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EXPLORING BODY SWAY TO DISCLOSE CHANGES IN POSTURAL CONTROL STRATEGY ASSOCIATED WITH PROPRIOCEPTIVE TRAINING

Franck Maze; María Teresa Blázquez-Tejada;
Francisco Javier Rojas

Faculty of Sport Science. Sports Biomechanics Laboratory. University of Granada, Spain

ABSTRACT

In the present study we analyze linear and nonlinear variability of body sway in young football players, in order to disclose changes in postural control strategy associated with proprioceptive training. It was investigated if these changes can be measured by detrended fluctuation analysis (DFA) or by centre of pressure (CoP) trajectory length analysis. CoP trajectories were obtained from 105 players. Upright stance posturography was performed before and after an intervention period, a football season, during which one half of the randomly assigned participants was proprioceptive trained and the other half was not. There are no significant differences between the results obtained for proprioceptive trained young football players and the not proprioceptive trained ones. The results showed the existence of a crossover from persistent to antipersistent behavior in the body sway. DFA has showed the skill to disentangle the highly complex multifractal dynamic of body sway, but this inner dynamics may hinder the detection of changes due to proprioceptive training. It was concluded that in the present work DFA and length analysis of body sway, have both emerged as unuseful tools for the objective assessment of proprioceptive training influence on postural control.

Key words: proprioceptive training, DFA, balance, body sway

ANÁLISIS DE LA OSCILACIÓN POSTURAL PARA INVESTIGAR CAMBIOS ASOCIADOS A UN ENTRENAMIENTO PROPIOCEPTIVO

RESUMEN

El objetivo del presente estudio ha sido valorar la posible influencia del entrenamiento propioceptivo sobre las oscilaciones del centro de presión (CdP) de futbolistas cadetes y juveniles. Se registraron, durante 102 s y a 80 Hz, las posiciones del CdP de 105 futbolistas utilizando una plataforma de presiones. El registro se realizó antes y después de una temporada de futbol, a lo largo de la cual un grupo (G1p) compuesto por la mitad de los participantes siguieron un entrenamiento propioceptivo y el resto actuó como grupo control (G1Np). Las trayectorias del CdP han sido analizadas mediante un método lineal, basado en longitud de trayectorias, y otro no lineal, utilizando la técnica detrended fluctuation analysis (DFA). No se encontraron diferencias estadísticamente significativas entre los resultados de G1p y G1Np. Los resultados han mostrado que mediante la técnica de DFA se ha podido desentrañar la compleja dinámica del comportamiento de la oscilación postural. Concluimos que la presente investigación ha mostrado que tanto la técnica DFA, como el análisis de la longitud recorrida por el CdP, no son procesamientos útiles para detectar, de forma sensible, la posible influencia del entrenamiento propioceptivo sobre el comportamiento del CdP.

Palabras clave: entrenamiento propioceptivo, DFA, equilibrio, oscilación postural

Correspondence:
Francisco Javier Rojas Ruiz
Faculty of Sport Science. Physical Education and Sports Department.
University of Granada
fjrojas@ugr.es

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INTRODUCTION

The human postural control system (PCS) enables bipedal stance along with the capacity to adapt to more complicated conditions such as standing on one leg or reaching for an object (Zhou, Manor, Liu, Hu, Zhang & Fang, 2013). This control system comprises a host of sensory elements integrated with spinal, supraspinal and peripheral motor circuitry (Mergner, Maure & Peterka, 2002). Information coming from the proprioceptive, vestibular and visual systems is integrated to achieve human body equilibrium. All the aforementioned systems are part of the PCS. This control system work is essential to perform sports. Playing football, for example, involves fundamental motor tasks that are influenced by numerous interacting systems (Weigelt, Williams, Wingrove & Scott, 2000). Proprioceptive information from various sources is integrated to control hundreds of muscles and bones to produce coordinated movements (Riemann & Lephart, 2002). Proprioceptive system performance is improved through experience, so specific training has been developing in this sense (Myer, Ford, Kevin, Palumbo & Hewett, 2005; Wong, Dinant, Kistemaker & Gribble, 2012).

A great number of recent works have focused on the effects of proprioceptive training (Ree, Murphy, Watsford, Mc-Lachlan & Coutts, 2007; Decicco & Fisher, 2005; Ingle & Nandu, 2009; Bergenheim, Ribot-Ciscar & Roll, 2000). Motor activity based on proprioceptive learning has also been put forward as an alternative to develop balance (Coubart, et al. 2014). Specifically proprioceptive training has been advocated as a promising program to boost motor control (Caplan, Rogers, Pan & Hayes, 2009). The proprioceptive system has also been a worth topic in football research (Molacek, Conley, Evetovich & Hinnerichs, 2010). The main tool used to investigate the PCS has been the stabilogram, which is a measure of the time behavior of the center of pressure (CoP) of a person standing on top of a force or pressures platform (Quatman-Yates et al. 2013; Romero, Martínez, Hita & Martínez, 2014).The time series of the position of CoP, or CoP trajectory, is an output of human PCS activity.

