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(Article begins on next page)

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Long Term Correlation and Inhomogeneity of the Inverted Pendulum Sway Time-Series under the Intermittent Control Paradigm

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Abstract

In this study the extended detrended fluctuation analysis (EDFA) was applied to the sway data generated from an inverted pendulum (IP) model, intermittently controlled at the ankle. The time series taken into account was the center of pressure (COP), since it represents the widest used time series in posturography, and it constitutes a natural link between model and data-based analysis approaches for studying the dynamics of the human balance maintenance. COP time-series were obtained by varying the intermittent control parameters (ICP) in a uniform distribution range that ensures IP stability to quantify changes in the long-term correlation and inhomogeneity of the time-series. Globally, EDFA coefficients (α and β) showed to be sensitive to the variations of derivative control gain (D), whereas for proportional gain (P) and ρ parameters no significant trends were observed. However, relations between EDFA coefficients and ρ arose whether derivative gain is examined within a low and high regions of value. For low D gains, both α and β showed a significant correlation with ρ, which disappears when higher D values were considered. Thus EDFA coefficients can provide useful insights about the long-term correlation and local characteristics of COP timeseries, which are strictly related to the control policy adopted

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for maintaining balance. This supports the validity of the intermittent motor control paradigm for the human upright stance and suggests the use of EDFA in real posturography applications, in order to extract meaningful information regarding the properties of COP timeseries for different groups of patients.

Keywords: Center of Pressure (COP), Intermittent control, Extended detrended fluctuation analysis (EDFA)

1. Introduction

The study of bipedal upright stance and balance maintenance has fascinated many different scientific disciplines. Indeed, understanding the hidden mechanisms that the central nervous system (CNS) employs to control the body mechanics is fundamental in neurorobotics to embody intelligence in humanoid robots [1, 2], but even in neuroscience and posturography, to better understand how pathologies affecting CNS may impact on the motor control [3, 4]. In this scenario, approaches that combine biomechanical modeling of the stance and the analysis of time-series, such as the evolution of the center of mass (COM) and the center of pressure (COP) [5, 6, 7], grounded the bases for a deeper comprehension of the motor control policies actuated by the CNS.

Although stiffness-based stabilizing mechanisms and continuous control paradigm are widely used in literature to model the neuromuscular control of stance [8, 9], the intermittent control approach demonstrated to be supported by physiological evidence [10]. As first, muscle activity is bursting, and it may be mirrored in the control torques at the human joints [6]. Furthermore, Morasso, Schieppati, and Sanguineti [11, 12] highlighted the inability of the ankle stiffness alone to compensate the whole body gravity pull, without an active mechanism played by the CNS [5]. Moreover, the intermittent control policy can generalize a continuous one, as highlighted in [7]. Thus, despite the real motor control paradigm of the stance maintenance is unknown, it is plausible that the CNS can take advantage from the body structure in order to develop a control strategy that does not act continuously [10]. Indeed, global stability of the system can be obtained switching between unstable dynamics [10, 13], hence trough a variable structure control policy. The idea of intermittency, meant as an agent that acts when necessary, was hypothesized also by Collins and De Luca [14], following a time-series analysis approach, i.e. the stabilogram diffusion analysis (SDA) [14].

Despite the two previous perspectives, i.e. model-based and time-series analysis, are different [7], the need for a unified perspective results of great importance when one would obtain highly explainable models. Indeed, in [7] the aforementioned approaches were combined through the approximate bayesian computation, in order to infer the parameters of the intermittent controller from posturographic data. This makes more underpinned the interpretation of the results if compared to models obtained through black box identification procedures, where high fidelity data fitting could be payed with a limited interpretability. Literature shows other studies that followed the inclusive approach stated above. In [15] for instance, SDA was applied to simulated COP data obtained by using a simple inverted pendulum (IP) model, commonly used to describe the mechanics of the body stance, varying the continuous controller parameters, and then examining their relation with the SDA coefficients [14]. Also in [10], changes in the intermittent control parameters (ICP) were related to changes in the power spectral density (PSD) of the sway data. Furthermore, such PSDs reproduced the multiple law scaling properties observed in data acquired during human quiet stance [10].

