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RESEARCH ARTICLE

What COP and Kinematic Parameters Better Characterize Postural Control in Standing Balance Tasks?

Carla Caballero, David Barbado, Francisco Javier Moreno

Centro de Investigación del Deporte, Universidad Miguel Hernández, Elche, Alicante, Spain.

ABSTRACT. The authors' aim was to determine which variables allow for the characterization of motor balance behavior. Traditional measures and nonlinear measures of center of pressure (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, mean velocity (mVel), permutation entropy (PE) and detrended fluctuation analysis (DFA) exhibited high consistency between trials and ranked individuals more accurately compare with other metrics. In the kinematic signal mVel, 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, mVel, PE, and DFA allow for the good characterization of motor balance behavior in a simplified protocol where velocity time series are analyzed.

Keywords: postural control, nonlinear measures, reliability, center of pressure, kinematic

The dynamic of center of pressure (COP) while standing is a collective variable, responsible for posture and balance (Riley & Turvey, 2002; Winter, 1995) that reflects the activities of many neuromuscular components acting together to keep the center of gravity within the base of support (Manor et al., 2010; Riley & 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 standard deviation (SD; Borg & Laxaback, 2010; Le Clair & Riach, 1996), root mean square (RMS; Haran & Keshner, 2008), resultant distance (RD; Roerdink, Hlavackova, & Vuillerme, 2011), central tendency measure (CTM; Ramdani et al., 2011), COP sway area (Hageman, Leibowitz, & Blanke, 1995; Manor et al., 2010), or mean velocity (Chiari, Cappello, Lenzi, & Della Croce, 2000; Le Clair & 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 what 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 mean velocity measure (Lafond, Corriveau, Hebert, & Prince, 2004; Lin, Seol, Nussbaum, & Madigan, 2008), although

no single measurement of COP appeared significantly more reliable than the others (Ruhe, Fejer, & Walker, 2010). T. L. Doyle, Newton, and Burnett (2005) indicated that the reliability of the traditional measures is questionable. However, Ruhe et al. 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-Weckler, Ragan, & Rosengren, 2007; Lafond et al., 2004; Santos, Delisle, Lariviere, Plamondon, & Imbeau, 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 & Riach, 1996; Schmid, Conforto, Camomilla, Cappozzo, & 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, & Parnianpour, 2010; Newell & Vaillancourt, 2001). Many authors have suggested that complexity is related to the capacity of the system to generate adaptive responses to stressors (Barbado, Sabido, Vera-Garcia, Gusi, & Moreno, 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 & Laxaback, 2010; Duarte & Sternad, 2008; Stergiou & Decker, 2011). For this purpose, the most used nonlinear measure has been approximate entropy (ApEn;

Correspondence address: Carla Caballero, Centro de Investigación del Deporte, Universidad Miguel Hernández, Av. de la Universidad s/n, CP: 03202, Elche, Alicante, Spain. e-mail: ccaballero@umh.es

Pincus, 1991). This tool, when applied to COP, has shown good reliability in assessing postural control. For example, Kyvelidou, Harbourne, Stuber, Sun, and Stergiou (2009), in an analysis of the development of sitting postural control in infants, concluded that ApEn had higher intra- and inter-session intraclass correlation coefficient (ICC) values than did the traditional parameters and another predictability measure, the Lyapunov exponent (LyE; Wolf, Swift, Swinney, & Vastano, 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, sample entropy (SampEn), to relieve the bias caused by self-matching. Van Dieen, Koppes, and Twisk (2010) analyzed the reliability of SampEn 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, & 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, & Wang, 2009). W. Chen et al. (2007) recently developed a new related family of statistics, fuzzy entropy (FuzzyEn). 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 permutation entropy (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, & 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 & 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 magnitude because it measures the entropy of sequences of ordinal patterns that are derived from m -dimensional delay embedding vectors (Frank, Pompe, Schneider, & 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 & Pompe, 2002). Nevertheless, the reliability results of SampEn, FuzzyEn,

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, & Lipsitz, 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 (SDA; Collins & De Luca, 1993) or detrended fluctuation analysis (DFA; Peng, Havlin, Stanley, & Goldberger, 1995). For example, DFA has been applied to analyze the changes in COP fluctuation with aging and disease (Goldberger, Peng, & Lipsitz, 2002). Amoud et al. (2007) assessed the reliability of these measures, and DFA appeared to show better reliability values than SDA. Van Dieen 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, & Topper, 1991), this type of measure can be limited in its ability to discern different postural strategies and movement patterns (Kuo, Speers, Peterka, & 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, & 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.

