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Interest of velocity variability and maximal velocity for characterizing center-of-pressure fluctuations

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Abstract. Postural control has for a long time been considered a position-based process: upright standing is preserved by engaging control processes when position exceeds a given threshold, in order to maintain the vertical projection of the center of mass within the polygon of sustentation. We recently proposed a new hypothesis, according to which postural control is velocity-based, rather than position-based (Delignières, D., Torre, K. & Bernard, P.L. (2011) Transition from persistent to anti-persistent correlations in postural sway indicates velocity-based control. *PLoS Computational Biology*, *7(2)*, e1001089). This hypothesis suggests that postural sway is left unchecked until a threshold in velocity is reached. Velocity series appear bounded between two (upper and lower) limits, reflecting this intermittent control. From this point of view, the limits that bound velocity dynamics over time seem particularly relevant for characterizing postural control. In the present paper we show that such velocity-based variables are more sensitive than more classical, position-based variables, for revealing the effects of experimental factors known to affect posture variability.

Key words: COP path, velocity control hypothesis, detrended fluctuation analysis, stabilogram diffusion analysis

Résumé. Intérêt de la variabilité de la vitesse et de la vitesse maximale pour caractériser les fluctuations du centre des pressions.

Le contrôle postural a longtemps été considéré comme basé sur un contrôle de la position : la station debout est préservée en engageant des processus de contrôle lorsque la position excède un certain seuil, de manière à maintenir la projection du centre de gravité à l'intérieur du polygone de sustentation. Nous avons récemment proposé une nouvelle hypothèse, selon laquelle le contrôle postural pourrait être basé sur un contrôle de la vitesse, plutôt que de la position (Delignières, D., Torre, K. & Bernard, P.L. (2011) Transition from persistent to anti-persistent correlations in postural sway indicates velocitybased control. *PLoS Computational Biology*, *7(2)*, e1001089). Cette hypothèse suggère que les oscillations posturales ne sont contrôlées que lorsqu'un certain seuil de vitesse est dépassé. Les séries de vitesse apparaissent ainsi bornées par deux limites inférieures et supérieures, reflétant ce contrôle intermittent. De ce point de vue, les limites qui bornent la dynamique de la vitesse semblent pouvoir fournir des variables particulièrement pertinentes pour rendre compte du contrôle postural. Nous montrons dans cet article que de telles variables, basées sur la vitesse, sont plus sensibles que des variables plus classiques basées sur la position, pour révéler les effets de facteurs expérimentaux connus pour affecter la stabilité posturale.

Mots clés : Trajectoire du COP, hypothèse du contrôle de la vitesse, *detrended fluctuation analysis*, *stabilogram diffusion analysis*

Introduction

The control of posture has been mainly studied through the analysis of the trajectory of the center-of-pressure (COP), which can be easily recorded using force platforms. This trajectory is highly complex, however, and a huge number of papers have tried to identify the most relevant variables to be extracted from COP trajectory in order to reveal the underlying control processes (*e.g.*, Cao, Kim, Kurths, & Kim, 1998; Cavanaugh, Mercer, & Stergiou, 2007; Collins & De Luca, 1993; Duarte & Zatsiorky, 2000; Roerdink, De Haart, Daffertshofer, Donker, Geurts, & Beek, 2006; Sabatini, 2000; Seigle *et al.*, 2009). In particular, Collins and De Luca (1993) developed a method called *stabilogram diffusion analysis* (SDA), which aimed at analyzing the correlation properties of COP time series. The authors showed that COP series were positively correlated in the short term (*i.e.*, over short observation times) but negatively correlated in the long term. Note that in the time series framework, a positive correlation signifies that an increasing trend in the past is likely to be followed by an increasing trend in the future. In this case the series is said to be persistent. Conversely, a negative correlation signifies that an increasing trend in the past is likely to be followed by a decreasing trend, and the series is said to be anti-persistent.