An important part of the investigations carried out by means of stabilograms were restricted to statistics of classical variables of the CoP trajectory, such as distances from the geometric mean CoP, CoP trajectory length, enclosed area, etc. (Romero et al. 2013; Weber, Villeneuve-Parpay, Nouhet & Villeneuve, 2001; Monzani, Bergamini, Luppi & Guidetti 1998; Prieto, Myklebust & Myklebust, 1994). This is a linear classical approach which is static in time, like a photo, and do not describe the characteristics of PCS that are predominately dynamic.

The concept of nonlinear dynamics suggests that variability in the PCS output reflected into the body sway is not randomness but highly structured. Nonlinear analysis such as DFA or Wavelet have showed the multifractal characteristics of CoP trajectory (Duarte & Zatsiorsky, 2001; Thurner, Mittermaier, Hanel & Ehrenberger, 2000; Blázquez, et al. 2009). DFA was first introduced by Peng, Havlin, Stanley & Goldberger, (1995) to determine the dynamic variability of heart rate. The application of DFA has reached various topics such as motor control (Hausdorff et al. 2005; Hu et al. 2004), heart rate dynamics (Ivanov et al. 1999), visual motor control (Mergenthaler & Engbert, 2007) or human walking (Dingwell & Cusumano 2010).

DFA analysis has also been a worth tool in sport research (Barbado, Elvira, Moreno & Vera-García, 2015; Bueno, Lizano, Montano, 2015; Casties, Mottet & Le Gallais, 2006; Jordan, Challis & Newell, 2006; Mann et al., 2015; Weippert et al. 2015). Vázquez, Hristovski & Balagué (2016) conducted DFA to prove the existence of a long-term variability in control strategies during exercise. Caballero, Barbado, Davids & Moreno, (2016) computed DFA to assess the complexity of CoP and investigate the extent to which specific interacting constraints of performance might increase or decrease the emergent complexity in a movement system. Combination of DFA and football is not a frequent topic but a few papers appeared (Hardiman, Richmond & Hutzler, 2011; Jelinek et al., 2014). Bruno, Pereira, Fernandes & de Mendoça (2011) applied DFA to discriminate different patterns during supramaximal exercise in children engaged in competitive sports: swimmers and football players.

Following the literature, DFA has not yet been applied to CoP trajectories of young football players to elucidate the effect of proprioceptive training. We consider that the flexibility of young players to exhibit different fractal patterns in the CoP trajectory due to proprioceptive training is a worth topic to be explored. Having at our disposal a large quantity of measurements, the main objective was to find out if the effect of proprioceptive training is reflected in CoP trajectory and can be disclosed by means of classical variables, such as the trajectory's length, or through the output of DFA which provides information about the dynamic characteristics of PCS.

METHOD

Participants

Upright stance posturography was performed in 105 male young football players aged 14-18 years. All the participants were male players participating in youth football teams in Granada and Cuenca. Prior to testing, all participants provided written informed consent and the measurements were done in compliance with the ethical principles enunciated in the Declaration of Helsinki.

All participants were randomly assigned in two groups:

G1Np: Control group. 58 participants were assigned to this group, and didn't follow a proprioceptive training. With an average age, weight and height of 15.9 ±1.1 years, 66.4 ± 8.9 kg and 1.74 ± 0.07 m, respectively.

G1p: Experimental group. Composed by 47 participants that followed a proprioceptive training. With an average age, weight and height of 16.1 ± 1.6 years, 63.3 ± 11.1kg and 1.73 ± 0.08 m, respectively.

The final number of participants in each group is not the same because those who didn't attend all the measurements were ruled out from the study.

In order to study the effect of number of subjects in the statistical results: randomly assigned trained participants formed G2p and G3p composed of 21 (15.7 ± 1.4 years, 62.3 ± 12.8 kg and 1.72 ± 0.09 m) and 13 (17.7 ± 1.6 years, 66.1 ± 9.2 kg and 1.77 ± 0.08 m) participants respectively, and randomly assigned not trained ones formed G2Np (18 participants 16.5 ± 1 years, 68.6 ±8.6 kg and 1.76 ± 0.09 m) and G3Np (18 participants 15.7 ± 0.9 years, 68.2 ± 10.9 kg and 1.76 ± 0.07 m).

Material and procedure

Measurements were performed in quiet standing on a pressures platform (Type PF2002; Satel, France, Figure 1) which captures force load exerted on foot support at a frequency of 80 Hz. This platform includes three force sensors situated at the vertices of an equilateral triangle with a side of 40 cm. The output permits one to obtain the projection of the CoP path on the plan xy.

Participants were instructed to remain in quiet upright stance on the force platform (feet barefoot splayed at an angle of 30º, arms in hanging position) and look in the forward direction. Each measurement lasted for 102 s and was repeated two times: first time at the beginning of the football season and second time at the end of it.

