

**Variations in task constraints shape emergent performance outcomes and complexity levels in balancing**

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12

1 **Variations in task constraints shape emergent performance outcomes and complexity levels in balancing**

2

3 **Abstract**

4         This study investigated the extent to which specific interacting constraints of performance might  
5 increase or decrease the emergent complexity in a movement system, and whether this could affect the  
6 relationship between observed movement variability and the central nervous system's capacity to adapt to  
7 perturbations during balancing. Fifty two healthy volunteers performed eight trials where different performance  
8 constraints were manipulated: task difficulty (three levels) and visual biofeedback conditions (with and without  
9 the center of pressure (COP) displacement and a target displayed). Balance performance was assessed using  
10 COP-based measures: Mean Velocity Magnitude (MVM) and Bivariate Variable Error (BVE). To assess the  
11 complexity of COP, Fuzzy Entropy (FE) and Detrended Fluctuation Analysis (DFA) were computed. ANOVAs  
12 showed that MVM and BVE increased when task difficulty increased. During biofeedback conditions,  
13 individuals showed higher MVM but lower BVE at the easiest level of task difficulty. Overall, higher FE and  
14 lower DFA values were observed when biofeedback was available. On the other hand, FE reduced and DFA  
15 increased as difficulty level increased, in the presence of biofeedback. However, when biofeedback was not  
16 available, the opposite trend in FE and DFA values was observed. Regardless of changes to task constraints and  
17 the variable investigated, balance performance was positively related to complexity in every condition. Data  
18 revealed how specificity of task constraints can result in an increase or decrease in complexity emerging in a  
19 neurobiological system during balance performance.

20 **Keywords:** postural control, non-linear analyses, task constraints, biofeedback, center of pressure, movement  
21 variability.

22

## 1 **1. Introduction**

2           In humans, conceptualized as complex adaptive systems (Riley et al. 2012), movement variability is  
3 omnipresent due to the distinct constraints that shape each individual's goal-directed behaviors (Davids et al.  
4 2003). Movement variability has been studied as the natural variations that occur in motor performance across  
5 multiple repetitions of a task, reflecting changes in both space and time (Newell and Slifkin 1998; Stergiou et al.  
6 2006).

7           In dynamical system theory, these variations have a functional role to drive adaptive behaviors in  
8 movement systems, allowing the central nervous system (CNS) to exploit the high dimensionality offered by the  
9 abundance of motor system degrees of freedom (DOF) (Davids et al. 2003). Adaptive behavior refers to a form  
10 of learning characterized by gradual improvement in performance in response to altered conditions (Krakauer  
11 and Mazzoni 2011). The relationship between variability and adaptive behavior will change depending on task  
12 constraints faced by each individual. Several studies have related movement variability to the capacity of the  
13 CNS to adapt behaviors to environmental changes (Davids et al. 2006; Davids et al. 2003; Renart and Machens  
14 2014; Riley and Turvey 2002).

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

20           Previous analyses of the relationship between postural control and variability in movement  
21 coordination have examined two different global dimensions: the magnitude of observed variability and the  
22 structural dynamics of variability, addressed by analyzing its complexity (Stergiou et al. 2006). Complexity has  
23 been defined as the number of system components and coupling interactions among them (Newell and  
24 Vaillancourt 2001). **Some researchers have indicated that complexity in different physiological processes can be**  
25 **observed through nonrandom fluctuations on multiple time scales in physiological dynamics (Costa et al. 2002;**  
26 **Lipsitz and Goldberger 1992; Manor et al. 2010).** This second dimension provides additional information about  
27 properties of the dynamics of observed variability on multiples scales, which reveals important information on  
28 strategies used by the CNS during task performance (Caballero et al. 2014).

1           The complexity of center of pressure (COP) has been a prominent measure used for assessing the  
2 relationship between the complexity shown in a biological signal, and a neurobiological system's capacity to  
3 adapt to perturbations in motor tasks like postural control and balance (Decker et al. 2010; Goldberger et al.  
4 2002b; Menayo et al. 2014).

