European Journal of Human Movement, 2014: **32**, 61-81

NON-LINEAR TOOLS AND METHODOLOGICAL CONCERNS MEASURING HUMAN MOVEMENT VARIABILITY: AN OVERVIEW

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ABSTRACT

In recent years, several works have explored variability using different approaches, trying to describe the variations in motor movement. Traditionally, movement variability was regarded as a system error due to noise of neuromuscular mechanisms, but alternative theories suggest that motor variability seems to reflect a functional behaviour improving motor control and enhancing learning. Controversial results have been reported about variability characteristics and its role in motor control and learning, and several works suggest that the main difficulty lies in how to measure this variability. In this work, we have outlined the most used non-linear tools to assess human variability, their applications, advantages and disadvantages. We have also suggested different methods about how to achieve a multidimensional approximation to motor variability. Finally, we have called attention to some methodological issues frequently reported as important aspects to take into account when measuring human movement variability.

Key Words: variability, motor control, non-linear tools, time series

RESUMEN

En los últimos años, varios trabajos han explorado la variabilidad desde diferentes enfoques con el objetivo de describir las variaciones del movimiento. Tradicionalmente, la variabilidad del movimiento fue considerada un error del sistema causado por el ruido de los mecanismos neuromusculares, pero actualmente, teorías alternativas sugieren que la variabilidad motora parece reflejar un comportamiento funcional que ayuda a mejorar el control del movimiento y el aprendizaje. Sin embargo, existen resultados controvertidos acerca de las características de la variabilidad motora y su rol en el aprendizaje y control motor. En la literatura se ha sugerido que uno de sus principales motivos puede ser las herramientas utilizadas para intenta analizar la variabilidad. En este trabajo hemos realizado un resumen sobre las herramientas no lineales más utilizadas para valorar la variabilidad humana, su aplicación, ventajas e inconvenientes. Además, sugerimos diferentes métodos para obtener una aproximación multidimensional de la variabilidad motora. Finalmente, hemos hecho hincapié en algunos problemas metodológicos que se han considerado importantes a la hora de medir la variabilidad del movimiento humano.

Palabras clave: variabilidad, control motor, herramientas no lineales, series temporales

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Submitted: 15/06/2014
Accepted: 30/06/2014

INTRODUCTION

In recent years, human movement variability has appeared as a remarked research topic in motor control. Several works have tried to explore variability using different approaches, trying to describe the variations in motor performance across multiple repetitions of a task (Stergiou, Harbourne, and Cavanaugh, 2006).

Variability is clearly inherent in nature (Edelman, 1992), especially in biological systems. Variability in human movement can be observed quite easily: it is impossible to perform two identical movements as much as one tries, even though every repetition is successful. Bernstein (1967) used the expression ''repetition without repetition'' meaning that each movement is unique and it's impossible to repeat identical motor patterns.

Variability in motor performance has been considered from different theoretical perspectives (Newell and Corcos, 1993). Traditionally, movement variability was regarded as a system error due to noise or random fluctuations of neuromuscular mechanisms (Schmidt, Zelaznik, Hawkins, Frank, and Quinn, 1979). According to this theory, too much motor variability may indicate low motor control or health issues (Borg and Laxaback, 2010; Duarte and Sternad, 2008), and with practice, variability is gradually eliminated or minimized, optimizing the accuracy and efficiency of the movement pattern.

However, recent theories suggest that motor variability seems to be necessary for the system's functionality, being an index of the ability to adapt (Adami, Ofria and Collier, 2000; Davids, Glazier, Araujo and Bartlett, 2003; Goldberger, 1996; Goldberger, Amaral, et al., 2002; Lamoth, van Lummel and Beek, 2009; Latash, 1993; Lipsitz, 2002; Moreno and Ordoño, 2010; Newell, 1993; Rabinovich and Abarbanel, 1998; Riley and Turvey, 2002). In this sense, motor variability would reflect a functional behavior that improves motor control and enhances learning. Under this new perspective, the lack or the reduction of variability can be related to a low ability to adapt (Barbado, Sabido, Vera-Garcia, Gusi and Moreno, 2012; Manor et al., 2010) or to the effect of disease and aging (Byl, Nagarajan, Merzenich, Roberts and Mc Kenzie, 2002; Goldberger, Amaral, et al., 2002; Roerdink et al., 2006).