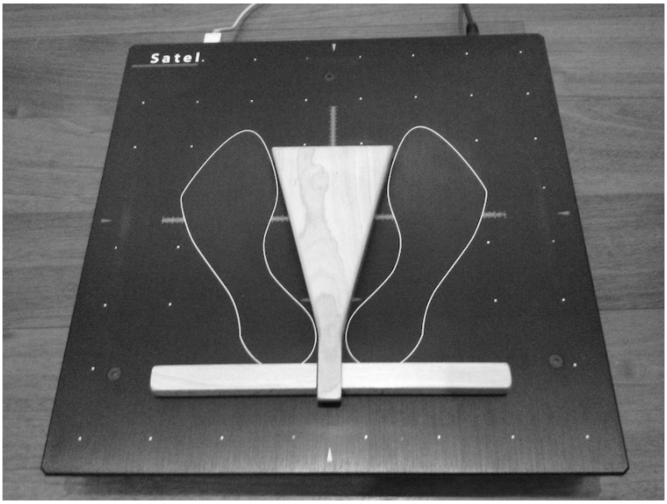

FIGURE 1: The pressures platform used in this study.

The analysis was carried out using the CoP displacement (Figure 2 shows a typical CoP trajectory). For the analysis, this CoP trajectory is separated in its mediolateral, x(t) and anteroposterior y(t) components which provides time series shown in Figure 3.

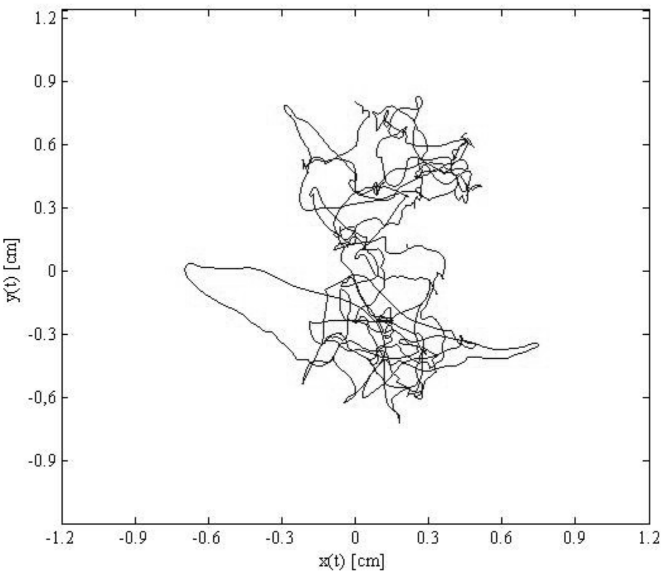

FIGURE 2: Typical CoP trajectory obtained from the pressures platform measurements.

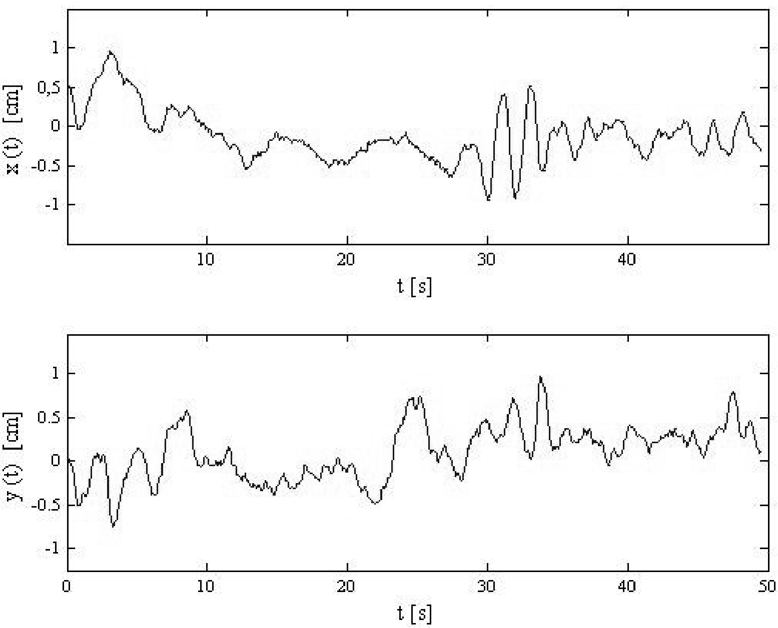

FIGURE 3: The two components of a CoP trajectory: x(t) and y(t).

Proprioceptive training

The experimental group carried out a proprioceptive exercise protocol after the warm-up. This proprioceptive performance lasted 6-7 minutes and it was included in their team training sessions all along the football season during 6 months. The proprioceptive protocol included the stimulation through mobilization of (a) feet sole, (b) astragal astragal-calcaneus ligaments, (c) cruciate knee ligaments, (d) ilio-lumbo-sacrum ligaments, (e) joints between L3-L4, D8-D9 and C5-C6, and (f) sternum-clavicle ligaments, in different positions of body structures. The proprioceptive training was performed with an emphasis on proper technique instructed to the participants using: landing technique, stressing "soft landing" and deep hip and knee flexion as opposed to landing with a "flat foot" in lower extremity extension. Visual examples of proper and improper biomechanical technique were given for each individual exercise by the physical trainer. The control group performed a warm-up designed by their coach.