Method

Subject Inclusion and Exclusion Criteria

Thirty healthy volunteers took part in this study (M age = 27 ± 6.48 years; M height = 1.74 ± 0.09 m; M mass = 73.94 ± 10.77 kg), 11 women (M age = 25.18 ± 6.86 years; M height = 1.65 ± 0.06 m; M mass = 64.93 ± 5.79 kg) and 19 men (M age = 28.05 ± 6.19 years; M height = 1.79 ± 0.07 m; 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.

Experimental Procedure and Data Collection

To assess postural stability, ground reaction forces were recorded at 20 Hz by a Kistler 9287BA 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, & Moreno, 2013).

Synchronized kinematic data were collected from ten of the participants, using a 6-camera 100 Hz VICON MX-System with the associated workstation software (Vicon, Oxford, England). According to the plug-in gait model (Vicon), we placed 19 markers (Figure 1): over the incisura jugularis (CLAV), on the right and left shoulder (R/LSHO), on the acromioclavicular joint, on the right and left anterior superior iliac spines (R/LASI), on the right and left posterior superior iliac spine (R/LPSI), on the right and left mid-thigh stick (R/LTHI), on the lateral epicondyle of the right and left knee (R/LKNE), on the right and left midshank stick (R/LTIB), on the right and left lateral malleolus of the ankle along an imaginary line that passes through the trans-malleolar axis (R/LANK), on the right and left heel

(R/LHEE), 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 (R/LTOE), 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).

Participants performed two tests separated by 10 min each. Each test consisted of two trials in two different sway tasks conditions: (a) standing still on a force platform (stable condition) and (b) standing on a foam surface (unstable condition; Figure 2). In both conditions participants were asked to stand as still as possible (Cavanaugh, Mercer, & Stergiou, 2007; Duarte & 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.

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 nonstationarity related to the start of the measurement (Van Dieen et al., 2010). In addition using the protocol of Holden (2005), we used DFA to assess the stationarity of the signal (Tables 1 and 2). DFA values greater than 1 indicate that the signal is a nonstationary 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 affect the nonlinear results (Kyvelidou et al., 2009).

Postural sway was assessed using traditional COP-based measures in anteroposterior (AP) and mediolateral (ML) displacement: the SD (SD_AP/SD_ML) and mVel (mVel_AP/mVel_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 mVel magnitude (mVel_Magnitude) 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, & Fischman, 1995).

The variables used to assess the complexity of COP and movement kinematics were SampEn, FuzzyEn, PE, and DFA.

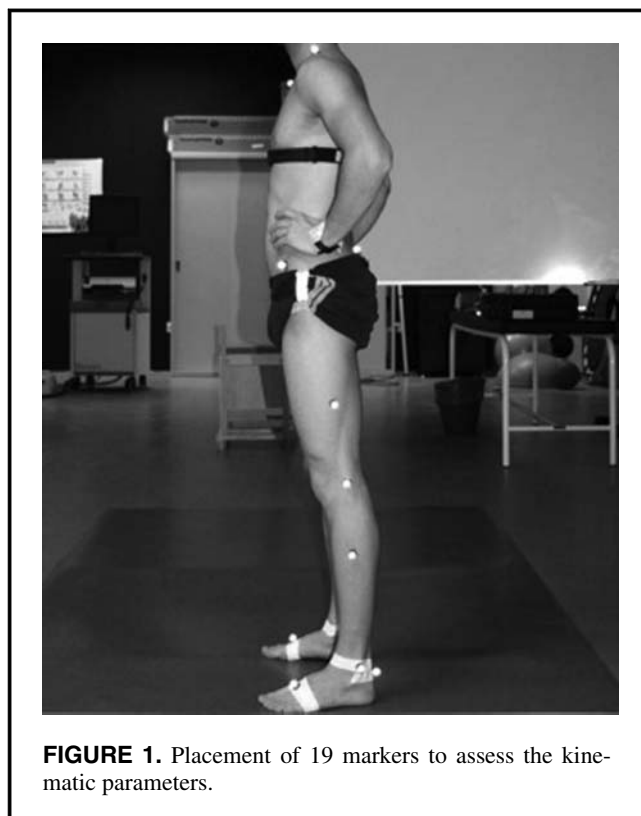


FIGURE 1. Placement of 19 markers to assess the kinematic parameters.

