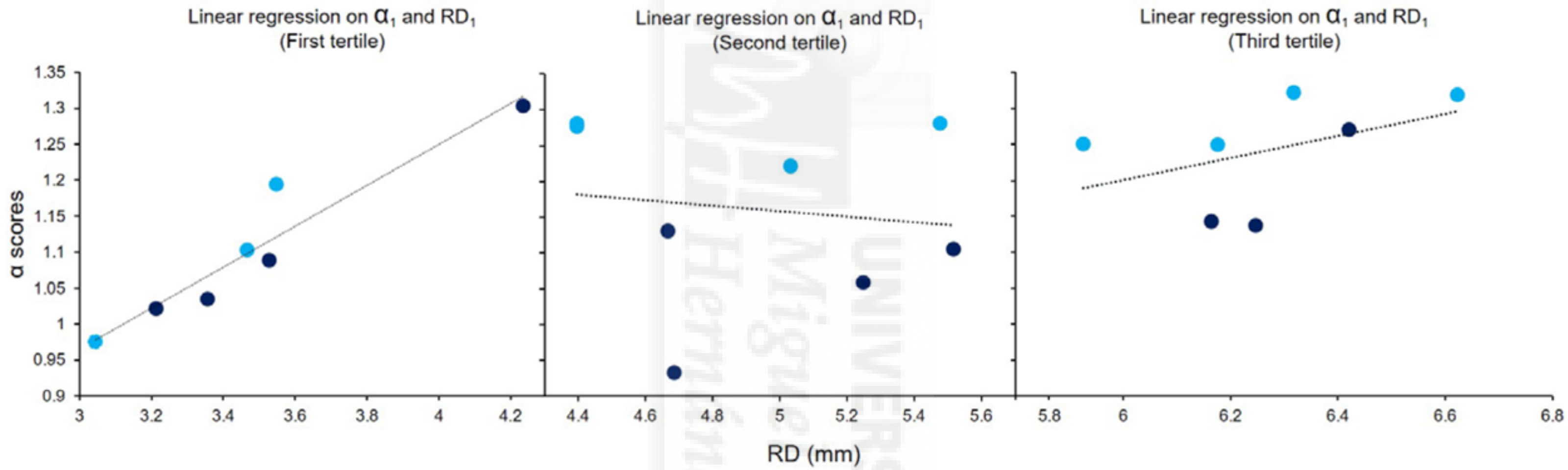


Figure 16. Linear regression of the initial structure of the variability (α_1) and the initial performance (RD_1) during the sitting balance protocol in the three performance group. Light blue dots represent the participants included in the “High auto-correlated variability” group (HAV), and navy blue dots represent the participants included in the “Low auto-correlated variability” group (LAV).

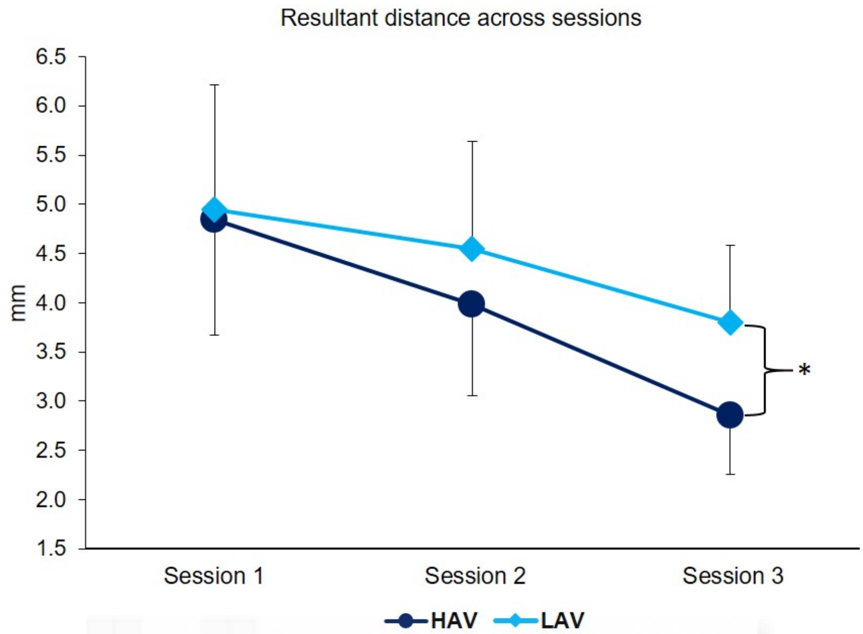


Figure 17. Resultant distance values (RD) from the “High auto-correlated variability” (HAV) and “Low auto-correlated variability” (LAV) groups across sessions.
* Significant differences between the groups in session 3.

Finally, the PCA performed among the initial performance, the initial structure of the variability and the learning rates between sessions 1 and 3 supported the aforementioned results. PC_1 accounted for 60.28% of the total variance, showing that a higher $RLR_{1\text{-}3}$ was related to a higher RD_1 and α_1, and thus, less skillful individuals had greater room for improvement than more skillful ones but showed higher auto-correlation of the CoP variability. PC_2 accounted for 27.99% of the total variance and showed that a higher $RLR_{1\text{-}3}$ was related with low α_1 and was unrelated to RD_1. As shown in Figure 17, individuals with low PC_2 values showed a higher learning rate ($R^2 = 0.446$; $p < 0.001$), lower auto-correlated CoP variability ($R^2 = 0.373$; $p = 0.003$) and no difference in their initial performance ($R^2 = 0\ .001$; $p = 0.920$) compared to individuals with high PC_2 values.