This transition from persistent to anti-persistent correlation regimes over different time scales is known as a "cross-over phenomenon" (Liebovitch & Yang, 1997). Cross-over is typically related to the fact that the variable under study is bounded within given limits (Liebovitch & Yang, 1997). Such bounding effects are essential because they suggest that a kind of control, direct or indirect, is exerted on the variable under study. Following this line of thought, Collins and De Luca (1993, 1994) supported the idea that postural control may be position-based. The authors argued that postural sway displacements "are left unchecked by the postural control system until they exceed some systematic threshold" (Collins & De Luca, 1993, p. 317) and that "the presence of longer-range negative correlations in the COP data suggests that closed-loop mechanisms are utilized over long-term intervals of time and large displacements" (Collins & De Luca, 1994, p.767).

However, Delignières, Torre, & Bernard (2011) showed that the method used by Collins and DeLuca presented some statistical shortcomings, and suggested that the interpretation proposed by the authors could be erroneous (see also Delignières, Deschamps, Legros, & Caillou, 2003). SDA is based on the framework of fractal analysis, and especially on the scaling law that characterizes *fractional Browian motion* (fBm) according to which the variance of displacement is a power function of the time interval over which this displacement is observed (Mandelbrot & van Ness, 1968):

$$\mathrm{Var}(\Delta x) \propto \Delta t^{2H} \tag{1}$$

This scaling law expresses the *diffusion property* of fBm processes, whose characteristics depend on the exponent H. The higher H, the more diffusive the fBm. For the special case $H = 0.5$, variance is proportional to time, and the process x is an ordinary Brownian motion with uncorrelated successive increments. For $0 < H < 0.5$, the successive increments are negatively correlated, and the process is sub-diffusive. Conversely for $0.5 < H < 1$ the successive increments are positively correlated, and the process is said to be over-diffusive. SDA is the direct application of this scaling law. This method computes the square of the displacement [$(\Delta x)^2$; *i.e.* an estimate of $\mathrm{Var}(\Delta x)$] between all pairs of points separated by a time interval Δt. These squared displacements are then averaged, and this process is repeated for increasing values of Δt. H exponent is then determined as the slope of the double logarithmic plot of $<\Delta x^2>$ as a function of Δt.

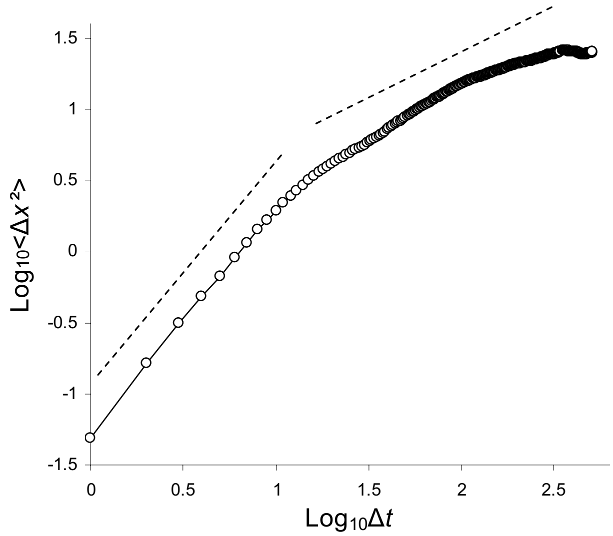

Fig. 1. Example of diffusion plot obtained by Stabilogram Diffusion Analysis (SDA) with COP position series. The dashed lines represent the regression slopes, in the short and the long terms (adapted from Delignières *et al.*, 2011).

Applying this method to COP trajectories, Collins & De Luca (1996) showed that this double logarithmic plot (or diffusion plot) was composed of two distinct parts, with different slopes for short Δt on the one hand, and long Δt on the other. More precisely, H was higher than 0.5 in the short-term, but lower than 0.5 in the long-term. This constitutes the cross-over phenomenon, clearly illustrated in Figure 1.