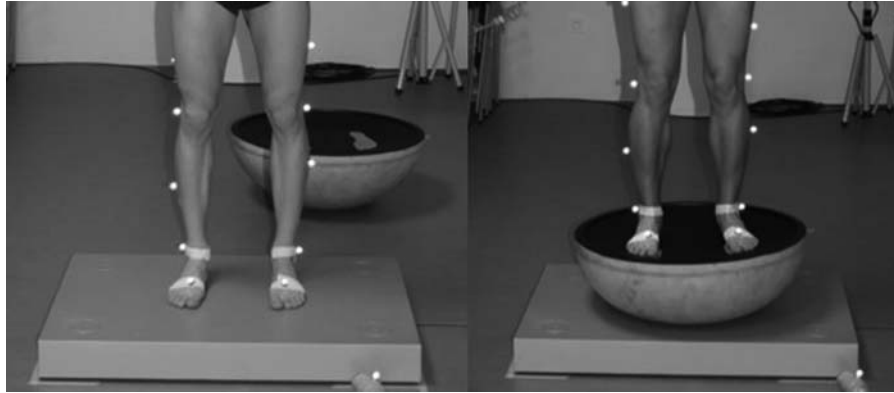


FIGURE 2. Stable (left) and unstable (right) conditions.

SampEn and FuzzyEn typically return values that indicate the degree of irregularity in the signal: higher SampEn and FuzzyEn values indicate greater irregularity in the time domain of the signal whereas lower SampEn and FuzzyEn 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 SampEn and FuzzyEn thus indicate that vectors of length m 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 SampEn and FuzzyEn we used the following parameter values: vector length, $m = 2$; tolerance window, $r = .2 * SD$; and gradient, $n = 2$ for FuzzyEn. 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, & 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, Bartsch, Kantelhardt, & Havlin, 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, & Stergiou, 2010). This procedure estimates the fractal scaling properties of a time series (Duarte & Sternad, 2008) and it has also been used to describe the

TABLE 1. Average Values of Variables of COP in the Displacement and Velocity Signals

	Displacement					Velocity			
	SC		UC			SC		UC	
	AP	ML	AP	ML		AP	ML	AP	ML
<i>SD</i>	2.77 ± 0.9	1.44 ± 0.72	10.95 ± 3.88	10.89 ± 3.49	<i>MV</i>	5.66 ± 1.58	4.46 ± 1.3	29.12 ± 11.76	27.35 ± 11.10
<i>be</i>	2.75 ± 0.81		13.69 ± 4.32		<i>MVM</i>	8.03 ± 1.98		44.68 ± 17.06	
<i>SE</i>	0.43 ± 0.11	0.67 ± 0.23	0.51 ± 0.14	0.5 ± 0.2	<i>SE</i>	1.87 ± 0.24	1.98 ± 0.19	1.39 ± 0.21	1.47 ± 0.28
<i>FE</i>	0.37 ± 0.11	0.6 ± 0.22	0.47 ± 0.15	0.45 ± 0.19	<i>FE</i>	1.76 ± 0.21	1.85 ± 0.16	1.46 ± 0.22	1.52 ± 0.30
<i>PE</i>	0.76 ± 0.06	0.82 ± 0.05	0.68 ± 0.07	0.72 ± 0.09	<i>PE</i>	0.95 ± 0.04	0.97 ± 0.03	0.83 ± 0.04	0.91 ± 0.04
<i>DFA</i>	1.24 ± 0.22	0.93 ± 0.26	1 ± 0.2	1.18 ± 0.19	<i>DFA</i>	0.53 ± 0.13	0.48 ± 0.22	0.55 ± 0.15	0.68 ± 0.18

Note. Units of center of pressure (COP) measures are as follows: mm (SD and BVE); mm/s (MV and MVM). SC = stable condition; UC = unstable condition; AP = anteroposterior axis; ML = mediolateral axis.