5           This methodological prominence has emerged because it has been considered a collective variable,  
6 responsible for capturing postural organization and balance in individuals (Riley and Turvey 2002).

7           Data on balance performance have suggested that complexity in a biological signal may be related to  
8 the CNS's capacity to re-organize degrees of freedom to adapt to perturbations (Barbado et al. 2012; Goldberger  
9 et al. 2002b). Adaptive movement responses have also been considered to exemplify functional exploratory  
10 behaviors, which reveal useful sources of information to perform and learn new skills (Stergiou et al. 2006). In  
11 this regard, less complexity in COP dynamics has been associated with less capacity to adapt (Barbado et al.  
12 2012; Manor et al. 2010). Moreover, in some cases, the loss of complexity in COP dynamics has been related to  
13 disorders in the CNS (Cattaneo et al. 2015; Schmit et al. 2006).

14           However, the direction of this relationship remains somewhat unclear. Other studies of performance in  
15 balance tasks have reported data which do not support the aforementioned relationship, reporting greater  
16 complexity in fluctuations of COP associated with worse task performance (Duarte and Sternad 2008;  
17 Vaillancourt and Newell 2002). For example, in Duarte and Sternad's (2008) study comparing young and elderly  
18 people, they found a higher degree of complexity in older people over an extended time (30 min) during  
19 performance in a standing balance task. This finding indicates that high levels of complexity could reflect a  
20 decreased adaptive capacity of CNS over longer time scales. Vaillancourt and Newell (2002; 2003) suggested  
21 that increases or decreases in the complexity of CNS behaviors can be functional, but may be dependent on the  
22 nature of both the intrinsic dynamics of the system and the task constraints that need to be satisfied. Due to  
23 specific performance constraints encountered, there may be a reduction in the number of configurations  
24 available to a dynamical system through a re-structuring of the state space of all possible configurations  
25 available (Davids et al. 2003; Newell and Vaillancourt 2001). Here, we sought to understand the extent to which  
26 specific interacting constraints of performance might lead to an increase or decrease of emergent complexity in  
27 a movement system, during task performance.

28           Another important question concerns whether the 'controversy' surrounding the relationship between  
29 observed movement variability and the capacity to adapt to unexpected perturbations may actually be due to the

1 specific experimental procedures of analysis selected to address complexity (Goldberger et al. 2002b; Stergiou  
2 et al. 2006). For instance, it has been suggested that entropy measures which analyze the regularity of a signal  
3 do not measure the complexity of system dynamics (Goldberger et al. 2002b). These studies did not consider  
4 whether signal regularity was clearly related to the complexity of system dynamics. Instead, it may be more  
5 appropriate to use fractal measures or long-range autocorrelation analysis, such as Detrended Fluctuation  
6 Analysis (DFA), to investigate complexity in complex adaptive systems. Regardless, several studies have shown  
7 the utility of entropy measures in interpreting the randomness in experimental data from physiological systems  
8 in relation to postural control (Barbado et al. 2012; Donker et al. 2007; Menayo et al. 2014), heart rate (Lake et  
9 al. 2002; Wilkins et al. 2009), neuromotor control of movements early in life (Smith et al. 2011), mental fatigue  
10 (Liu et al. 2010), intracranial pressure (Hornero et al. 2005) or local muscle fatigue (Xie et al. 2010).

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

## 24 **2. Methods**

### 25 *2.1. Participants.*

26 Fifty two, healthy volunteers (13 women) took part in this study (age = 25.5 (6.01) years, height = 1.70  
27 (0.25) m, mass = 70.66 (10.33) Kg). They had no previous experience in the balance task used in this study.