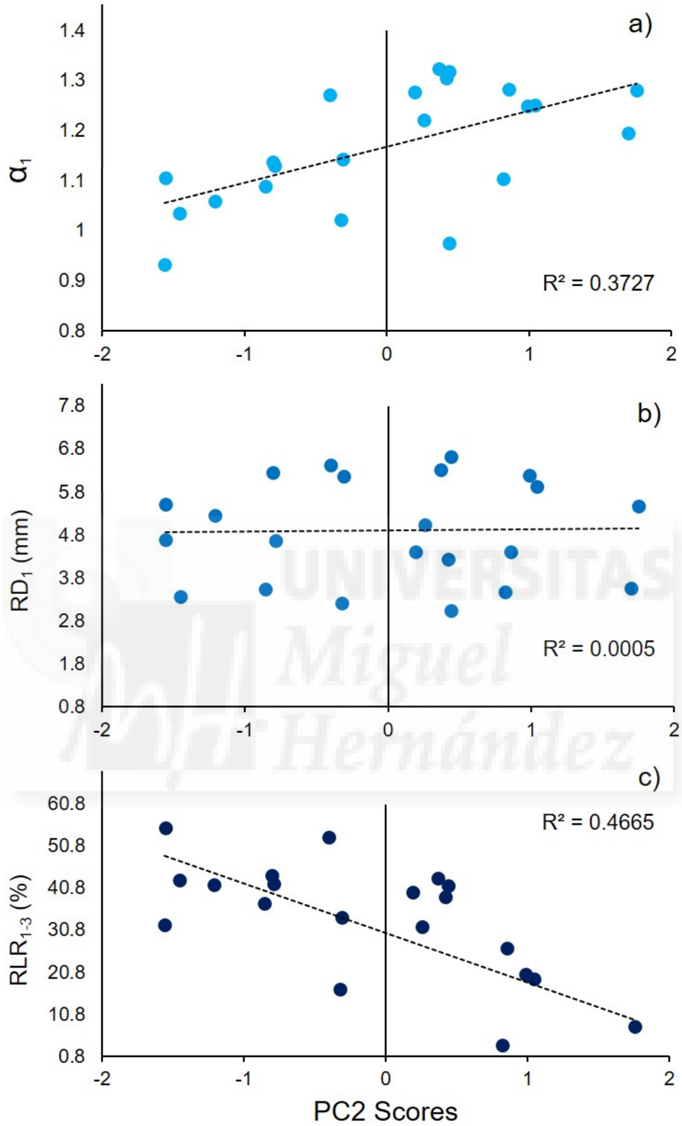


Figure 18. Relationship between PC_2 scores and the three variables analyzed: a) the initial long-range auto-correlation of the CoP variability (α_1), b) the initial performance (RD_1), and c) the relative learning rate ($RLR_{1\text{-}3}$) during the protocol of experiment 2.

Table 16. Principal component factors (PC) obtained from Principal Component Analysis during the sitting protocol.

Components	PC_1	PC_2	PC_3
RD_1	0.897	-0.023	-0.442
RLR_{1-3}	0.732	-0.611	0.302
α_1	0.684	0.683	0.255

α_1 = long-range auto-correlation index shown in the first session.
RD_1 = resultant distance shown in the first session.
RLR_{1-3} = relative learning rate between sessions 1 and 3.

5.4.3. Discussion.

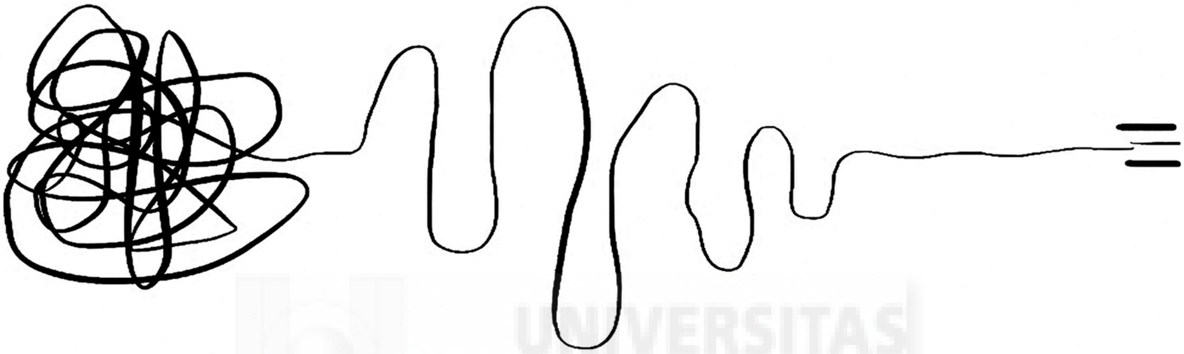
Our second experiment, using a sitting balance task, confirmed the preliminary results found in experiment 1. On the one hand, individuals with less auto-correlated CoP variability showed a better performance but a lower learning rate. On the other hand, when the bias caused by initial performance was controlled, individuals with less auto-correlated CoP variability showed a higher learning rate not only in the relative sense but in the absolute values as well. In spite of the fact that the statistical procedures used in both experiments are correlational and they do not permit the establishment of causal links, a less auto-correlated CoP variability during the balance tasks seems to mean a higher ability to perform postural adjustments (Amoud et al., 2007; Wang and Yang, 2012), which allows for the individuals to achieve a better performance and faster learning. The lower learning rate found in experiment 1 means that the exploitation strategies predominated over the exploration ones (Herzfeld and Shadmehr, 2014; Wu et al., 2014). Nevertheless, even in such easy and common tasks in which the exploitation of the current knowledge prevails, individuals who showed higher motor exploration (lower α_1) showed a higher learning rate, suggesting that they are forgoing, in some way, their performance in view of an increased learning rate. A higher effect-size found in experiment 2 means that during unusual and more difficult tasks, such as the sitting balance, exploration strategies prevail, increasing the functional role of the variability as a learning facilitator. Overall, these results agreed with previous findings on both reward-based and error-based pointing tasks (Wu et al., 2014); however, to the best of our knowledge, this is the first study to assess the relationship between the structure of motor variability and learning rate, avoiding the influence of the initial performance level.