One could note, however, that this kind of analysis provides information about the correlational properties of the increments in the series, but not about those of the series itself. Most classical fractal analysis methods, for example the *Rescaled Range Analysis* (Hurst, 1965) or the *Detrented Fluctuation Analysis* (Peng, Mietus, Hausdorff, Havlin, Stanley, & Goldberger, 1993), take into account this point by integrating the series in a first step. As such, these methods give information about the correlation properties of the series under study, by analyzing the diffusion properties of its integrated counterpart. In other words, one could suppose that the cross-over from positive to negative correlation, or from persistence to anti-persistence, identified by Collins & De Luca (1993), is likely to characterize COP velocity (*i.e.*, increments), rather than COP position.

In order to test this hypothesis, Delignières *et al.* (2011) applied the Detrended Fluctuation Analysis to COP position series on the one hand, and to COP velocity series on the other hand. They showed that the

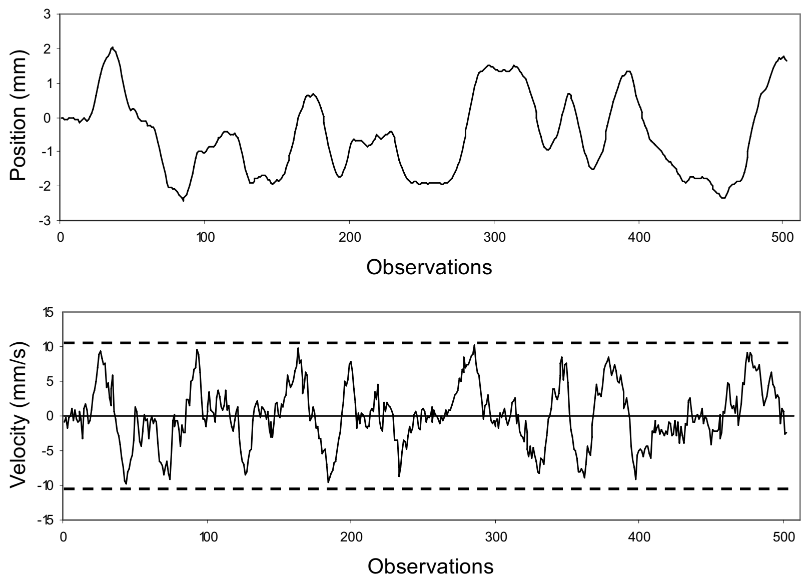

Fig. 2. Example time series of COP position (upper graph) and COP velocity (bottom graph). The dashed lines in bottom graph represent the hypothetical upper and lower limits that bound COP velocity.

diffusion plot evidenced a cross-over for velocity series, but not for position series.

With this regard, Delignières *et al.* (2011) argued than COP dynamics was primarily characterized by a bounding of velocity. In concrete terms, this bounding suggests that COP velocity evolves between two (upper and lower) limit values. Its evolution from one limit to the other looks similar to that of a fractional Brownian motion, yielding the persistent correlations evidenced in the short term. The long-term evolution of COP velocity is characterized by a quite systematic to and fro motion within the range defined by the upper and lower limits, and these systematic reversals yield the anti-persistent correlations observed in the long term. Figure 2 illustrates this specific dynamics.

In sum, Delignières *et al.* (2011) showed that the cross-over described by Collins and De Luca should be interpreted in terms of a velocity-based control instead of a position-based control of posture, and that the complex trajectory of the COP could be explained by a rather simple process, based on a bounding of COP velocity.

This hypothesis supposes that variables estimating the limits that bound velocity could be of special interest for analyzing COP dynamics. Two variables can be proposed in this aim: the average absolute maximal velocity (Delignières *et al.*, 2011), which represents a direct estimate of the absolute velocity threshold, and the standard deviation of the velocity signal, that could be assumed to be roughly proportional to the range between the upper and lower limits. In the present paper, we compare these two variables with COP position variability, and three variables extracted from SDA (short-term and long-term slopes, and inflexion point), with regards to their efficiency to reveal the effect of vision and age on postural stability. We hypothesized that velocity-based variables should be more relevant than position-based variables, and allow a better discrimination between experimental conditions or groups.

Methods

Experimental setup

Twenty-six male volunteers (19.3 yrs ± 2.1) took part in the experiment. The informed consent procedures were approved by local ethics committee.