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

#### 4 5 *2.2. Experimental Procedure and Data Collection*

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

8 The task required the participants to stand on a wooden platform (0.50 m x 0.50 m) and perform eight  
9 trials of 70 seconds each, with 1-minute rest periods between trials. Standing stability and availability of visual  
10 biofeedback were manipulated. The decision to manipulate these two different task constraints was taken  
11 because both are heavily used in the literature to analyze and train postural control. In particular, the use of  
12 biofeedback was chosen to control “error sensitivity”. According to Herzfeld and Shadmehr (2014) (pp. 149)  
13 “when we make a movement and experience an error, on the next attempt our brain updates motor commands to  
14 compensate for some fraction of the error”, and this error sensitivity term varies substantially from individual to  
15 individual and from task to task. Thus, error sensitivity remains constant for all participants. Two of the eight  
16 trials were performed on a solid floor (stable condition or SC). The other six were performed on an unstable  
17 platform (unstable condition or UC). All trials were performed under four different levels of difficulty, defined  
18 by the stability of the base of support. To achieve this aim, a wooden platform (0.02 m thick) was affixed to the  
19 flat surface of three polyester resin hemispheres with the same height (0.1 m) and different diameters: UC1 =  
20 0.50 m of diameter; UC2 = 0.40 m of diameter and UC3 = 0.30 m of diameter (Figure 1). Each condition was  
21 experienced under two different visual biofeedback conditions: A) without visual biofeedback, where the  
22 representation of COP displacement was not displayed. Here, the instruction to participants was to stay “as still  
23 as possible” (Duarte and Sternad 2008); and B) with visual biofeedback, where COP displacement, beside a  
24 static center target (0.003 m of diameter on the base of support and 0.05 m projected on the wall in front of the  
25 participant; scale displays: 16.6 to 1), was displayed in real-time. Participants were instructed to keep their COP  
26 on the target (Figure 1).

27 **Figure 1 around here**

#### 28 *2.3. Data analysis and reduction*

29  
30 An application under Labview 2009 (Mathworks, Natick MA, USA), developed in our laboratory, was  
31 used to perform the data analysis. COP time series were previously down sampled from 1000 Hz to 20 Hz due

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

18 Postural sway was assessed using traditional bivariate COP-based measures combining the anterior-  
19 posterior (AP) and medial-lateral (ML) displacement trajectories: Bivariate Variable Error (BVE) and Mean  
20 Velocity Magnitude (MVM). These variables were used to assess task performance and were calculated over the  
21 signal, filtered using a low-pass filter. We used just the filtered signal using a low-pass filter because static  
22 balance is characterized by small amounts of postural sway which is analyzed at low frequencies.

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

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

25 (1)

26 where  $N$  is the number of data points in the COP displacement time series and  $i$  is each successive data point.

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



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

(2)

where T is the trial duration (60 s).

The variables used to assess the complexity of COP were Fuzzy Entropy (FE) and Detrended Fluctuation Analysis (DFA). These variables were calculated after both were filtered and processed (low-pass and high-pass filters). The variables were calculated over the resultant distance (RD) COP time series (Figure 2), instead of the AP and ML time series, due to the fact that the orientation of the base-of support is only approximately aligned with the axes of the force platform, especially in unstable situations (Prieto et al. 1996). Thus, measures based on the AP time series probably reflect some ML movements of the participant, and vice versa, while the RD vector is not sensitive to the orientation of the base of support with respect to the force platform (Prieto et al. 1996; Roerdink et al. 2011). RD is the vector distance from the center of the posturogram to each pair of points in the AP and ML time series (Equation 3).

$$RD \text{ time series}_{i=1} = \sum_{i=1}^N \sqrt{\left( (X_i - \bar{X})^2 + (Y_i - \bar{Y})^2 \right)}$$

(3)

**Figure 2 around here**

FE typically returns values that indicate the degree of irregularity in the signal. This measure computes the repeatability of vectors of length m and m + 1 that repeat within a tolerance range of r of the standard deviation of the time-series (Equations from 4 to 12). Higher values of FE thus represent lower repeatability of vectors of length m to that of m + 1, marking a greater irregularity in the time domain of the signal. Lower values represent a greater repeatability of vectors of length m + 1, and are, thus, a marker of lower irregularity in signal output. To calculate this measure we used the following parameter values: vector length, m = 2; tolerance window, r = 0.2\*SD; and gradient, n=2. In previous research these parameter values have shown high levels of consistency, which underlies their frequent use (Chen et al. 2007). FE was calculated according to the procedures of Chen et al. (2007). We also conducted analyses of other related complexity measures, such as Sample Entropy1. However, we chose FE because it displays some advantages, such as a stronger relative consistency, less dependency on data length, free parameter selection and more robustness to noise (Chen, Zhuang, Yu and Wang, 2009; Xie et al., 2010).