One of the main aims of this study was to test whether the analysis of the motor variability structure reveals motor system properties to promote learning when a low magnitude of the variability is required to have a good performance and what it does mean during an error-based task. During reward-based learning, the motor variability magnitude is successfully interpreted as the exploration needed to find the most beneficial solutions, which will subsequently be exploited (Pekny et al., 2015; Wu et al., 2014). Even more, it has been observed that individuals increase their motor variability when they do not achieve success during an attempted motor task, which has been interpreted as a search for rewarding outcomes (Galea, Ruge, Buijink, Bestmann, and Rothwell, 2013; Pekny et al., 2015). A similar interpretation about the functional role of variability is shown in error-based learning (Wu et al., 2014). However, during the learning process of an error-based task, which is thought to depend mainly on the cerebellum (M. A. Smith and Shadmehr, 2005), learning not only depends on the exploration capacity but also on the ability to measure and predict the motor error. That is, the capacity to detect differences between the desired behavior and the actual motor outcome (M. A. Smith and Shadmehr, 2005). It would be expected that when individuals are more sensitive to their own motor error, more motion adjustment is needed to reduce it. The analysis of the structure of the variability through DFA reveals how the motor output changes over time instead of the magnitude of those changes. Therefore, the relationship between the α scores and the learning rate found in our study would be more related to the individual's error sensitivity rather than exploration processes. Previous studies that assessed the long-range auto-correlation of step-by-step variability during gait (Jordan, Challis, and Newell, 2007) or postural sway during balance tasks (Amoud et al., 2007; Wang and Yang, 2012) identified less auto-correlated motor variability as an individual's greater ability to perform motion adjustments. In our experiments, individuals with a less auto-correlated CoP variability mostly showed better performance, indicating that the α scores are an index related to skill level. That is, high skillful individuals are more sensitive to their own motion, allowing them to reduce the magnitude of their body fluctuation. Additionally, when they were compared with their counterpart who had similar performance but higher auto-correlated variability, they showed a higher learning rate. Therefore, the analysis of the structure of motor variability without the influence of performance level seems to reveal the ability to perform motion adjustment, conditioned by the individual sensitivity to one's own motor errors (Herzfeld and Shadmehr, 2014b; M. A. Smith and Shadmehr, 2005).

Finally, it should be noted that motor variability can be a motor system feature that is actively and centrally regulated to promote learning (Churchland et al., 2006; Mandelblat-Cerf et al., 2009; Sober, Wohlgemuth, and Brainard, 2008). Previous studies show that motor variability depends largely on individual factors, such as effort, motivation or attention (Borg and Laxåback, 2010; Diniz et al., 2011; Roerdink, Hlavackova, and Vuillerme, 2011; Stins et al., 2009; van Orden, Holden, and Turvey, 2003). In this sense, Correll (2008) assessed the influence of the effort on the time response latencies during a “shooting decision making task” and found that higher effort was associated with a lower auto-correlated time response variability. Under this perspective, and taking into account the results of our study, low long-range auto-correlation values mean that the participants have a high implication to perform motion adjustment to reduce the motor output error.

Despite these implications, our results point out that the analysis of the structure of the variability can be useful to predict the individual learning rate, but the underlying process that influences it is still uncertain. Future studies should address to what extent individual constraints affect the structure of the variability and whether it can be modulated during the practice period to promote faster learning.

In conclusion, our findings show that analysis of the long-range auto-correlation reveals a relevant role for motor variability during motor error-based learning even when a reduction of the magnitude of the output variability is required to achieve a good performance and individuals show a similar performance level.



6. Epilogue

6.1. Discussion and conclusions.

Postural control analysis has been one of the most studied research fields in motor control. Balance is a fundamental motor ability for everyday life and it is also a complex ability that involves controlling many neuromuscular components. CoP seems to be a collective variable that reflects the activities of many neuromuscular components acting together to maintain balance (Manor et al., 2010; Riley and Turvey, 2002; Winter, 1995). Traditionally, CoP fluctuations have been studied through their variability, using variables to measure the dispersion and amount of CoP changes. Despite the reliability of these variables having been previously analyzed, there is no clear agreement about what is the best variable to use in assessing postural control (Ruhe et al., 2010). Even the reliability of this kind of variables has been questionable (T.L. Doyle et al., 2005). However, our results support that some of these variables are reliable for assessing balance. The MV of CoP provides very high reliability and accuracy values, better than scattering values.