The participants were asked to maintain quiet stance on a force platform (Medicapteurs "40 Hz/16b"®) of 530 mm × 460 mm × 35 mm, equipped with three pressure gauges. Participants held their arms alongside their body and focused on a visual reference mark fixed 90 cm in front of them. The feet were oriented with an angle of 15° from the sagittal midline, and the heels were positioned 4 cm apart. The participants had a 30-sec familiarization period before testing.

The vertical ground reaction forces were recorded using a 12-bit A/D converter, with a sampling frequency of 40 Hz. The system was linked to Medicapteurs Winposture2000® software, providing COP series on the antero-posterior (AP) and medio-lateral (ML) axes. The duration of each recording was of 25.6 sec, in order to obtain time series of 1024 points. The collected series were filtered by a low-pass filter, with a cut-off frequency of 8 Hz.

Table 1. Mean results (standard deviations in parentheses) obtained for each group and each condition for the 6 dependent variables: Standard deviation of COP position, short-term slope of SDA diffusion plot, long-term slope of SDA diffusion plot, inflection point of SDA diffusion plot, standard deviation of COP velocity, and average absolute maximal velocity.

	Young				Elderly			
	Eyes open		Eyes closed		Eyes open		Eyes closed	
	ML	AP	ML	AP	ML	AP	ML	AP
SD position	2.75	3.63	3.02	4.55	3.43	4.70	4.24	6.24
	(1.12)	(1.37)	(0.89)	(1.59)	(1.40)	(1.61)	(1.94)	(1.92)
SDA short-term slope	1.74	1.60	1.73	1.67	1.74	1.56	1.71	1.54
	(0.09)	(0.19)	(0.12)	(0.15)	(0.13)	(0.27)	(0.11)	(0.24)
SDA long-term slope	0.36	0.50	0.14	0.20	0.17	0.31	0.09	0.08
	(0.34)	(0.40)	(0.22)	(0.22)	(0.34)	(0.27)	(0.19)	(0.26)
SDA inflexion point	17.26	20.76	19.25	21.44	25.49	17.91	23.80	19.17
	(8.28)	(11.52)	(6.96)	(10.19)	(10.35)	(10.1)	(9.95)	(9.69)
SD velocity	7.44	9.09	10.52	14.87	10.47	21.92	15.23	35.70
	(2.80)	(2.96)	(3.34)	(5.33)	(6.30)	(18.72)	(10.79)	(25.84)
AAMV	17.34	21.52	23.76	34.72	23.32	52.39	34.47	82.54
	(6.76)	(7.07)	(8.15)	(13.53)	(14.76)	(45.78)	(25.21)	(60.17)

Variables and analyses

We first computed the standard deviation of the series of position, in the AP and ML direction. Second, we applied SDA on position series, following the procedure proposed by Collins & De Luca (1993). This method consists of computing the square of the displacement $(\Delta x)^2$ within all pairs of points separated by a time interval Δt. This computation is repeated for increasing values of Δt. The resulting diffusion plot represents the mean squared displacements against the time intervals Δt, in bi-logarithmic coordinates. We considered time intervals ranging between $\Delta t = 1$ and $\Delta t = 341$, (*i.e.*, between 25 ms and 8525 ms). Note that the highest values still allow the estimation of $(\Delta x)^2$ to be based on three non-overlapping intervals.

In order to avoid any bias due to the logarithmic distributions of the points in the diffusion plots, we divided the abscissa into intervals of equal lengths (24 intervals of $0.1(\log_{10}\Delta t)$), computed the average points within each interval, and determined the regression slopes over these average points. Finally, for an accurate estimation of the regression slopes in the short-term and long-term regions, we excluded the central part of the plots and performed the regressions on the first and the last parts of the graph (from points 1 to 8 and 17 to 24). These intervals were chosen after visual inspection of the individual graphs, in order to maintain the inflection point within the central zone in all cases.