The investigation of intermittent control models of human stance through time series analysis approaches is far to be completely assessed. In particular, as emerged from previous works [15, 16, 6, 17], a possible way to carry on such investigation is to employ COP model-generated data. This for two main reasons: firstly, the COP can be directly measured from force platforms without the need for any motion capture systems, commonly used to estimate the COM. Thus, the knowledge extracted from the model can be validated through real data. Secondly, COP is directly related with the control torques generated at the ankle and upper joints of the body [11, 8, 14], and hence it contains the sign of the CNS control action. Another important aspect regards the selection of adequate descriptors used to evaluate the COP time-series. In [18] different spatial, temporal and frequency COP descriptors were presented. However, they do not account for the nonlinear properties and long-term correlation of COP data. Instead, other authors approached the study of COP time-series through the use of SDA, rambling and trembling decomposition, sway density curve and detrended fluctuation analysis (DFA) [14, 19, 4, 20, 21]. These are only few of the methodologies employed to capture more detailed information regarding the nature of biological processes behind balance maintenance.

Recently, an extension of the DFA, named extended DFA (EDFA), was proposed in [22]. EDFA grounds its basis on the fact that experimental data often present inhomogeneity due to changes in the dynamics of the systems. This aspect can be encountered in many biological time series, ranging from heart rate to electroencephalography [23, 24]. Moreover, behind EDFA there is the idea to quantify not only the slow variations in the local mean value, as done by DFA, but also to consider other types of non-stationary behaviors, such as those induced by intermittency or faster oscillations [23]. Thus in this study, EDFA was applied to simulated COP time course obtained through intermittent control paradigm, applied to an IP model, and by varying the ICP within a plausible range [10, 7]. Then, EDFA coefficients were computed to asses how changes in the ICP affect posturographic data, and if EDFA can highlight hidden properties of the motor control paradigm employed to stabilize the IP.

The paper is organized as follows. Methods section describes the human stance model based on the intermittent controller used to generate simulated COP, then EDFA principles are recalled. Results are thus presented and discussed in the third section, and concluding remarks reported in the last section end the paper.

2. Materials and Methods

2.1. Upright stance balance maintenance model and data generation

The human balance maintenance model considered in this study was presented in [10], and it basically develops a variable structure control system to describe the body sway in quiet conditions. The latter can be modeled through an IP linearized in the neighborhood of the vertical equilibrium point [10]. Thus, the dynamics is given by:

$$I\ddot{\theta} = mgh\theta - T \tag{1}$$

where θ is the COM sway angle in the sagittal plane, m is the subject body mass, h is the distance of the COM with respect to the ankle, g is the gravity acceleration, and I is the moment of inertia of the body around the ankle. The term $mgh\theta$, hence represents the gravitational toppling torque that is dynamically counterbalanced by T, i.e. the control torque applied at the pendulum joint. The latter can be modeled as in [10, 6]:

$$T = K\theta + B\dot{\theta} + f_P(\theta_\Delta) + f_D(\dot{\theta}_\Delta) + \sigma\xi \tag{2}$$

The first two terms ($K\theta$ and $B\dot{\theta}$) model the passive feedback torques due to ligament and muscle tone. On the contrary, $f_P(\theta_\Delta)$ and $f_D(\dot{\theta}_\Delta)$ model the active role played by the CNS that has been thought intermittent, depending on the portion of the phase plane the state is at a given time [10]. To be noted, the two terms depend respectively to the delayed sway angle and its time derivative. Indeed $\theta_\Delta = \theta(t - \Delta)$, where Δ represents the physiological neural delay that accounts for both the afferent and efferent neural information transmission [10]. The last term in the right hand side of (2) represents the internal postural noise, modeled as an additive Gaussian white noise $\xi(t)$ with standard deviation σ [10].