Recently, the use of nonlinear variables has allowed researchers to assess the structure and dynamics of the CoP to understand the interaction of the neuromuscular components. There are only a few studies that analyzed the reliability of this kind of variables. The findings achieved in the first study of this thesis show that nonlinear variables, such a FE, PE and DFA, have good reliability values and high accuracy to rank individuals, even greater than traditional variables, as it has been suggested previously (T.L. Doyle et al., 2005).

Another aim of this doctoral thesis was to test if, such as previous studies have indicated (Barbado et al. 2012; Goldberger, Peng, et al., 2002), complexity of the CoP variability in balance tasks reveals the system´s ability to adapt. We have found in the literature controversial results regarding this hypothesis. Some studies support that greater system complexity in balance control is connected to better ability to adapt (Manor et al. 2010). In contrast, other studies indicate the opposite: participants with higher values of complexity in CoP fluctuations exhibited lower performance and, therefore, they had less ability to adapt (Duarte and Sternad, 2008). Vaillancourt and Newell (2002; 2003) indicated that the reason for this controversy could be that the increase or decrease of complexity depends on the nature of both the intrinsic dynamics of the system and the task constraints that need to be satisfied. Thus, we tested the effect of different constraints on the relationship between complexity and performance in standing balance tasks. The results of the second study supported that the relationship between complexity and performance was positive, as previous studies have indicated. Individuals who showed higher complexity values showed better performance in balance tasks (Barbado et al. 2012; Manor et al. 2010). However, the changes in CoP structure and, therefore, in CoP complexity, were affected by constraints such as the level of difficulty and the availability of biofeedback, thus agreeing the Vaillancourt and Newell´s hypothesis (2002; 2003).

Finally, we wanted to take another step forward regarding the usefulness of motor variability as an intrinsic feature of the system. Thus, we tested if motor variability was also related to learning rate (Wu et al., 2014). The study of Wu et al. (2014) showed that high motor variability during the baseline period predicted faster learning in humans in different point-to-point reaching tasks and in a force field reaching task. However, we consider that the use of nonlinear variables to assess the structure of the variability would provide more information about the extent to which motor variability is a consequence of an avoidable stochastic neuromuscular system function (Churchland et al., 2006; Harris and Wolpert, 1998; Osborne et al., 2005; Schmidt et al., 1979) or whether it is the result of an active behavior centrally regulated to promote learning (Mandelblat-Cerf et al., 2009; Sober et al., 2008). In the third study presented in this thesis two protocols were developed to analyze postural control in standing and sitting balance tasks. The results indicated that individuals who show higher variability in the structure of CoP initially demonstrate a faster learning process in different balance tasks. This study verified that motor variability in balance tasks is related to the ability to adapt, to perform movement adjustments and to improve learning. Taking into account the general hypothesis considered in this doctoral thesis, we can establish the following conclusions:

I. Nonlinear variables show greater consistency (intraclass correlation coefficient) and accuracy (standard error of measurement) than traditional scattering variables in the CoP analysis.

I.I. FE and PE are the nonlinear variables with highest consistency and accuracy values in the CoP analysis.

I.II. DFA shows good consistency and accuracy values in the CoP analysis, and provide complementary information about the structure of CoP variability.

I.III. MV of CoP shows greater consistency and accuracy values than scattering variables, with similar values to nonlinear variables. This variable could provide information about the amount of adjustments performed during the task, related to the *error sensitivity* showed by the individuals.

I.IV. Non-stationary data series can affect the reliability of nonlinear variables. The increase of recording time and detrending processes such as the first derivative have been shown to improve the reliability of the entropy variables.

II. The relationship between the complexity of CoP variability and the performance in a standing balance task is dependent on the level of difficulty and the availability of biofeedback.

II.I. The presence of biofeedback reduces the complexity of CoP variability.

II.II. When biofeedback is available, the complexity of CoP decreases as the difficulty increases. When biofeedback is not available, the complexity of CoP increase as difficulty increase. This is due to the fact that the most difficult levels in balance tasks reduce the number of possible solutions available to keep balance, being biofeedback redundant.

III. Motor variability structure in balance tasks seems to reveal the system´s ability to perform movement adjustments and is related to learning rate despite the individual´s initial performance level.

III.I. Individuals who show less DFA values initially in the CoP structure (more complex CoP displacements) during balance tasks show a higher relative learning rate.

III.II. The relationship between the CoP structure, ability to adapt and learning rate in balance tasks appears even in tasks where it is necessary to reduce the amount of variability to get a good performance.

6.2. Study limitations and future research

In this doctoral thesis, we have checked the hypothesis, taking into account the most relevant aspects related to the research topic. Nevertheless, we have found some difficulties and limitations that encourage new experiments, taking into account different considerations, so the limitations detected can serve as a starting point for future studies. In our research group, other studies are currently being performed about the research topic of this thesis, trying to go into detail about the knowledge on motor variability and its relationship with the ability to adapt and learning processes.

The starting point of this thesis was to know what CoP and kinematic parameters better characterize postural control in standing balance tasks. The results obtained helped us to select the most reliable and accurate variables to assess the variability of postural control in balance task. However, the number of mathematical tools used in the literature is wide and in continuous development. In our work the most used variables to characterize postural control in the literature have been assessed but the analysis of the reliability of additional tools, both traditional and nonlinear variables, is necessary. Future works will be focused on increasing the number of analyzed variables. In addition, the balance tasks analyzed in this doctoral thesis are classic lab-based tasks, thus, despite having found good reliability results in the variables used, it would be also interesting to apply these variables to another balance task postural regulation in contexts with nested tasks, for example, movements we perform in everyday life or in sports. In this way, we could see if these variables are also appropriate to assess motor variability in tasks in which there are several interactions between the different body segments to perform successfully complex movements in which balance is also a main element.