1 DFA represents a modification of classic root mean square analysis with random walk to evaluate the  
2 presence of long-term correlations within a time series using a parameter referred to as the scaling index,  $\alpha$   
3 (Bashan et al. 2008; Peng et al. 1995). The scaling index  $\alpha$  corresponds to a statistical dependence between  
4 fluctuations at one time scale and those over multiple time scales (Decker et al. 2010). This procedure estimates

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

9 the fractal scaling properties of a time series (Duarte and Sternad 2008) and has also been used to describe the  
10 complexity of a process (Goldberger et al. 2002a).

11 This measure was computed according to the procedures of Peng et al. (1995). In this study, the slope  $\alpha$   
12 was obtained from the window range  $4 \leq n \leq N/10$  to maximize the long-range correlations and reduce errors  
13 incurred by estimating  $\alpha$  (Chen et al. 2002). Different values of  $\alpha$  indicate the following:  $\alpha > 0.5$  implies  
14 persistence in position (the trajectory tends to remain in its current direction);  $\alpha < 0.5$  implies anti-persistence in  
15 position (the trajectory tends to return from where it came) (Roerdink et al. 2006).

#### 16 17 2. 4. Statistical Analysis.

18 Normality of the variables was evaluated using the Kolmogorov\_Smirnov test with the Lilliefors  
19 correction. Mixed repeated measures ANOVA with two intra-individual factors, task difficulty level and  
20 biofeedback availability, was used to assess effects of both factors on performance outcome measures and  
21 complexity variables. Outcomes of the ANOVAs were considered to be statistical significant when there was a  
22 <5% chance of making a type I error ( $p < 0.05$ ). Bonferroni adjustment for multiple comparisons was performed  
23 to ascertain differences between task performance under different constraints according to each intra-individual  
24 factor. Partial eta squared ( $\eta_p^2$ ) was calculated as a measure of effect size and to provide a proportion of the  
25 overall variance that is attributable to the factor. Values of effect size  $\geq 0.64$  were considered strong, around 0.25  
26 were considered moderate and  $\leq 0.04$  were considered small (Ferguson 2009).

27 Finally, Pearson product moment correlation coefficients were calculated to assess relationships  
28 between performance variables (BVE and VMM) and complexity measures (FE and DFA).

### 29 3. Results

1 Mean values obtained under each balance condition and pairwise comparisons between difficulty  
2 conditions and biofeedback conditions are displayed in Table 1.

3 MVM showed higher values in biofeedback condition ( $F_{1,51}=74.876$ ;  $p<.001$ ;  $\eta_p^2=.595$ ). In contrast,  
4 despite BVE not revealing overall differences between biofeedback availability conditions ( $F_{1,51}=2.637$ ;  $p=.111$ ;  
5  $\eta_p^2=.049$ ), at lower levels of difficulty, lower values of BVE were observed in the biofeedback condition (Figure  
6 3). BVE differences observed between biofeedback conditions did decrease as task difficulty level increased,  
7 and even disappeared at the most difficult performance levels. Additionally, both performance variables  
8 displayed higher values when task difficulty increased, being significantly different between conditions (BVE:  
9  $F_{1.83,93.36}=374.305$ ;  $p<.001$ ;  $\eta_p^2=.880$ ; MVM:  $F_{1.89,96.6}=491.241$ ;  $p<.001$ ;  $\eta_p^2=.906$ ) (Figure 3).