DFA analysis

In this work, we have used the DFA method to analyze the CoP trajectories obtained in the way described at the beginning of this section. DFA, which was first introduce by Peng, Havlin, Stanley & Goldberger (1995), is a signal analysis method that provides a scaling exponent, α, which gives information concerning the inner dynamics of the signal.

Dynamic properties of CoP trajectory can be assessed with the exponent α which is the output of DFA. This exponent α can be called scaling exponent because it gives information according to different time or space scale. For instance, this paper explores the values of alpha in a small (short) time scale (0.3 s) and in a larger one (3.8 s). The value of $\alpha = 0.5$ indicates that the signal analyzed has a random or brownian dynamic. Values of α bigger than 0.5, $\alpha > 0.5$, are associated with persistent dynamics, while $\alpha < 0.5$ indicates anti-persistence. Thus, DFA provides a valid indicator of the statistical "persistence" or "anti-persistence" in time series.

"Persistence" means that deviations in a time series, or signals, are statistically more likely to be followed by subsequent deviations in the same direction (i.e., they "persist" across subsequent data points). "Anti-persistence" means that deviations in one direction are statistically more likely to be followed by subsequent deviations in the opposite direction. Applied to CoP trajectory this means that if the distance to the equilibrium point increase at a certain moment, this increase in size will go on if the dynamic of the CoP trajectory is persistent, whereas it would be more likely to decrease in the next moment in case of having an anti-persistent dynamic.

In case there is not inner dynamics in the signal, DFA indicates no value for α. A certain mathematical behaviour must be found in the signal to calculate this α exponent. From a mathematical point of view this behaviour is named fractal. This word was created by Mandelbrot (1975), and refers to a iterative structure that doesn't change from whatever scale is observe. Thus if a value of α is found in the CoP trajectory this means that is a fractal signal, and if different values of α are found in different scales this means is a multifractal signal.

The length of each CoP trajectory was also calculated. This variables, exponent α and length, were computed in the mediolateral, x(t) and anteroposterior y(t) components of CoP trajectory, which is a time serie, or signal, composed by the different CoP's positions in time. An example of these CoP trajectory components was already shown in Figure 3.

The detrended fluctuation analysis (DFA) was computed using MATLB (Mathworks Natick MA) developed following instructions sent by Dr Peng (DFA creator), described by Blázquez, et al. (2009).

RESULTS

To start examining the effects of proprioceptive training on nonlinear inner dynamics of body sway we compared the changes in α exponents, obtained through DFA, between the beginning (A) and the end (B) of a football season ($\Delta\alpha = \alpha(B) - \alpha(A)$). The values of α exponents were computed in two different time-scales. A small one: 0.3 s; we named this time scale short-time (ST). And a large one: 3.8 s; named large-time (LT).

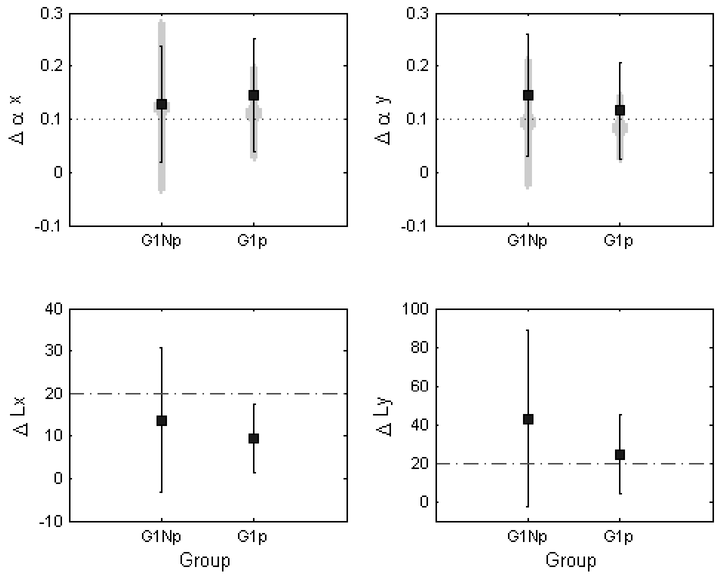

FIGURE 4: Change of the two variables analyzed between A and B. In upper panels the results for ST are depicted with a thick line and for LT with a thin one. Mean values and standard deviation for 1 σ are shown.

Upper panels of Figure 4 show the mean value and standard deviation of the change of α exponent (Δα), in ST and LT, for the control group G1Np (no proprioceptive training) and the experimental one G1p (proprioceptive trained), in the mediolateral x and anteroposterior y components of CoP trajectory. These results indicate that there is no significant difference between changes in α exponents related to G1p and G1Np.