Finally, we computed two variables based on velocity. The first one was the standard deviation of COP velocity. The second one was the *average absolute maximal velocity* (AAMV) of the COP. The computation of AAMV can be easily done from velocity series by extracting the maximum and minimum values of the series within non-overlapping windows. The length of these windows is chosen in order to allow the collection of at least one maximum and one minimum (*e.g.*, 2 s). The absolute values of these extrema are then averaged. AAMV is supposed to provide an empirically-based estimation of the limits that bound COP velocity. All variables were submitted to a three-way ANOVA 2 (Age) × 2 (Vision) × 2 (direction).

Results

We present in Table 1 the mean and standard deviation obtained for each variable in all experimental conditions. The results of the ANOVA are presented in Table 2.

The standard deviation of position revealed significant main effects for the three factors, but only for one of the potential interactions (Vision × Direction). The short-term SDA slope revealed only the main effect of Direction. Two dual interactions and the triple interaction Age × Vision × Direction were also significant. The long-term SDA slope presented two main effects (Vision and Direction), as well as the interaction Vision × Direction. There was no effect of Age, nor effect of any interaction involving Age. The inflexion point appeared the less sensitive variable, with a unique significant interaction (Age × Direction).

The two velocity-based variables, in contrast, appeared particularly sensible to experimental factors and their combinations: all main effects and interactions were significant. We obtained a significant effect of Age, indicating that SD velocity and AAMV increased with age.

Table 2. Statistical results (F-statistics and p-value) of the three-way ANOVA 2 (Age) $\times$ 2 (Vision) $\times$ 2 (direction), for the 6 selected variables. Statistically significant results ($p < 0.05$) are indicated in bold.

		SD position	SDA short-term slope	SDA long-term slope	SDA inflexion point	SD velocity	AAMV
Age	F	**12.77**	1.23	3.99	0.56	**11.01**	**10.31**
	p	**0.001**	0.273	0.051	0.458	**0.002**	**0.002**
Vision	F	**22.47**	0.13	**21.9**	0.22	**50.6**	**50.13**
	p	**0.000**	0.719	**0.000**	0.643	**0.000**	**0.000**
Direction	F	**73.53**	**58.75**	**4.17**	0.99	**41.42**	**42.92**
	p	**0.000**	**0.000**	**0.047**	0.325	**0.000**	**0.000**
Age $\times$ Vision	F	2.41	**4.73**	2.20	1.11	**6.21**	**6.23**
	p	0.127	**0.034**	0.145	0.297	**0.016**	**0.016**
Age $\times$ Direction	F	2.90	3.07	0.06	**9.60**	**18.08**	**18.19**
	p	0.095	0.086	0.802	**0.003**	**0.000**	**0.000**
Vision $\times$ Direction	F	**8.49**	**8.89**	**4.63**	0.12	**45.40**	**46.25**
	p	**0.005**	**0.004**	**0.036**	0.729	**0.000**	**0.000**
Age $\times$ Vision	F	0.37	**4.49**	0.58	1.95	**13.35**	**10.62**
$\times$ Direction	p	0.547	**0.039**	0.451	0.169	**0.001**	**0.002**

The effect of Vision was also significant, showing an increase of both SD velocity and AAMV in the absence of vision. Finally SD velocity and AAMV were higher in the AP than in the ML direction.

The interaction between Age and Vision indicated that the effect of the absence of vision was larger in elderly for both variables, and the interaction between Age and Direction showed that the effect of age was higher in the AP direction. The interaction between Vision and Direction showed that the effect of vision was higher in the AP direction. Finally the interaction Age X Vision X Direction showed that SD velocity and AAMV increased with age, especially in the absence of vision, and in the AP direction. We illustrate in Figure 3 the results obtained for AAMV.