Whatever the perspective followed, one of the most important issues regarding variability is: what is the way to assess these variations? There are controversial results about variability characteristics and its role in motor control and learning, and several works suggest that the main difficulty lies in how to measure this variability (Caballero, Barbado and Moreno, 2013; Goldberger, Peng and Lipsitz, 2002; Stergiou and Decker, 2011; Vaillancourt and Newell, 2002). The first works trying to analyze movement variability measured it through the scattering variables; however, these variables don't provide enough information about the nature of variability because they do not consider it as motion changes in time (Stergiou and Decker, 2011). It is necessary to develop and use other tools to assess not only the magnitude but also the structure or the time-dependence of the variations. Non-linear tools have been applied to address this point but, do these tools actually measure variability? and, what kind of variability?

Probably, the answer to these questions is that variability is multidimensional and to assess variability, a macroscopic view and a global approach is necessary. With this purpose in mind, we will first review the most used tools to assess human variability, their different uses, the advantages and disadvantages of each of them, and we will suggest different methods about how to achieve a multidimensional approximation to motor variability. Finally we will discuss some methodological issues frequently reported as important aspects to take into account when measuring human movement variability.

Analyzing Motor Variability

According to literature, two different global dimensions about motor variability have been assessed: the magnitude of the variability and the dynamics of the variability, also addressed by its complexity (Stergiou et al., 2006).

Traditionally, linear measures, such as the standard deviation or the range of the time series, have been used to provide a description of the magnitude of the variability around a central point. Evaluating variability using this kind of tools arises from the idea that the mean is the goal performance and everything away from the mean is error (Stergiou and Decker, 2011). From a statistical point of view, 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, 2007).

However, several studies have indicated that these variations have deterministic properties (Dingwell and Cusumano, 2000; Dingwell and Kang, 2007; Harbourne and Stergiou, 2009; Miller, Stergiou and Kurz, 2006) and they may reflect changes in the biological systems' behavior in presence of changing environmental conditions in order to find the best solution to achieve the desired objective (Clark and Phillips, 1993; Hamill, van Emmerik, Heiderscheit and Li, 1999; Kamm, Thelen and Jensen, 1990; Kelso, 1995; Thelen, 1995; Thelen, Ulrich and Wolff, 1991). In this way, several mathematical tools have been applied to assess how motor behavior changes in time, its temporal dynamics or its complexity. These mathematical tools are termed non-linear tools.

Non-linear tools seem to provide additional information about the dynamics of variability and several works have analyzed the variability from this perspective (Adjerid et al., 2014; Borg and Laxaback, 2010; Buzzi, Stergiou, Kurz, Hageman and Heidel, 2003; Duarte and Sternad, 2008; Stergiou, Buzzi, Kurz and Heidel, 2004). There are many statistical tools developed to assess the complexity and each of them measures different properties of variability (Shelhamer, 2006).

One of the most common properties assessed is the local dynamic stability (Bruijn, Bregman, Meijer, Beek and van Dieën, 2012; Buzzi et al., 2003; Van Schooten et al., 2011). Traditionally, higher instability has been linked to higher linear variability. In this way, an increased variability in elderly or diseased people was related with a higher instability during gait (Buzzi et al; 2003, Dingwell and Cusumano, 2000; Dingwell et al., 2000). However, findings in balance task in participants who sustained a cerebral concussion indicate large variability may be accompanied by high stability (Cavanaugh, Guskiewicz and Stergiou, 2005). Granata and England (2007) indicated that variability is not necessarily related to biomechanic stability and Stergiou et al. (2011) stated that "variability and stability represent different properties within the motor control process". Local dynamic stability is defined as the degree of sensitivity of the system to small perturbations (Buzzi et al., 2003) and it is usually measured by LyE (Wolf, Swift, Swinney and Vastano, 1985). One-dimensional maps are characterized by single LyE which is positive for chaos, zero for a marginally stable orbit, and negative for a periodic orbit (Wolf et al., 1985). When Lyapunov exponent values are negative (periodic systems) the trajectories converge and this represents local stability in a particular direction. When Lyapunov exponent values are positive, (the attractor is chaotic) the trajectories diverge and this represents local instability in a particular direction (Eckmann and Ruelle, 1985). Nevertheless, some authors suggest that this tool needs a validation method because the presence of determinism within a time series and completely random data produce positive LyE index (Rapp, Zimmerman, Albano, Greenbaun and Bashore, 1986). The method to validate this tool is the Surrogation (Dingwell and Cusumano, 2000). Several authors have used Lyapunov Exponent (LyE) to assess local stability of a dynamical system in human movement (Abe, Chen and Pham, 2014; Buzzi et al., 2003; Rispens et al., 2014; Rosenstein, Collins and De Luca, 1993; Sano and Sawada, 1985; Zeng, Eykholt and Pielke, 1991). The LyE provides a qualitative picture of a system's dynamics and it has been used, for example, to assess aging changes (Buzzi et al., 2003), to assess the sitting postural control in infants (Cignetti, Kyvelidou, Harbourne and Stergiou, 2011) or to describe patterns of gait variability across the lifespan in people with Down Syndrome (Smith, Stergiou and Ulrich, 2011). For more information about LyE see Wolf et al. (1985) and about Surrogation see Theiler, Eubank, Longtin, Galdrikian and Doyne-Farmer (1992).