To examine the linear characteristics of body sway the length (L (cm)) was calculated of each CoP trajectory registered. In order to compare this variable in the experimental and control groups, a protocol as the previously described was done. The lower panels of Figure 4 shows the changes in length (ΔL) found between A and B. As in the upper panels here we found that margin results overlaps between the trained and not trained groups.

In addition we calculated α exponents for the first and the second half of each measurement. We refer to them as H1 and H2 respectively. This is a way to analyze the effects of signal size; it means: the duration of a measurement, or the number of data point registered. Total measurement lasted 102.4 s, at a sampling frequency of 80 Hz (so 8192 data points were registered in each measure); whereas H1 and H2 correspond to half total measurement (51.2 s, 4096 data points). Figure 5 shows the change of α exponents for H1 and H2. When we compare them to those of total measurements (left section) no significant differences are found, it rather indicate that they are very similar. So no evidence is found about the influence of measurement size at this range.

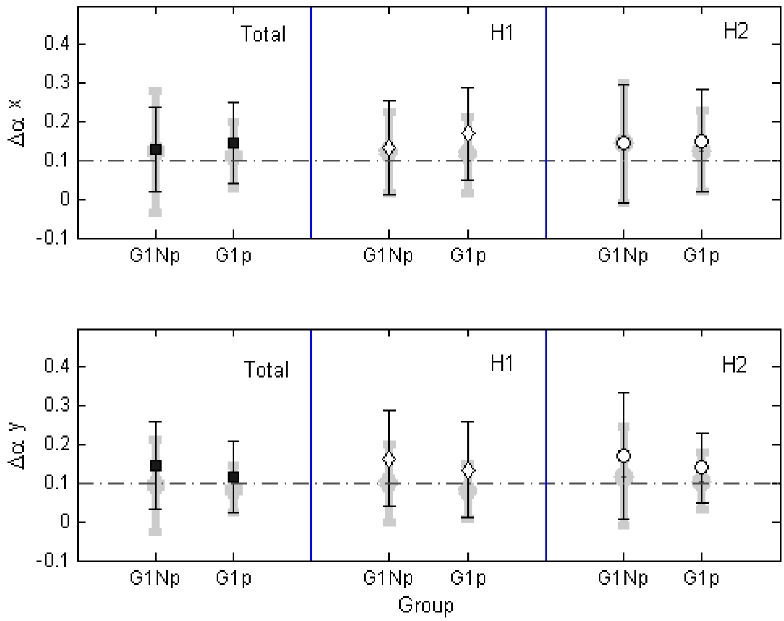

FIGURE 5: Change of exponent α between A and B, calculated for each of the total measurements, and for the first and second half of the total ones (H1 and H2). The results for ST are depicted with a thick line and for LT with a thin one. Mean values and standard deviation for 1 σ are shown.

As a second part, we analyzed the effect of group size. For this purpose we calculated α exponents for smaller groups: G2p and G3p (p trained), and G2Np and G3Np (not p trained) which were described in previous section. Fig. 6 shows the results of the change in α between the beginning and the end of a football season. We observe that results are very similar in all the groups, times scales and direction components of CoP trajectories. There is overlap in all the comparison among standard deviations. So, in this case, no evidence about group size is found at this range.

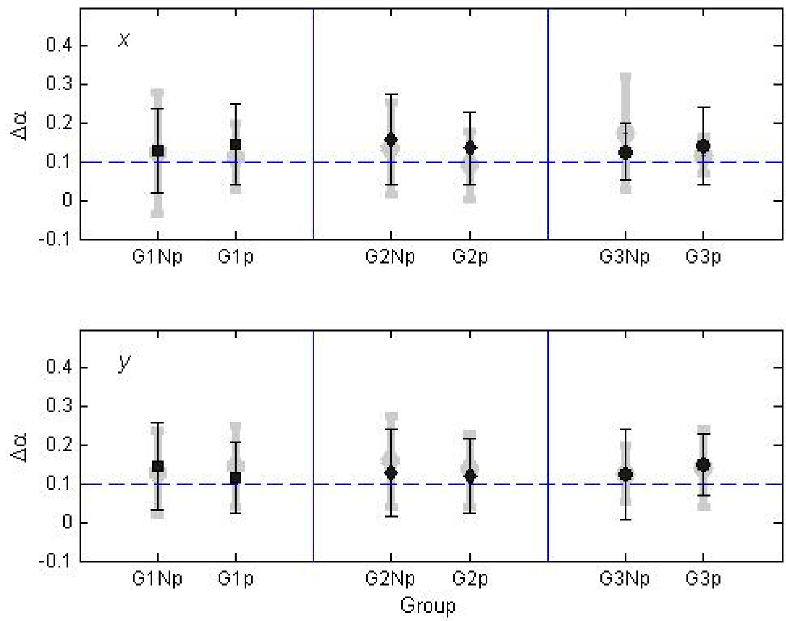

FIGURE 6: Change of exponent α between A and B, calculated for groups of different size. The results for ST are depicted with a thick line and for LT with a thin one. Mean values and standard deviation for 1 σ are shown.