10 With regard to complexity variables, in the low-pass filtered signal, higher FE ( $F_{1,51}= 77.660$ ;  $p< .001$ ;  
11  $\eta_p^2=.604$ ) and lower DFA values ( $F_{1,51}= 65.392$ ;  $p<.001$ ;  $\eta_p^2=.562$ ) were observed when biofeedback was  
12 available. However, differences in these dependent measures decreased as task difficult level were increased  
13 (figure 4). Regarding the high-pass filtered signal, the presence of biofeedback did not display effects on any  
14 complexity variable (FE:  $F_{1,51}= 3.949$ ;  $p= .052$ ;  $\eta_p^2=.072$ ; DFA:  $F_{1,51}= 1.744$ ;  $p=-.192$ ;  $\eta_p^2=.033$ ).

15 Complexity values at different task difficulty levels varied according to the filter used, the biofeedback  
16 condition and the variable recorded (Figure 4). When variables were calculated over the low-pass filtered signal,  
17 in the presence of biofeedback, FE values were significantly different between SC and UC3 and between UC3  
18 and UC1, decreasing as difficulty increased. However, without biofeedback, FE increased with task difficulty,  
19 displaying significant differences in the value between SC and every UC condition. Regarding DFA in the  
20 conditions with biofeedback, significant differences were observed between UC1 and UC3 and between UC2  
21 and UC3, reaching the highest values at the most difficult task level. Without biofeedback, DFA values  
22 decreased from SC to UC2 and UC3, and from UC1 to UC2, attaining the highest values at the least difficult  
23 task level.

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

---

Table 1. Average values (mean  $\pm$  SD) in each balance condition of every variable calculated in the study.

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

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

4 **Figure 3 and 4 around here**

5 Performance variables (BVE and MVM) were positively correlated, but showed an inverse correlation  
6 with complexity variables. Furthermore, the degree of dependence between them varied according to the filter  
7 used and biofeedback availability. When the low-pass filtered signal was used (table 2), and in conditions  
8 without biofeedback, BVE was negatively correlated with FE and positively correlated with DFA. Nevertheless,  
9 in conditions with biofeedback, this correlation was only found at the highest task difficulty level. MVM  
10 showed positively correlation with FE and negatively correlation with DFA despite the availability of  
11 biofeedback. Additionally, FE and DFA variables displayed an inverse relationship in every condition.

Table 2. Pearson product moment correlation coefficient calculated between performance variables and complexity variables, using a *low-pass filter*, in each balance condition.

	With biofeedback			Without biofeedback		
	SC					
	MVM	FE	DFA	MVM	FE	DFA
BVE	.834**	-.366**	.166	.392**	-.500**	.378**
MVM		.129*	-.161		.436**	-.337*
FE			-.631**			-.754**
	UC1					
	MVM	FE	DFA	MVM	FE	DFA
BVE	.613**	-.143	-.092	.333*	-.361*	.319*
MVM		.598**	-.421**		.662**	-.570**
FE			-.577**			-.830**
	UC2					
	MVM	FE	DFA	MVM	FE	DFA

BVE	.615**	-.263	.084	.336*	-.430**	.344*
MVM		.522**	-.315*		.605**	-.384**
FE			-.521**			-.623**
<b>UC3</b>						
	MVM	FE	DFA	MVM	FE	DFA
BVE	.425**	-.485**	.471**	.571**	-.432**	.466**
MVM		.477**	-.319*		.416**	-.211
FE			-.800**			-.736**

1 \*\* Correlation is significant at the 0.05 level (2-tailed).

2 \* Correlation is significant at the 0.01 level (2-tailed).

3 Note. SC = Stable condition; UC1 = Unstable condition difficulty level 1; UC2 = Unstable condition difficulty  
4 level 2; UC3 = Unstable condition difficulty level 3.

5 When the high-pass filter was used (Table 3) BVE was negatively correlated with FE, only in the most  
6 difficult task condition regardless of the availability of biofeedback. A positive correlation between BVE and  
7 DFA was found when biofeedback was available, only at the lowest and highest task difficulty levels, but no  
8 correlation between them was found in conditions without biofeedback. With regard to MVM, this variable was  
9 negatively correlated with FE in all of the unstable conditions (with or without biofeedback). MVM was  
10 positively correlated with DFA only in the stable condition when the biofeedback was available. In the condition  
11 without biofeedback, this correlation was observed in UC1 and UC2.