Another property of the variability complexity is the degree of irregularity of the time series (Adjerid et al., 2014; Chen, Wang, Xie and Yu, 2007; Guerreschi, Humeau-Heurtier, Mahe, Collette and Leftheriotis, 2013; Huang, Yen, Tsao, Tsai and Huang, 2014; Richman and Moorman, 2000; Wu, Wu, Lin, Lee and Peng, 2014; Zbilut, Webber, Colosimo and Giuliani, 2000). Several tools have been used to assess this characteristic. One of them is Recurrence Quantification Analysis (RQA). This tool combines recurrence plots (Eckmann, Kamphorst and 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). Previous works have used RQA to analyze postural fluctuations (Riley, Balasubramaniam and Turvey, 1999) or to analyze changes in heart rate variability (Javorka et al., 2008; Wilkins et al., 2009).

On the other hand, a relevant collection of tools called entropy measures have also been used to assess the degree of irregularity. Usually, high values of entropy indicate high irregularity. The first and most used entropy measure applied to human variability has been Approximate Entropy (ApEn) (see Pincus, 1991). This entropy measure has been used in a large number of studies, from physics to health and human performance. For example, ApEn has been applied to quantify impaired neuromotor control of movements early in life (Smith, Teulier, Sansom, Stergiou and Ulrich, 2011), to assess mental fatigue (Liu, Zhang and Zheng, 2010), or to study changes in intracranial pressure (Hornero, Aboy, Abásolo, McNames and Goldstein, 2005). Due to the relative inconsistency on ApEn and its dependence and the dependence on data series length, Richman and Moorman (2000) developed Sample Entropy (SampEn) as an improved entropy measurement. This statistic excludes the counts where a vector is compared with itself to relieve the bias caused by self-matching, thus, it shows more consistency than ApEn. SampEn has been used in several studies, for example to assess the regularity of center of pressure dependent on the amount of attention invested in postural control (Donker, Roerdink, Greven and Beek, 2007), to assess the effect of training in postural control (Menayo, Encarnación, Gea and Marcos, 2014), to find differences between Schizophrenia and Depression (Hauge, Berle, Oedegaard, Holsten and Fasmer, 2011) or to analyze neonatal heart rate variability (Lake, Richman, Griffin and Moorman, 2002). However, problems still exist in the validity of SampEn because the definition of vectors was very similar to ApEn. For this reason, Chen et al. (2007) have recently developed a new related statistic, Fuzzy Entropy (FuzzyEn).

FuzzyEn shows some advantages such as a stronger relative consistency, less dependency on data length, freer parameter selection and more robustness to noise (Chen, Zhuang, Yu and Wang, 2009). Consequently, it has been used in the last years to assess local muscle fatigue (Xie, Guo and Zheng, 2010) or to know the effects of increasing difficulty in standing balance tasks (Barbado et al., 2012).

Despite the improvements of the different measurements of Entropy, some authors suggested that traditional algorithms were single-scale based and, therefore, failed to account for the multiple time scales inherent in physiologic systems (Costa, Goldberger and Peng, 2005). Costa, Goldberger and Peng (2002) propose the use of Multiscale Entropy (MSE) to solve the apparent paradox between variability and complexity because it yields higher entropy values for correlated than for uncorrelated signals across a range of scales (Kang, Jia, Geocadin, Thakor and Maybhate, 2009). This method quantifies the information content of a signal over multiple time scales and it can be used with a variety of measures of entropy. This non-linear method has been used mainly in physiological signals like heart rate (Norris, Anderson, Jenkins, Williams and Morris, 2008; Thuraisingham and Gottwald, 2006) but it is also used for other topics such as to select wavelet for fault diagnosis of ball bearings (Vakharia, Gupta and Kankar, 2014).