Next step to examine the characteristics of the variables calculated is done thought the mathematical analysis of their distribution function. Figure 7 shows the histograms of the variable length (L) obtained for all the subjects of G1p. The shape of this histograms doesn't fit as a fine approximation to a gaussian or normal distribution. So to perform a statistical analysis based on gaussian or normal distributions, as the t of Student, a bigger number of participants or measurements is needed.

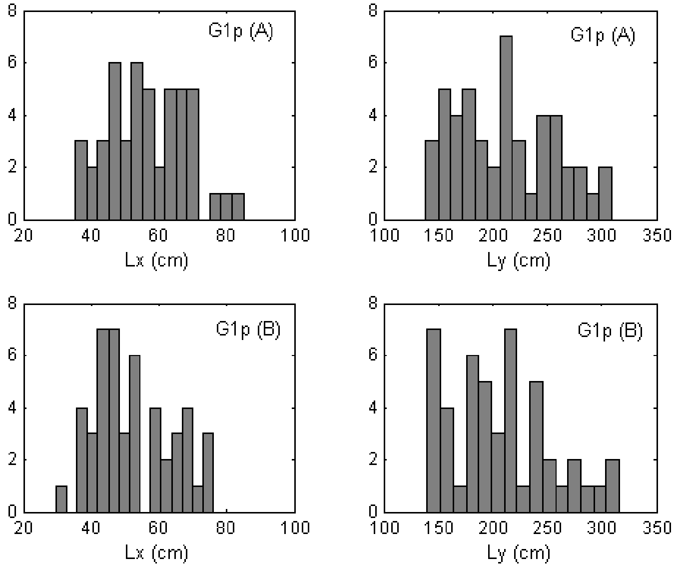

FIGURE 7: Distribution of CoP trajectories length values obtained for group G1p at A and at B.

Lower right and left panels of Figure 4 show that changes in length for the anteroposterior sway are larger than those for the mediolateral direction. This may be related to the difference that can be found in Figure 7 where the mean length along the component y is approximately three time larger than the x one.

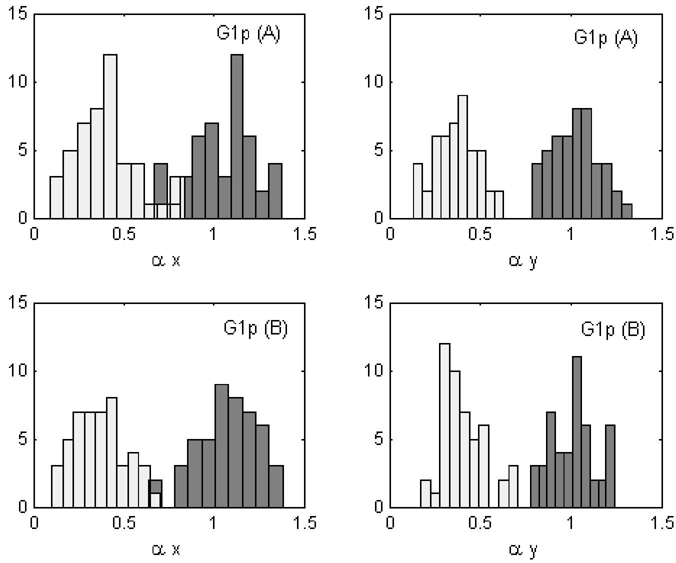

FIGURE 8: Distribution of α exponent values obtained for the CoP trajectories of group G1p at A and at B. The values found in ST are depicted with dark colour and those for LT with a pale one.

Figure 8 shows the histograms of the α exponents in short (ST) and large (LT) time scales, pictured in dark and pale colours respectively. The mathematical approximation to a gaussian or normal distribution is better than in the case of the linear variable L, but still if we apply t Student analysis its results wouldn't offer enough statistical robustness. To have a good approximation to a gaussian or normal distribution, a bigger number of participants or measurements of length is needed, but smaller than in the case of L.

The distributions of values of α exponents in the two time scale analyze have no overlap in the y-component, which indicate a significantly different dynamic behaviour (see Figure 8). Also the overlap in the x-component is very small which may also indicate this difference. The values of α exponent in ST are always bigger than 0.5, which means that the body sway has persistent dynamics in time scales of 0.3 s. The α values found in LT, are mainly smaller than 0.5 which indicate the presence of anti-persistent dynamic behaviour in times scales of 3,8 s for most of the participants.

The results suggest that these trajectories present a crossover in the scaling properties. So a new way to explore if DFA is useful to assess changes due to proprioceptive training is throught this transition time.

Figure 9 shows the values for transition time (*tc*), meaning the time scale in seconds when the dynamics of body sway swaps from persistence to anti-persistence. There are not significant differences between the results observed for trained and not trained groups. The point that deserves a comment is the size of the desviation standard margins, which show the wide range of postural control strategies of the body. This wide range may hinder the detection of changes in body sway due to external interventions. So this new variable is not able to elucidate the effect of the proprioceptive training on body balance.