TABLE 2. Average Values 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	MV_Hip_Mg	1.60 ± 0.61	11.39 ± 8.38	BVE_Hip	0.35 ± 0.15	2.15 ± 0.82	MV_Hip_Mg	1.47 ± 0.79	10.85 ± 8.06
BVE_Knee	0.25 ± 0.13	1.75 ± 1.11	MV_Knee_Mg	1.08 ± 0.23	7.77 ± 7.24	BVE_Knee	0.21 ± 0.09	1.58 ± 0.83	MV_Knee_Mg	1.26 ± 0.98	9.39 ± 9.93
BVE_Ankle	0.24 ± 0.09	2.22 ± 1.02	MV_Ankle_Mg	1.21 ± 0.24	11.39 ± 8.57	BVE_Ankle	0.25 ± 0.146	2.03 ± 0.71	MV_Ankle_Mg	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
PPE_Hip_FLEX	0.93 ± 0.02	0.83 ± 0.09	PPE_Hip_FLEX	0.99 ± 0.00	0.93 ± 0.08	PPE_Hip_FLEX	0.83 ± 0.09	0.93 ± 0.02	PPE_Hip_FLEX	0.98 ± 0.00	0.92 ± 0.09
PPE_Hip_ADD	0.97 ± 0.01	0.91 ± 0.11	PPE_Hip_ADD	0.98 ± 0.00	0.96 ± 0.08	PPE_Hip_ADD	0.97 ± 0.01	0.90 ± 0.11	PPE_Hip_ADD	0.98 ± 0.00	0.95 ± 0.09
PPE_Knee_FLEX	0.96 ± 0.02	0.86 ± 0.07	PPE_Knee_FLEX	0.98 ± 0.00	0.94 ± 0.07	PPE_Knee_FLEX	0.96 ± 0.02	0.86 ± 0.08	PPE_Knee_FLEX	0.98 ± 0.00	0.93 ± 0.07
PPE_Ankle_FLEX	0.92 ± 0.03	0.72 ± 0.09	PPE_Ankle_FLEX	0.98 ± 0.00	0.90 ± 0.08	PPE_Ankle_FLEX	0.90 ± 0.04	0.74 ± 0.09	PPE_Ankle_FLEX	0.98 ± 0.00	0.91 ± 0.08
PPE_Ankle_ADD	0.97 ± 0.02	0.89 ± 0.09	PPE_Ankle_ADD	0.98 ± 0.00	0.96 ± 0.07	PPE_Ankle_ADD	0.97 ± 0.01	0.88 ± 0.08	PPE_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

Note. Units of center of pressure (COP) measures are as follows: mm (SD and BVE); mm/s (MV). SC = stable condition; UC = unstable condition; FLEX = flexion; ADD = adduction.

complexity of a process (Goldberger, Amaral, et al., 2002). This measure was computed according to Peng et al. 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 the errors incurred by estimating α (Z. Chen, Ivanov, Hu, & 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 nonstationary signals, all variables were calculated over the displacement and velocity of COP data. COP displacement usually shows nonstationary time series. However, the COP velocity time series, as the first derivative of the COP displacement is much more stationary (Costa et al., 2007).

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 nonreproducibility of the tested values (Lin et al., 2008).

Results

The mean values obtained from the COP and kinematic variables, under stable and unstable conditions, are presented in Tables 1 and 2. The ICCs and SEM values obtained from the COP variables of the study under stable and unstable conditions are presented in Tables 3 and 4, respectively. In the stable condition, the relative intrasession reliability of SD and BVE were poor. However, mVel 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 mVel showed the best values of the traditional measures and that PE

TABLE 3. 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	MV _{Mg}	.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

Note. AP = anteroposterior; ML = mediolateral; Mg = magnitude.
* $p \leq .05$.

produced the best results of the nonlinear measures. Moreover, PE had better results with respect to SEM than did mVel.

In the unstable condition, all of the traditional variables analyzed produced good values of relative intrasession reliability, but mVel was again the most reliable variable.

TABLE 4. 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	MV _{Mg}	.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

Note. AP = anteroposterior; ML = mediolateral; Mg = magnitude.
* $p \leq .05$.

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 mVel.

The intrasession reliability of kinematic variables is shown in Tables 5 and 6. 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 mVel 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.

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, & Werner, 2008; Lin et al., 2008; Salavati et al., 2009; Santos et al., 2008) and nonlinear variables (Amoud et al., 2007; Donker, Roerdink, Greven, & Beek, 2007; T. L. Doyle et al., 2005; Harbourne & Stergiou, 2003; Lin et al., 2008).