In the study of Vakharia et al. (2014), MSE is applied using Permutation Entropy (PE). This recent entropy statistic, originally applied by Bandt and Pompe (2002), assess the frequency of the appearance of permutation patterns in a time series, only making use of the order of the time series values. In contrast with the other irregularity variables, PE shows a high robustness to noise and data length. Although this tool is less known in analyzing human movement variability, several works have used it to detect dynamical changes in time series, mainly in brain wave signal (Cao, Tung, Gao, Protopopescu and Hively, 2004; Kreuzer, Kochs, Schneider and Jordan, 2014; Li, Ouyang and Richards, 2007; Olofsen, Sleigh and Dahan, 2008), but it has also been used to find changes in heart rate variability (Bian, Qin, Ma and Shen, 2012) or to discriminate the stage of stock market development (Zunino, Zanin, Tabak, Pérez and Rosso, 2009).

However, although entropy measurement tools have been improved, some authors have argued that the regularity of the signal, measured by entropy parameters, is not clearly related with the complexity of system dynamic (Goldberger, Peng, et al., 2002; Stergiou et al., 2006). In this sense, there are other nonlinear measures frequently used to assess the complexity of movement variability by analyzing the long range auto-correlation of the signal or, termed by some authors, fractal features (Holden, 2005). In this way, a specific level of auto-correlation is related to a specific noise, pink noise or 1/f (Holden, 2005). Pink noise seems to be related with a functional dynamic of the system (Van Orden, Kloos and Wallot, 2011) and, in this sense, it has frequently been used to assess the complexity of data fluctuations by analyzing the long range auto-correlation of the signal. Detrended Fluctuation Analysis (DFA) (Peng, Havlin, Stanley and Goldberger, 1995) is a scaling analysis method used to quantify long-range power-law correlations in signals. DFA evaluates the presence of long-term correlations within the time series by a parameter referred to as the scaling index α (Bashan, Bartsch, Kantelhardt and Havlin, 2008; Peng et al., 1995). This procedure estimates the fractal scaling properties of a time series (Duarte and Sternad, 2008) so that an index α equal to 1 is related with pink noise and fractal characteristics (Holden, 2005) and it has also been used to describe the complexity of a process (Goldberger, Amaral, et al., 2002). DFA is one of the most used tools in variability analysis and it has been applied to health topics, like to assess heart rate variability (Ahmad et al., 2009; Castiglioni, Parati, Civijian, Quintin and Di Rienzo, 2009; Dutta, Ghosh and Chatterjee, 2013; Kirchner et al., 2014; Muskulus, Slats, Sterk and Verduyn-Lunel, 2010; Schmitt, Stein and Ivanov, 2009) or gait analysis (Kirchner, Schubert, Liebherr and Haas, 2014).

Is there a "best tool" to measure variability?

As we have said above, there is much controversy about the analysis of variability and how to measure it (Caballero, Barbado and Moreno, 2013; Goldberger, Peng and Lipsitz, 2002; Stergiou and Decker, 2011; Vaillancourt and Newell, 2002). The use of so many variables to assess the motor variability have caused problems with the lack of specificity about what variability is and what the way to measure it is.

There seems to be a generalized rationale about the "functional" variability and its relationship to deterministic non-linear dynamics of the fluctuations (Stergiou, 2004; Stergiou et al., 2006); thus, optimal variability is characterized by chaotic structure (Stergiou, Yu and Kyvelidou, 2013). Therefore, the use of non-linear tools to measure variability has the aim to find these characteristics in the movement fluctuations (Bandt and Pompe, 2002; Duarte and Sternad, 2008; Kodba, Perc and Marhl, 2005; Sano and Sawada, 1985; Zbilut and Webber, 2006). However, it is not so clear that all non-linear measures are able to detect chaotic structure. Several authors have used entropy measures to analyze movement complexity (Barbado et al., 2012; Chen et al., 2007; Pincus, 1991; Richman and Moorman, 2000; Xie et al., 2010; Zanin, Zunino, Rosso and Papo, 2012; Zbilut et al., 2000). Nevertheless, Stergiou et al. (2006) related the level of complexity with the level of predictability of the signal in a non-direct relationship but in an inverted U-shape relationship, with the presence of chaotic temporal variations in the steady state output of a healthy biological system.