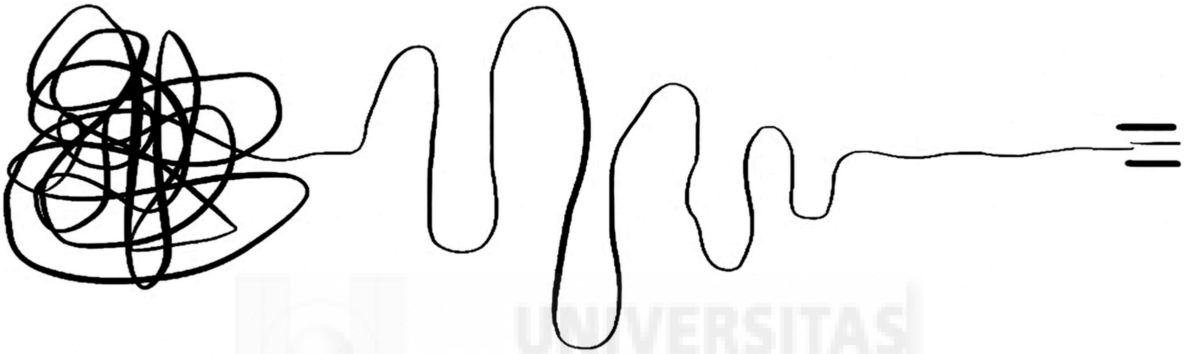
Following the aim of finding the best way to characterize postural control, we found that the mathematical tools used to characterize postural control decreased their consistency and accuracy when they were applied to kinematic data due to their non-stationary features. Kinematic signals were not used in the second and third study of this thesis, dismissing information about postural strategies and movement pattern (Kuo et al., 1998; Madigan et al., 2006). Future studies should try to increase the signal stationarity, either increasing the recording time to reach a larger number of data or using some detrended process of the signal, in order to use kinematic data.

As we have seen in the second experiment of this doctoral thesis, the type of the filter applied to the signal significantly modifies the signal's structure and, for instance, the complexity of CoP variability. According to some studies, different filters reveal different postural control behaviors that are related to two components of CoP displacement: rambling and trembling (Zatsiorsky and Duarte, 1999). These components are related to two types of motor control, central nervous system (volitional control) and peripheral control (involuntary control), respectively (Tahayori et al., 2012). In the second study, we have seen how in standing balance tasks the volitional control prevails over involuntary control in order to maintain balance. Future studies have to go in depth regarding to what extend voluntary and involuntary control are related to the analyzed adjustments known as *rambling* and *trembling* and what their role in postural control and movement coordination is.

We have found that some constraints have influence over the complexity of CoP variability, such as the effect of difficulty levels according to the availability of biofeedback. Future studies must be developed to analyze the effects of other constraints that the literature has related to motor control, such as aging or performance level. In the same way, the effects of cognitive processes, such as attention or motivation, on the variability characteristics and the achievement of better performance in the learning process have to be also addressed.

In the third experiment, it was pointed out that the amount of practice is a fundamental factor in causing a clear learning effect. Therefore, we consider it necessary to perform experimental designs with enough practice time and tasks that are difficult enough to cause adaptation processes and, thus, maximize the learning effect. This way, the relationship between variability and learning processes will be easier to contrast.

The Motor Control and Learning Group at the Research Sport Center of the Miguel Hernandez University is currently working on experimental protocols to assess motor variability and its relationship with the ability to adapt and the learning process. We are developing a research project, supported by the Spanish Government, in which one of the main aims is to assess the motor variability structure as an index for predicting the ability to adapt and learning. Therefore, the discussed limitations are being taken account, increasing the sample size and practice time. A larger sample size will allow us to group the participants according to their initial variability and performance considering that these variables can affect in the relationship between initial variability and the ability to adapt. The amount of practice has also been increased to maximize the learning process, and new protocols will be developed in which different motor abilities will be analyzed in order to extrapolate our conclusions. Some of the suggested motor abilities in the current research project will be discrete basic tasks (e.g., throwing a ball toward a target) and more specific sport tasks to check if the relationship between variability and the ability to adapt also appears in other kinds of motor tasks and if it can be extrapolate sport situations.



6. Epílogo

6.1. Discusión y conclusiones.

El análisis del control postural ha sido uno de los ámbitos de mayor interés dentro del área del control motor ya que el equilibrio es un aspecto motriz fundamental en el día a día, además de ser una tarea motriz compleja que conlleva el control de numerosos componentes neuromusculares. El centro de presiones (CoP) es considerado una variable colectiva que refleja la actividad de numerosos componentes neuromusculares actuando de forma conjunta para conseguir mantener el equilibrio (Manor et al., 2010; Riley and Turvey, 2002; Winter, 1995). Tradicionalmente, éste se ha estudiado a través de la variabilidad de sus fluctuaciones, utilizando variables que miden la dispersión y la magnitud de los cambios del CoP. A pesar de que diversos estudios han analizado la fiabilidad de este tipo de variables no existe un acuerdo claro sobre cuál es la mejor variable para evaluar el control postural (Ruhe, Fejer, and Walker, 2010). Incluso la fiabilidad de estas variables ha llegado a ser cuestionada por algunos autores (T.L. Doyle, Newton, and Burnett, 2005). Sin embargo, nuestros resultados indicaron que algunas de estas variables son fiables para analizar el control postural. La velocidad media del CoP proporciona unos valores de consistencia y precisión en la medida muy altos, siendo mayores que los de las variables de dispersión.