In stable and unstable conditions, mVel 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, mVel had higher consistency between trials (lower results in SEM) compared to SD and BE. Consequently, mVel seems to be a more consistent variable to detect changes in performance than SD and BVE (Raymakers, Samson, & Verhaar, 2005). SD and BVE showed poorer intrasession reliability results in stable situations and good results under unstable situations, but their results were lower than mVel. Our results 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 mVel is reliable despite the short time series used. In the present study, mVel has showed good intrasession reliability in a protocol that used sample durations of only 30 s (Le Clair & 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 (2010) 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 center of gravity (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 & Granata, 2010). 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 nonstationarity 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 magnitude 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.

TABLE 5. 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	65.90	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*	32.60	MV_Knee _{FLEX}	.461	25.50	
SD_Ankle _{FLEX}	.321	22.88	MV_Ankle _{FLEX}	.772*	16.90	SD_Ankle _{FLEX}	.325	26.60	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	MV_Hip _{Mg}	-.214	39.36	BVE_Hip	.654*	27.33	MV_Hip _{Mg}	-.022	51.80	
BVE_Knee	.317	35.16	MV_Knee _{Mg}	.156	24.56	BVE_Knee	.770*	17.20	MV_Knee _{Mg}	.059	59.50	
BVE_Ankle	.477	25.42	MV_Ankle _{Mg}	.385	16.42	BVE_Ankle	.106	31.80	MV_Ankle _{Mg}	.500	28.97	
SE_Hip _{FLEX}	.503	50.73	SE_Hip _{FLEX}	.026	23.80	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}	.595*	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	21.50	
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	62.70	FE_Knee _{FLEX}	-.266	12.80	
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	20.30	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	10.30	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	17.10	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	

Note. FLEX = flexion; ADD = adduction;

* $p \leq .05$.