We previously underlined the arguments against the use of entropy to characterize the complexity of a time series (Costa et al., 2002; Goldberger, Peng, et al., 2002), mentioning other methods like MSE or fractal measures like DFA. Hence, we could not say that higher values of entropy measures indicate higher variability or, at least not by themselves alone. Harbourne and Stergiou (2009) indicate that one of the features of complexity is its dynamic stability and another is the degree or regularity, and they measured them through LyE and entropy measures. Entropy measures should not be enough to characterize the motor variability but they may provide useful information. Several authors suggest the need to use more than one non-linear tool to be able to assess the variability (Goldberger, Peng, et al., 2002; Harbourne and Stergiou, 2009; Stergiou and Decker, 2011), and, for this purpose, a manifold of different tools would be useful to address the dynamics of a system and characterize its variability.

Principal Component Analysis (PCA) and Cluster Analysis two of the most used statistic tools that could help us understand the relationship between the different variables and the importance that each of them has in the definition of the motor variability.

Principal component analysis (PCA) is a multivariate statistical technique used to know to what extent the variability within a group of variables is related between them and, therefore, allows to reduce the dimensionality of the dataset (Harbourne and Stergiou, 2009). This is achieved by transforming the original variables into new, uncorrelated variables (Jackson, 2005). The matrix used to transform the data contains information describing the way the data varies. PCA has allowed the examining of EMG activation relation among a large number of muscles during lifting task (Moreside, Quirk and Hubley-Kozey, 2014). In the same way, PCA has shown its utility to recognize kinematic and kinetic pattern during gait (Robbins, Astephen Wilson, Rutherford, and Hubley-Kozey, 2013).

A recent study by Harbourne and Stergiou (2009) has used PCA to assess to what extent the variability factors are related between them. These authors suggest that this tool could be useful to aid in the interpretation of the time series dynamic variability. Thus, PCA could be available to reduce the large number of non-linear tools in factors according to the characteristics of the complexity and to establish the relationship between them.

On the other hand, Cluster analysis was developed to identify patterns in high-dimensional datasets (Rein, Button, Davids, and Summers, 2010).

Agglomerative hierarchical analysis is the most common cluster analysis used in the literature (Blashfield and Aldenderfer, 1978; Gnanadesikan, Kettenring and Srinivas, 2007) and its results yields a hierarchical tree (termed a dendrogram) in which it is possible to identify groupings in the dataset (Rein et al., 2010). In human movement analysis this statistical tool has been used to assess sports kinematics movements (Bauer and Schöllhorn, 1997; Schöllhorn, 2003; Seifert et al., 2014; Seifert et al., 2013), or to assess postural control (Ball and Best, 2007; Toro, Nester and Farren, 2007). Cluster Analysis has been also used to identify different motivation profiles in sport populations (Chian and Wang, 2008; McNeill and Wang, 2005; Vlachopoulos, Karageorghis and Terry, 2000). In this sense, this statistical method could be used to define profiles grouping different properties of variability dynamics according to the state of the system.

Some final methodological concerns

The statistical tools reviewed can be useful to assist to the interpretation of dynamic of variability, but we cannot forget the importance of the methodological process to apply the non-linear variables in a reliable way. In fact, the application of the correct measuring processes could be another reason for the controversial results. Thus, we will introduce some considerations to keep in mind when applying non-linear tools.

First of all, we have to be careful with the type of the signal we are working with. Time series data from biological systems are generally typically non-stationary noisy series containing extreme values (Wijnants, Bosman, Hasselman, Cox and Van Orden, 2009). The non-stationarity reflects the changes occurred over periods of time that are observed on many time scales (Newell, Slobounov, Slobounova and Molenaar, 1997). Stationarity condition is dependent on the type of data evaluated (Costa et al., 2007) and on the length of the data (Carroll et al, 1993). Many non-linear tools need the stationarity condition to be reliably used. Regarding the non-linear tools discussed above, LyE and entropy measures seem to be affected by the non-stationarity. LyE needs to check the result to ensure robust exponent estimates (Wolf et al., 1985). Regarding entropy measurements, Costa et al. (2007) suggested that such non-stationarities may lead to a spurious increase in the apparent degree of irregularity of a time series for the shortest scales, so it is necessary to remove it to obtain reliable results. One possible solution to solve the effect of non-stationarity is to use statistical tools which do not make assumptions regarding stationarity of data, like DFA or RQA (Hausdorff, Peng, Ladin, Wei and Goldberger, 1995; Marwan, Carmen Romano, Thiel, and Kurths, 2007), or to apply procedures to avoid the non-stationarity of the time series. Costa et al.