Recientemente, el uso de variables no lineales ha permitido analizar la dinámica de la estructura del CoP para conocer la interacción de los componentes neuromusculares involucrados en el control postural, pero los estudios de fiabilidad de este tipo de herramientas son escasos. Los hallazgos obtenidos en el primer estudio presentado en este trabajo muestran que las variable no lineales, tales como *entropía borrosa (FE)*, *entropía de permutación (PE)* y el *análisis de fluctuaciones tras la eliminación de tendencia (DFA)*, presentan una buena consistencia y precisión de la medida, incluso superior a las variables tradicionales, tal y como ya se ha sido sugerido previamente (T.L. Doyle et al., 2005).

Otro de los objetivos de esta tesis doctoral fue comprobar si, tal y como indican estudios previos (Barbado et al. 2012; Goldberger, Peng et al. 2002), la complejidad de la variabilidad del CoP en tareas de equilibrio permite revelar la capacidad de adaptación del sistema. Este objetivo fue planteado debido a los resultados controvertidos respecto a esta hipótesis. En la literatura podemos encontrar estudios donde indican que una mayor complejidad del CoP está asociada a una mayor capacidad de adaptación (Manor et al., 2010), mientras que otros autores indican lo contrario, que una mayor complejidad del CoP está relacionada con un menor rendimiento en la tarea y por lo tanto, menor adaptación a la misma (Duarte and Sternad, 2008). Vaillancourt y Newell (2002, 2003) indicaron que esta controversia es debida a que el incremento o la disminución de la complejidad es dependiente de la naturaleza intrínseca del individuo y de los condicionantes de la tarea. Por ello, comprobamos el efecto de diferentes constreñimientos sobre la relación entre la complejidad y el rendimiento en tareas de equilibrio en bipedestación. Los resultados del segundo experimento confirmaron que la relación entre complejidad y rendimiento siempre fue positiva, tal y como indican estudios previos, los cuales encontraron que individuos que presentan una mayor complejidad muestran mejor rendimiento en tareas de equilibrio (Barbado et al., 2012; Manor et al., 2010). Sin embargo, las modificaciones en la estructura del CoP y, por lo tanto, de su complejidad, se vieron afectadas por constreñimientos tales como la dificultad de la tarea y la disponibilidad de *biofeedback*, con lo que se confirmarían las afirmaciones de Vaillancourt y Newell (2002, 2003).

Por último, hemos querido dar un paso más allá en cuanto a la funcionalidad de la variabilidad motora como característica intrínseca del sistema. De este modo, comprobamos si la variabilidad posee relación, no sólo con la capacidad de adaptación, sino con el proceso de aprendizaje, tal y como indican estudios muy recientes (Wu et al., 2014). El estudio de Wu et al. (2014) mostró que los individuos con una alta cantidad de variabilidad motriz presentaban un proceso de aprendizaje más rápido. Sin embargo, nosotros consideramos que con el análisis de la estructura de la variabilidad a través de las herramientas no lineales se podría obtener más información sobre si la variabilidad mostrada es la consecuencia de procesos aleatorios del sistema (Churchland et al., 2006; Harris and Wolpert, 1998; Osborne et al., 2005; Schmidt et al., 1979) o el resultado de comportamientos exploratorios que facilitan el aprendizaje (Mandelblat-Cerf et al., 2009; Sober et al., 2008). En este sentido, en el último estudio de esta tesis doctoral se desarrollaron dos experimentos, donde se analiza el control postural en bipedestación y sedestación. Los resultados mostraron cómo individuos que presentaban un alto nivel de variabilidad inicial tuvieron un aprendizaje más rápido en diferentes tareas de equilibrio. Este estudio confirmó que la variabilidad motora en tareas de equilibrio está relacionada con la capacidad del sistema para realizar ajustes en su movimiento y mejorar así el proceso de aprendizaje.

Teniendo en cuenta las hipótesis generales de esta tesis doctoral, se pueden extraer las siguientes conclusiones:

I. Las variables no lineales muestran una mayor consistencia (coeficiente de correlación intraclase) y precisión (error estándar de la media) que las tradicionales herramientas lineales de dispersión en el análisis del CoP.

I.I. La *entropía borrosa (FE)* y la *entropía de permutación (PE)* son las variables con mayores valores de consistencia y precisión en el análisis del CoP.

I.II. El *análisis de fluctuaciones tras la eliminación de tendencia (DFA)* presenta buenos valores de consistencia y precisión en el análisis del CoP, y aporta información complementaria sobre la estructura de la variabilidad del CoP.

I.III. La velocidad media del CoP muestra valores de consistencia y precisión superiores a las variables de dispersión, encontrando similitudes a los mostrados por las variables no lineales. Esta variable podría aportar información sobre la cantidad de correcciones realizadas durante la tarea, relacionadas con la *sensibilidad al error* mostrada por los individuos.

I.IV. Series de datos no estacionarios pueden alterar la fiabilidad de las variables no lineales. El incremento del tiempo de registro o los procedimientos de destendimiento de la señal, como el cálculo de la primera derivada, han mostrado mejorar los valores de fiabilidad en las medidas de entropía.