TABLE 6. 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	.897*	23.82	SD_Hip _{FLEX}	.802*	41.79	MV_Hip _{FLEX}	.860*	41.79
SD_Hip _{ADD}	.631*	22.68	.918*	18.21	SD_Hip _{ADD}	.675*	26.67	MV_Hip _{ADD}	.953*	14.79
SD_Knee _{FLEX}	.617*	53.83	.885*	16.003	SD_Knee _{FLEX}	.303	56.56	MV_Knee _{FLEX}	.926*	12.29
SD_Ankle _{FLEX}	.319*	40.83	.921*	17.81	SD_Ankle _{FLEX}	.476	22.16	MV_Ankle _{FLEX}	.934*	15.17
SD_Ankle _{ADD}	.635*	41.01	.932*	13.82	SD_Ankle _{ADD}	.746*	23.49	MV_Ankle _{ADD}	.972*	11.60
BVE_Hip	.909*	12.28	.905*	16.26	BVE_Hip	.789*	20.54	MV_Hip _{Mg}	.940*	12.19
BVE_Knee	.711*	42.60	.895*	14.92	BVE_Knee	.450	40.16	MV_Knee _{Mg}	.175	75.94
BVE_Ankle	.425	35.82	.927*	14.93	BVE_Ankle	.700*	14.87	MV_Ankle _{Mg}	.964*	11.41
SE_Hip _{FLEX}	.727*	33.46	-.084	11.15	SE_Hip _{FLEX}	.844*	18.57	SE_Hip _{FLEX}	.013	11.02
SE_Hip _{ADD}	.672*	23.37	.754*	4.49	SE_Hip _{ADD}	.820*	17.09	SE_Hip _{ADD}	.123	7.78
SE_Knee _{FLEX}	.753*	36.50	.098	9.07	SE_Knee _{FLEX}	.735*	25.57	SE_Knee _{FLEX}	.004	11.73
SE_Ankle _{FLEX}	.472	20.60	.484	10.14	SE_Ankle _{FLEX}	.703*	23.86	SE_Ankle _{FLEX}	.601*	11.51
SE_Ankle _{ADD}	.820*	16.17	-.272	5.63	SE_Ankle _{ADD}	.874*	17.80	SE_Ankle _{ADD}	.472	6.50
FE_Hip _{FLEX}	.784*	29.64	.422	8.14	FE_Hip _{FLEX}	.787*	20.48	FE_Hip _{FLEX}	.605*	6.34
FE_Hip _{ADD}	.737*	22.93	.844*	1.92	FE_Hip _{ADD}	.761*	22.30	FE_Hip _{ADD}	.870*	2.40
FE_Knee _{FLEX}	.771*	35.35	.207	7.43	FE_Knee _{FLEX}	.712*	24.27	FE_Knee _{FLEX}	.616*	7.12
FE_Ankle _{FLEX}	.410	23.62	.659*	6.50	FE_Ankle _{FLEX}	.685*	25.94	FE_Ankle _{FLEX}	.773*	7.56
FE_Ankle _{ADD}	.833*	15.56	.704*	3.68	FE_Ankle _{ADD}	.896*	16.66	FE_Ankle _{ADD}	.790*	4.03
PE_Hip _{FLEX}	.432	4.79	.434	1.44	PE_Hip _{FLEX}	.614*	3.54	PE_Hip _{FLEX}	.664*	1.37
PE_Hip _{ADD}	.414	2.29	.586*	0.85	PE_Hip _{ADD}	.390	2.13	PE_Hip _{ADD}	.834*	0.604
PE_Knee _{FLEX}	.409	3.42	.546*	1.12	PE_Knee _{FLEX}	.507	3.96	PE_Knee _{FLEX}	.058	1.98
PE_Ankle _{FLEX}	.701*	5.08	.662*	1.59	PE_Ankle _{FLEX}	.743*	5.42	PE_Ankle _{FLEX}	.766*	1.67
PE_Ankle _{ADD}	.432	3.48	.780*	0.55	PE_Ankle _{ADD}	.829*	1.55	PE_Ankle _{ADD}	.693*	0.79
DFA_Hip _{FLEX}	.512	16.76	.586*	18.00	DFA_Hip _{FLEX}	.280	16.75	DFA_Hip _{FLEX}	.907*	10.22
DFA_Hip _{ADD}	.872*	6.38	.591*	14.24	DFA_Hip _{ADD}	.701*	9.31	DFA_Hip _{ADD}	.759*	21.55
DFA_Knee _{FLEX}	.325	13.38	.820*	20.43	DFA_Knee _{FLEX}	.264	12.63	DFA_Knee _{FLEX}	.857*	22.30
DFA_Ankle _{FLEX}	.774*	8.45	.815*	13.53	DFA_Ankle _{FLEX}	.679*	12.99	DFA_Ankle _{FLEX}	.896*	11.72
DFA_Ankle _{ADD}	.250	12.50	.824*	11.35	DFA_Ankle _{ADD}	.469	11.42	DFA_Ankle _{ADD}	.588*	15.36

Note. FLEX = flexion; ADD = adduction.

* $p \leq .05$.

Regarding nonlinear measures, SampEn and FuzzyEn showed a moderate ability to rank individuals and good consistency in the stable condition, but FuzzyEn showed slightly better results than did SampEn. In the unstable condition, the intrasession reliability values were better than those in the stable condition, and FuzzyEn again showed better results than did SampEn. W. Chen et al. (2007) proposed FuzzyEn 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 nonstationary signal (Newell et al., 1997; Schumann, Redfern, Furman, el-Jaroudi, & 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 & Granata, 2008). In stable the condition, as indicated previously, the lower motion of the COP allows different places of the COG within the surface of support to maintain stability. Nonstationarity caused in the stable condition produces lower reliability values because stationarity is a basic requirement of entropy measures derived from ApEn (Costa et al., 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 & Pompe, 2002). PE has also shown stronger consistency in both stable and unstable conditions, so it is less affected by the nonstationarity of the time series.

DFA is another nonlinear measure frequently used to assess the complexity of the COP by analyzing the long-range autocorrelation 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., 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. 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. Nonstationarities 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 persistence than the original time series and that there is no need to detrend the velocity time series. Therefore, when SampEn and FuzzyEn 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 *mVel* 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 *mVel* 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. FuzzyEn produced good SEM values using the derived data, and SampEn produced the same trend as FuzzyEn, 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, SampEn and FuzzyEn 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 & Granata, 2005). This filtering behavior can 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 & Granata, 2010). 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.

Conclusions

In the COP signal, mVel was the best measure for ranking individuals in a motor balance task among the traditional measures. Furthermore, mVel 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 be 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 SampEn or FuzzyEn, 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.

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