(2007) suggested two different methods to detrend the data. The first method is based on the derivation of the original time series as the derivative time series are much more stationary than the original time series. The second solution is based on the use of an empirical mode decomposition (EMD) method. It has been developed to decompose nonlinear, non-stationary signals into their intrinsic frequencies components and it has the advantage of using a fully adaptive basis derived from each data set by means of a sifting process with regard to wavelet and Fourier analyses (for more information about EMD method see Wu et al. (2014). On the other hand, several authors find some solutions to avoid the non-stationarity according to the protocol conditions, like in the study of Carroll and Freedman (1993) or Van Dieën, Koppes and Twisk (2010), which suggest ignoring the first seconds of data in the case of analyzing postural control on unstable conditions.

Another important methodological issue to keep in mind is the length of the data time series. Almost all non-linear measures are affected by the length of the time series, so if we used short times series of data, the reliability of the tools can be reduced. In the literature we can find different recommendations in this regard according to the type of non-linear tools applied. For example, to use LyE, Wolf et al. (1985) conclude that for up to about a 10-dimensional system a number of data points ranging from 10_d to 30_d is required (being d=dimension of the attractor) and DFA needs at least 256 data points series (Delignières et al., 2006). Regarding entropy measures, the evolution of the different entropy tools developed has tried to improve the dependence to time series length. So that, although SampEn seems to be less sensitive to time series length that ApEn (Rhea et al., 2011), both need a minimum between 10_m-20_m number of data (being m= the length of vector to be compared) (Richman and Moorman, 2000). Regarding FuzzyEn, (Chen et al., 2009) suggested that it seems to be less dependent on data length but it is not completely independent.

It seems to be that the non-linear tools less affected by length of data are RQA (Riley et al., 1999; Wijnants et al., 2009) and PE (Zunino et al., 2009). To use the most of non-linear tools it is necessary to adjust the length of data according to the non-linear measure used. One possible solution for that is to increase the time recording but it leads to lengthy protocols. It might be thought that another way is to use higher sampling rate. However, some authors have warned against increasing the sampling frequency because it increases the number of data points artificially without added information and it is not a viable solution to generate the long time series that are necessary (Duarte and Sternad, 2008). For example, Rhea et al. (2011) observed a decrease in SampEn at higher frequencies suggesting SampEn is sensitive to the co-linearities that are present in an oversampled signal. It has been suggested to use frequencies close to the dynamics of signal (Caballero et al., 2013), so that we have the optimal sampling rate to allow us a reliable analysis of the system dynamic.

The last point to take into account is the noise of the signal. Noise can affect both the magnitude and the structure of the variability. Despite the fact that complex and chaotic patterns are different from random noise (they can be modeled using completely deterministic equations), it is often difficult to determine if fluctuations in biological data are chaotic or they are the result of random neuromuscular noise (Glass, 2001). Some works have analyzed how noise could influence various non-linear measures, for example, Rhea et al. (2011) used three deterministic signals with known noise properties, and by adding white noise to signals they found different results according to the level of the noise. LyE seems to be affected by the noise but just when it is estimated in high-noise environments (Rosenstein et al., 1993). Regarding entropy measures, PE and FuzzyEn seem to be the most robust to noise (Chen et al., 2009; Bandt and Pompe, 2002). On the other hand, RQA is also affected but it could solve the effect of the noise with a proper choice of the parameters used to compute it (Webber and Zbilut, 2005). For example, if an embedding dimension is chosen too high, the effects of noise may be amplified. To analyze biological data, Webber and Zbilut (2005) recommend beginning with an embedding dimension in the range of 10–20 and working downward from there to avoid the effect of the noise. Regarding DFA, previous works have noted the advantage of this tool over other scaling analyses because this analysis reduces noise effects (Hausdorff et al., 1995).

In conclusion, variability is an important aspect of the human movement and it can be related with the functional state of the system. The use of new tools seems to aid in the analysis of the movement dynamic but there are controversial results about this topic. One way to improve the analysis of variability dynamic could be the use of a statistical method that groups the variables that measure the different characteristics of the variability dynamic and to show the relationship between them. We must take into account the importance of experimental setting because these methodological processes could be other reasons for the controversial results.

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