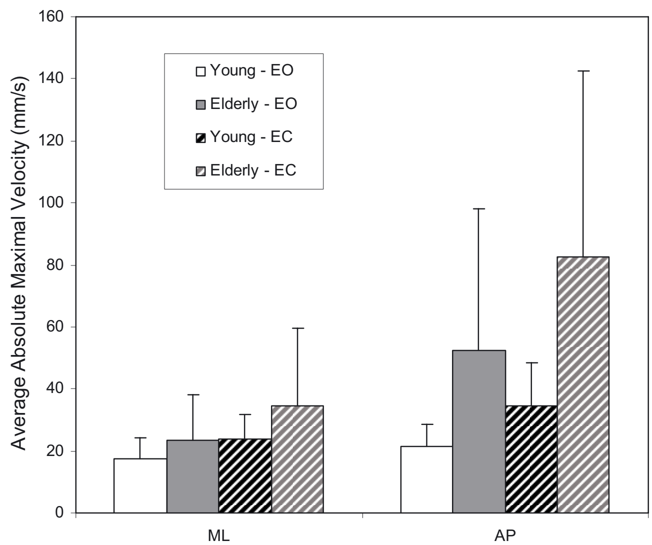

Fig. 3. Effects of age and vision on average absolute maximal velocity, in medio-lateral (ML) and antero-posterior (AP) directions.

Discussion

The main result of the present experiment was to evidence the good sensitivity of velocity-based variables (velocity variability and average absolute maximal velocity), as compared to position variability and measures obtained from SDA, for revealing the effects of group or experimental factors on postural control. In a similar experiment, Seigle *et al.* (2009) compared the efficiency of various variables (length and surface of COP displacement, percentage of determinism and entropy, computed from recurrence quantification analysis). They showed that the length of the COP displacement was the best discriminating stabilometric variable for both visual and aging effects. This result could be considered as consistent with the present one, as the length of displacement over a given duration of observation is a measure of average velocity (see also Prieto, Myklebust, Hoffmann, Lovett, & Myklebust, 1996). Average velocity, however, is not a direct assessment of the threshold that seems to characterize COP velocity dynamics. One could suppose, however, that average velocity roughly covaries with the maximal absolute velocities of COP.

The interest of the velocity variable for analyzing COP dynamics has been recently highlighted by Ramdani *et al.* (2009) and Ramdani, Seigle, Varoqui, Bouchara, Blain, and Bernard (2010). The main arguments of the authors, however, were methodological, and related to the methods they intended to use (central tendency measure and sample entropy): The non-stationarity of COP position series hinders phase space reconstruction methods and long-term correlations in the signal are not compatible with the selection of a proper time delay. According to the authors, differencing the original time series significantly reduces the non-stationarity and the correlations which characterize postural sway data, and allows a proper application of these sophisticated methods.

Our arguments for favoring the use of velocity variables are different: considering that postural control acts at the level of velocity, we argue that the relevant variables for analyzing COP dynamics should be derived from velocity signals, and especially should estimate the limits that bound velocity dynamics.

The velocity-based hypothesis suggests that sway is left unchecked until a threshold in velocity is reached. In others words, we suggest that an intermittent control of velocity underlies COP trajectory, reversing its dynamics when the absolute value of velocity reaches a given threshold. This hypothesis could be clearly conceived as a velocity-based analog of the two-regime model proposed by Collins and De Luca (1993). However, it supposes some counterintuitive implications. Notably, it suggests that the active control or correction processes do not intervene at the periphery of the COP trajectory, *i.e.*, when postural sway exceeds a given surface, as generally assumed (*e.g.*, Collins & De Luca, 1993, 1994), but, rather, in the central region of the stabilogram, where COP velocity reaches its maximal absolute values.

Note that the velocity-based hypothesis is consistent with the theoretical predictions of the *noisy-computation* model proposed by Kiemel, Oie, and Jeka (2002) and the subsequent experiment performed by Jeka, Kiemel, Creath, Horak, and Peterka (2004), suggesting the crucial role of velocity information for postural stability. In their experiment, Jeka *et al.* (2004) degraded the velocity information by removing/attenuating the sensory information from the visual and proprioceptive systems. They showed that a deficit in information about velocity, rather than position or acceleration, affected postural sway and concluded that velocity information was the most accurate form of sensory information to stabilize posture.

In sum, we consider that velocity represents a key variable in postural control. The dynamics of COP velocity over time provides essential information about the true nature of postural control, and velocity-based variables, especially those revealing the bounding limits of velocity dynamics, are of special interest for fundamental or clinical purposes. One may wonder, for example, whether those velocity variables could be relevant for the prediction of risk fall in elderly.

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