II. La relación entre la complejidad de la variabilidad del CoP y el rendimiento en una tarea de equilibrio en bipedestación es dependiente de la dificultad de la tarea y la disponibilidad de *biofeedback.*

II.I. La presencia del *biofeedback* disminuye la complejidad de la variabilidad del CoP.

II.II. En presencia de *biofeedback* el nivel de complejidad del CoP disminuye conforme aumenta la dificultad. Sin embargo, cuando el *biofeedback* no está disponible, el nivel de complejidad del CoP aumenta conforme aumenta la dificultad. Esto se debe a que los niveles más elevados de dificultad en la situación de equilibrio reducen las posibles soluciones para conseguir mantener el equilibrio, siendo redundante el uso de *biofeedback*.

III. La estructura de la variabilidad motora en tareas de equilibrio parece revelar la capacidad del sistema para realizar ajustes en su movimiento y está relacionado con la capacidad de aprendizaje, independientemente del nivel del rendimiento inicial del aprendiz.

III.I. Los individuos que presentan menores niveles iniciales de DFA en la estructura del desplazamiento CoP (desplazamientos del CoP más complejos) en tareas de equilibrio muestran una mayor ratio de aprendizaje relativo.

III.II. La relación entre la estructura del desplazamiento del CoP, la capacidad de adaptación y aprendizaje en tareas de equilibrio aparece incluso en tareas donde para conseguir un buen rendimiento se requiere de una reducción de la magnitud de la variabilidad.

6.2. Limitaciones y prospectivas de investigación.

En esta Tesis Doctoral nos hemos encontrado con ciertas dificultades y limitaciones que nos dan pie a continuar con nuevos experimentos. De este modo, las limitaciones encontradas pueden servirnos como punto de partida para futuros estudios, los cuales actualmente están siendo llevados a cabo. Dichos trabajos están relacionados con la temática de esta tesis, permitiéndonos profundizar en mayor medida en los conocimientos sobre la variabilidad motora y su relación con la capacidad de adaptación y los procesos de aprendizaje.

El punto de partida que se planteó en este trabajo fue conocer cuáles son las variables que mejor caracterizan el control postural. Los resultados obtenidos nos ayudaron a seleccionar las variables más consistentes y precisas para analizar la variabilidad del control postural en tareas de equilibrio. Sin embargo, el abanico de herramientas matemáticas que podemos encontrar en la literatura es muy amplio y se encuentra en continuo desarrollo. En nuestro trabajo, se han analizado algunas de las herramientas más utilizadas para la caracterización del control postural pero existe la necesidad de realizar análisis de fiabilidad de un mayor número de herramientas, tanto tradicionales como no lineales. Futuros trabajos irán encaminados a incrementar el número de herramientas a analizar. Además, la tarea de equilibrio analizada en nuestro estudio es una tarea básica de laboratorio, por lo que, a pesar de haber encontrado buenos resultados de fiabilidad y consistencia en las herramientas medidas, también sería interesante que éstas sean aplicadas a tareas más cercanas a los movimientos que se dan tanto en el día a día como en la práctica deportiva. De este modo, podríamos ver si estas herramientas también son adecuadas para analizar la variabilidad motora en tareas donde aparecen numerosas interacciones de diferentes partes de nuestro cuerpo para poder realizar con eficacia movimientos complejos donde el equilibrio también es parte fundamental.

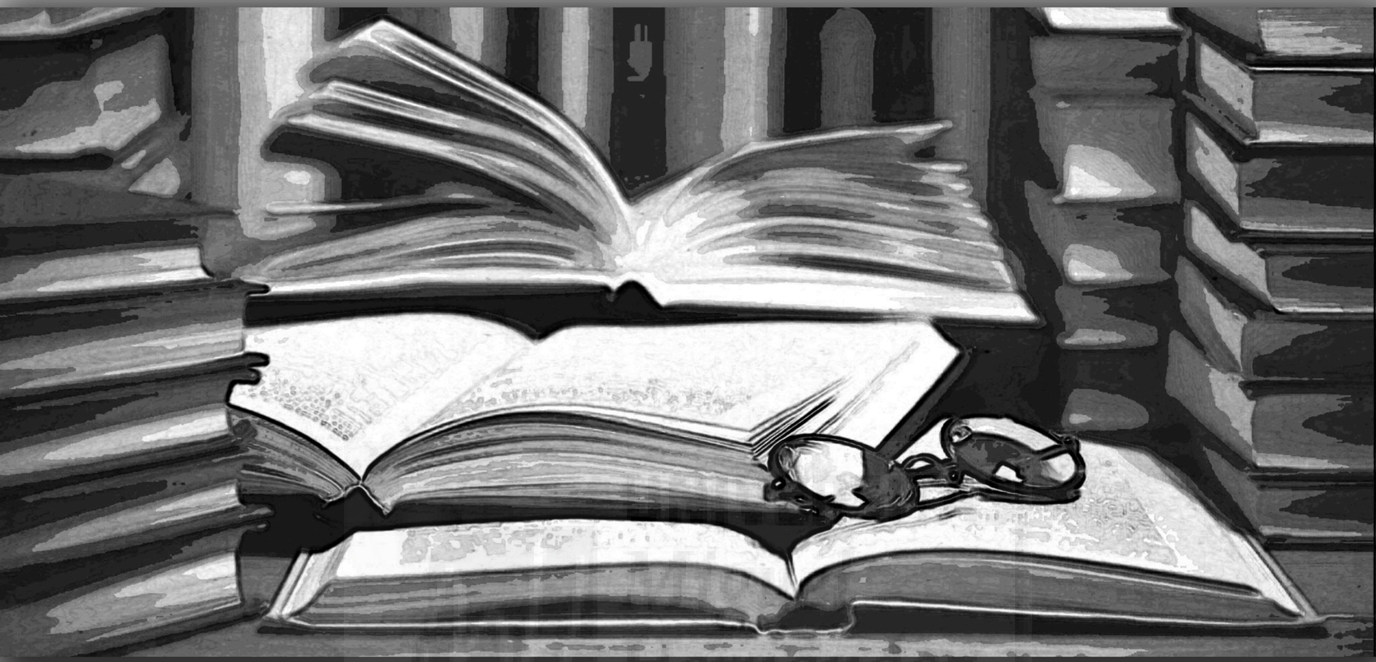
Continuando con el objetivo de encontrar la mejor manera de caracterizar el control postural, encontramos que las herramientas matemáticas utilizadas para caracterizar el control postural disminuyen su consistencia y precisión cuando son aplicadas sobre datos cinemáticos debido a sus características no estacionarias. De este modo, en el segundo y tercer estudio de este trabajo no se utilizaron señales cinemáticas, perdiendo información acerca de las estrategias posturales y patrones de movimiento (Kuo et al., 1998; Madigan et al., 2006). Futuros estudios deberían intentar incrementar la estacionariedad de la señal, ya sea aumentando el tiempo de registro para conseguir un mayor número de datos o utilizando algún procedimiento de destendimiento de la señal, lo que permitiría el uso de datos cinemáticos.