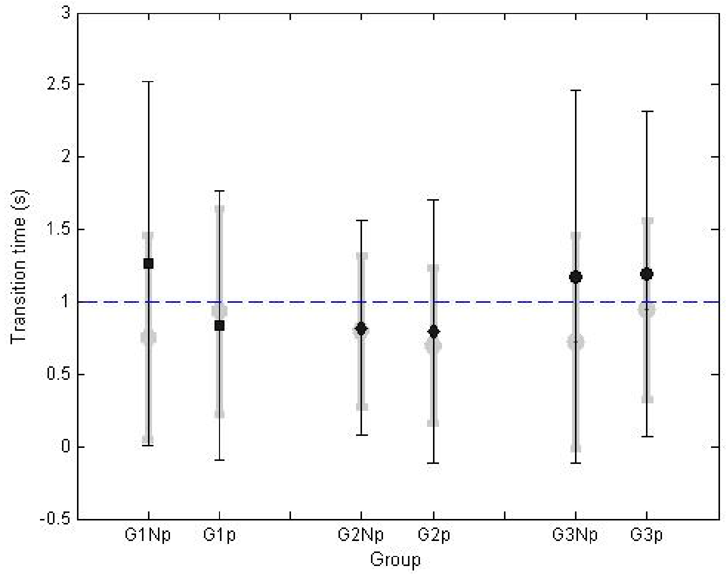

FIGURE 9: Transition time calculated for groups of different size. The results for x-component are depicted with a thick line and for y-component with a thin one. Mean values and standard deviation for 1 σ are shown.

Finally we compare the change of the variables calculated in two cases. On one hand we compare the results at the beginning (A) and at the end (B) of the football season. On the other hand the comparison is done between the first (H1) and the second (H2) half of each measurement. Our purpose is twofold: first to quantify the changes described, second to compare these changes. In Figure 10 we show the changes in length (ΔL) in the cases previously described. These changes are slightly larger in (B-A), specially in the y-component, due to the larger movements in the anteroposterior directions that were showed before. The attention must be directed to the fact that a change is also found when we compare the beginning and the end of a measurement, and moreover that the difference in the ΔL is not very significant between both cases: (B-A) and (H2-H1).

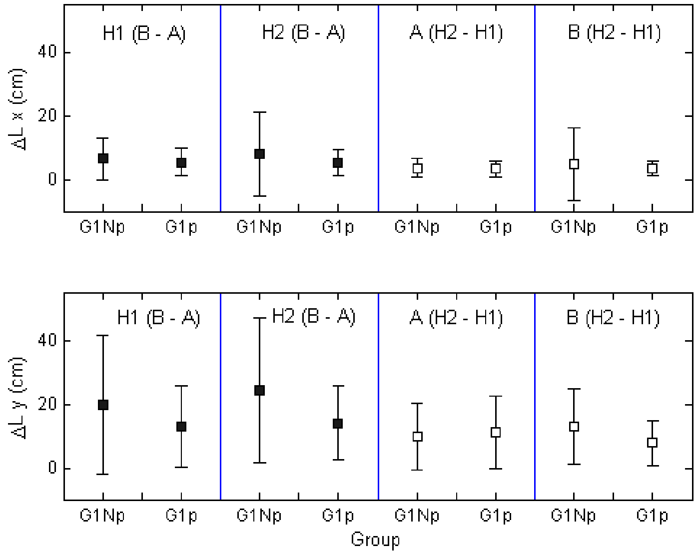

FIGURE 10: Changes in length (ΔL). Left side shows the change between B and A, for first half measurements (H1(B-A)) and for second half (H2(B-A)). Right side shows the change between H2 and H1, at the beginning of the football season (A(H2-H1)) and the end (B(H2-H1)). Mean values and standard deviation for 1 σ are shown.

To find a change in a variable between two measurements done before and after a football season seems natural, whereas to find a change in a variable measured under the same conditions is not so expected. This is so when there is a living process under study. The change between two measurements done one after the other manifests the presence of complex living processes working out of the researcher's control. The change between H1 and H2 shown in Figure 10 indicates the variability of postural control dynamics, it means that even in similar external conditions the inner balance processes have a variability along time.

To deepen in the quantification of inner balance processes's effects independent of experimental conditions we have calculated the proportion between the mean values of the variable change (under similar conditions: H2-H1 and under an intervention period of time: B-A) and the mean values of the variable. Table 1 show results for (ΔL / L)*100. The changes of the variable L between A and B, and H1 y H2 are express as 100 % percentage of variation of L. Table 2 shows similar results for (Δα / α)*100. Note that this is not a comparison between standard deviation and mean value, but between two mean values, express as a 100 % percentage.

TABLE 1
Results for (ΔL / L)*100.