Table 3. Pearson product moment correlation coefficients calculated between performance variables and complexity variables, using a *high-pass filter*, in each balance condition.

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

12 \*\* Correlation is significant at the 0.05 level (2-tailed).

13 \* Correlation is significant at the 0.01 level (2-tailed).

14 Note. SC = Stable condition; UC1 = Unstable condition difficulty level 1; UC2 = Unstable condition difficulty  
15 level 2; UC3 = Unstable condition difficulty level 3.

#### 16 4. Discussion

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

7           Performance decreased when balance task difficulty was increased as reported in previous research  
8 (Barbado et al. 2012; Borg and Laxåback 2010). Values in performance measures, both in BVE and MVM,  
9 increased as task difficulty level increased (figure 3). However, availability of biofeedback had different effects  
10 on BVE and MVM values. With biofeedback, BVE values decreased significantly, but only at lower task  
11 difficulty levels. However, as difficulty level was increased, biofeedback availability did not influence the  
12 amount of variability observed in COP measures. In stable or less challenging unstable task conditions, different  
13 locations of the COP on the surface of support allowed a participant to maintain stability (Caballero et al. 2014).  
14 However, increasing task difficulty limited the region of stability, signifying that in the difficult balancing  
15 conditions, there were a limited number of COP locations where system stability could be maintained (Lee and  
16 Granata 2008). Under more stable balancing conditions visual biofeedback was used to maintain COP location  
17 on the target. Under more challenging postural control conditions, visual biofeedback information might have  
18 been redundant, because participants did not have many COP locations where they could maintain system  
19 stability. They only had possible outcome solution: the same as displayed by the available biofeedback signal.  
20 From a dynamical systems viewpoint, differences between biofeedback conditions could be interpreted as the  
21 existence of different types of attractors in a performance landscape. It seems that participants used a behavior  
22 similar to a fixed-point attractor when biofeedback was available, characterized by a fixed point in state space  
23 where no movement is observed (van Emmerik and van Wegen 2000). Nevertheless, participants explored the  
24 oscillatory COP dynamics (Vaillancourt and Newell 2003) without biofeedback in the least challenging  
25 conditions. Availability of biofeedback seemed to change postural control strategies by decreasing the number  
26 of configurations available to a dynamical movement system (Davids et al. 2003). In this regard, available  
27 information seemed to constrain the system to one area of the attractor landscape in this task.

28           On the other hand, MVM values displayed an increase in biofeedback conditions compared to when  
29 biofeedback was not available. Although there are a greater number COP locations where stability can be

1 maintained, this increase in MVM could be due to the fact that under the less challenging task constraints, visual  
2 biofeedback drives the system to one specific location. Without biofeedback, participants focused on avoiding  
3 falling. In the conditions with biofeedback they tried to adjust their COP to the target, performing a greater  
4 number of adjustments. The increased values of MVM in biofeedback situations can also be related to an  
5 increased error sensitivity of the individuals regulated by the CNS (Herzfeld and Shadmehr 2014). In this sense,  
6 MVM could be an index of the amount of corrections needed to adjust the COP location, increasing  
7 neuromuscular effort and resulting from participant exploratory behaviors. Higher COP velocity would be an  
8 index of exploratory behaviors in discovering stable performance solutions under relatively novel task  
9 constraints (Davids et al. 1999).

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

1 Vaillancourt (2001) who suggested that the increase or the decrease of complexity can be independent of the  
2 number of component mechanical degrees of freedom being harnessed as a system, but the direction of the  
3 changes in complexity is driven by task constraints.

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

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

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



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

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

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

#### 19 **Conflict of interest statement**

20 This is to inform you that there are no conflicts of interest that could inappropriately influence (bias) this work.

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