Tal y como hemos visto en el segundo estudio de esta tesis doctoral, el tipo de filtrado de la señal modifica considerablemente la estructura de la misma y, como consecuencia, los valores de complejidad de la variabilidad del CoP. Según algunos estudios, la utilización de diferentes filtros puede revelar diferentes comportamientos en el control postural, los cuales están relacionados con dos componentes del desplazamiento del CoP: *rambling* y *trembling* (Zatsiorsky and Duarte, 1999). Estos componentes están asociados a diferentes tipos de control motor, sistema nervioso central (control voluntario) y control periférico (control involuntario), respectivamente (Tahayori, Riley, Mahmoudian, Koceja, and Hong, 2012). En el segundo estudio, hemos visto cómo en tareas de equilibrio en bipedestación el control voluntario predomina en el mantenimiento del equilibrio. Futuros estudios deberán profundizar en qué medida el control voluntario e involuntario están relacionados con los ajustes conocidos como *rambling* y *trembling* y cuál es su rol en el control postural y la coordinación motriz.

En el segundo estudio presentado en este trabajo también encontramos que algunos constreñimientos influyen en la complejidad de la variabilidad el CoP, como es el caso del efecto de los niveles de dificultad en función de la presencia o no de *biofeedback*. Consideramos necesario abordar un análisis en profundidad del efecto de otro tipo de constreñimientos con respecto al control del movimiento, como pueden ser la edad o el nivel de rendimiento. Del mismo modo, el efecto de algunos procesos cognitivos, como pueden ser la atención o la motivación, sobre las características de la variabilidad y el proceso de aprendizaje tienen también que ser analizados en futuros estudios.

En el tercer estudio, se remarcó que la cantidad de práctica es un factor fundamental para provocar un claro efecto de aprendizaje. Por ello, consideramos necesario realizar diseños experimentales en los que haya un tiempo suficiente de práctica y en los que la tarea conlleve una dificultad suficiente como para provocar un proceso de adaptación y, así, maximizar el efecto del aprendizaje. De este modo, se facilitará contrastar la relación entre la variabilidad y la capacidad de aprendizaje.

Actualmente, el grupo de investigación del Laboratorio de Aprendizaje y Control Motor del Centro de Investigación del Deporte de la Universidad Miguel Hernández está trabajando en diseños experimentales para valorar la variabilidad motora y su relación con la capacidad de adaptación y aprendizaje. Se está desarrollando un proyecto de investigación, financiado por Plan Estatal de Investigación Científica y Técnica y de Innovación, en el que uno de los principales objetivos es evaluar si la estructura de la variabilidad motora puede predecir la capacidad de adaptación y la evolución del rendimiento. Para ello, se están teniendo en cuenta las limitaciones comentadas, incrementando el tamaño de la muestra y el tiempo de práctica. Un mayor tamaño de muestra permitirá agrupar a los participantes en función de su nivel inicial de variabilidad y de destreza, puesto que estas variables pueden afectar en la relación entre la variabilidad inicial del individuo y su capacidad de aprendizaje. La cantidad de práctica también ha sido incrementada para maximizar el proceso del aprendizaje y se desarrollarán nuevos protocolos donde se aborden diferentes habilidades para poder extrapolar las conclusiones obtenidas, con el fin de potenciar la fuerza estadística de los resultados obtenidos hasta ahora. Algunas de las habilidades planteadas en el actual proyecto serán habilidades básicas de carácter discreto (p.e., lanzamiento de una pelota a una diana), y habilidades más específicas dentro del deporte para poder comprobar si la relación entre variabilidad y capacidad de adaptación y aprendizaje encontrada en este trabajo también aparece en otro tipo de habilidades y puede ser extrapolable a situaciones deportivas.



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