L	G1Np		G1p	
Axe	H2 - H1	B - A	H2 - H1	B - A
x	14.5%	23.4%	12.2%	17.2%
y	9.2%	29.7%	9.1%	11.8%

TABLE 2
Results for (Δα / α)*100.

α	G1Np		G1p	
Axe	H2 - H1	B - A	H2 - H1	B - A
x(ST)	8.9%	11.4%	8.3%	10.7%
x(LT)	30.8%	35.6%	26.7%	37.7%
y(ST)	8.3%	8.93%	7.3%	8.29%
y(LT)	30.9%	36.9%	25.3%	29.8%

ST: Short time scale LT: Large time scale.

It was aimed to observe the relation between the proportional change in B from A, and H2 from H1. In Table 1 this observation points out the short margin of difference between length change with similar and different conditions, (H2-H1) and (B-A) respectively, and with and without proprioceptive training (G1p and G1Np). Similar results are observed in Table 2, where α exponent proportional change also shows slight differences in the cases previously compared. So the inner dynamics of body sway, meaning balance control mechanism of PCS, hinder the effects of external interventions as a proprioceptive training.

It should also be noted that the values found in large time scales (LT) are three times bigger that those found in small time scales (ST), which may indicate the complex running of balance control mechanisms working in large time scale where antipersistent behaviour is present in the body sway.

DISCUSSION AND CONCLUSIONS

The main aim of this research was to clarify whether the influence of proprioceptive training on body sway, which is the reflection of PCS work, is detectable by analytic technique DFA.

The values of the scaling exponent α, the output of DFA, found for CoP trajectories are very similar for all the cases analyzed. So there are no significant differences between the results obtained for proprioceptive trained young football players and the not proprioceptive trained ones. This may suggest that analysis of nonlinear dynamics in body sway through DFA doesn´t carry the potential to achieve objective measurements for the influence of proprioceptive training.

The same aim was fixed for the linear variable length of CoP trajectory. Here we found a foreseeable result: linear variables associated to the postural control output are not an useful tool for objetive assesment of experimental intervention on PSC.

The first point that deserves a comment is the fact that the exponent α reveals a significant different value in each of the time scales studied. The results showed that the inner dynamic characteristics of human balance, reflected in the body sway, exhibit a persistent behaviour in small time scales (0.3 s) and an antipersistent one in larger time scales (3.8 s). As two different α exponents are founded, the PCS is multifractal.

The meaning of these results is that in small time scales the body balance mechanisms seem not to work properly as its persistente behaviour indicates risk of falling: when the body is getting away from the equilibrium point it persist in doing so. While in larger time scales, where antipersistent behaviour is present, whenever the distance from the equilibrium point increases the balance mechanisms foster an aproach to equilibrium in the next period. This behaviour has been pointed out by various authors (Blázquez, et al., 2009; Duarte & Zatsiorsky, 2000; Thurner et al., 2001) and we suggest that it may due to energy save strategies of PCS, the complex control mechanism that achieve antipersistence are only use at time scales where there is fall risk. This work shed light on the fact that healthy postural control exhibits highly irregular, complex dynamics which operates on different time scales.

The crosseover from persistence to antipersistence points happens at a precise time named transition time (*tc*). Several authors have published results for *tc* values (Blázquez, et al. 2009). In this work we've given a step forward by providing the change margins of *tc*; meaning the range of different values of the change in *tc* between two different measuments. For the control group (G1Np), the quantification of *tc changes where done between measurements done in different days: variation margins of 1.2 ± 1.3 s were found* for the dynamics of anteroposterior movement and 0.7 ± 0.7 s for the mediolateral one. This result shows that the crosseover from persistence to antipersistence can take place at quite different time-scales.

On one hand DFA has showed the skill to disentagle the highly complex multifractal dynamic of PCS. And in the other hand, this multifractal inner dynamics hinder the detection of changes in body sway due to external interventions, such as a proprioceptive training. This means that the inner dynamics produce changes in the calculated variables that may hinder changes due to a proprioceptive training.

To deepen in the quantification throught DFA of changes due to the inner dynamics of body balance, comparisons between measuments done under similar and different conditions were done. The results of the α exponent show evidence about the not significant differences between changes due to inner dynamics and those due to external interventions. The same calculations were done for variable length, and similar results were found. In our work results showed no differences for groups composed by 13 to 58 participants, and measurements of 4096 and 8192 registered data points. So in order to study if this lack of significant difference is due to effect of group and measurement size, bigger groups and larger measurements can be analyzed.

It was concluded that DFA analysis is not an useful tool for objective assesment of proprioceptive training influence on PSC, at least when CoP trajectories were analysed at 80 Hz for 102 s or less, for a groups of 105 participants or less. Future studies should further explore a larger number of measurements sampled at higher frecuencies for a longer time. DFA method includes statical calculations, so results in DFA have associated a statistical robustness that depends on the number of data points analyzed. Working in this direction may shed light to utterly clarify DFA possibilities to disclose changes in postural control strategy associated with training.

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