The switching policy adopted for the model was defined in [10] and used also in [6]. It can be summarized as follows:

$$\begin{cases} f_P(\theta_\Delta) = P\theta_\Delta; \quad f_D(\dot{\theta}_\Delta) = D\dot{\theta}_\Delta; \quad \text{if } \theta_\Delta(\dot{\theta}_\Delta - l\theta_\Delta) > 0 \\ f_P(\theta_\Delta) = 0; \quad f_D(\dot{\theta}_\Delta) = 0; \quad \text{otherwise} \end{cases} \tag{3}$$

where P and D represents the proportional and derivative gains of the active controller, while l characterizes the slope of the on-off boundary lines $\dot{\theta}_\Delta = l\theta_\Delta$ [10, 7]. As highlighted in [7], for the closed loop system described above, the switching activity is driven by the portion of the phase plane where the active controller is turned on with respect to the whole phase plane (Fig. 1). This quantity can be defined as ρ and it is formally equivalent to [7]:

$$\rho = \frac{S_{on}}{S_{on} + S_{off}} \equiv 0.5 - \frac{\arctan(l)}{\pi} \tag{4}$$

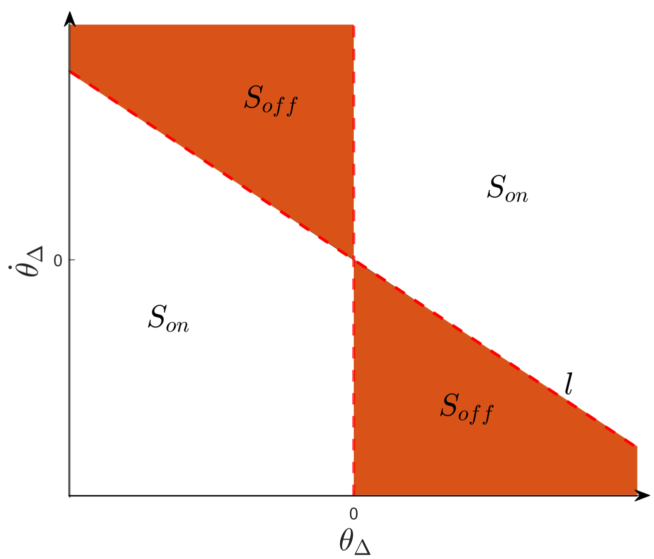

Figure 1: Schematic representation of the phase space portion in which the active controller is turned on (S_{on}) and off (S_{off}). The two regions were determined by the switching condition in equation (3) where l determines the on-off boundary region.

To be noted, if the active controller is continuously turned on, the S_{off} area is equal to zero ($\rho = 1$), and the model generalizes the continuous motor control paradigm [15, 7]. For a non-null S_{off} the active controller is turned on and off ($\rho < 1$) and the motor control paradigm is the intermittent one. Eventually, if the S_{on} area is zero ($\rho = 0$), the active controller never turns on and the pendulum stabilization can be reached only through the passive components of T.

However, as reported in [12], ankle stiffness alone cannot stabilize the upright stance, and by following the line proposed in [10], the stiffness term K (see equation (2)) was set at the 80% of mgh. In this way, an active control is always required [7, 11]. To run the simulations, the model parameters and the ICP, i.e. (P, D, ρ), were set as reported in table 1. The forward Euler method with a time step of 0.001 s was used to solve the delayed differential equation given by (1) after substitution of T through (2). Further details regarding the discretization and integration procedures can be found in [10, 7].

One thousand stable simulations of 60 s were run sampling (P, D, ρ) from opportune uniform distributions (Table 1). For each simulation, the COP with respect to the ankle joint was obtained following the relation [25]:

$$COP = COM - \frac{h}{g}C\ddot{O}M \tag{5}$$

where COM can be obtained by the sway data since is the projection of the center of mass in the anterior posterior direction. More precisely, COM is obtained as $COM = h\sin(\theta)$.

Table 1: Table shows the model parameters and the ICP used to simulate the model. P, D and ρ were sampled from uniform distributions in plausible ranges [6, 7, 13]

m (kg)	I (kg·m^2)	h (m)	B (N·m·s/rad)	K (N·m/rad)	g (m/s^2)	Δ (s)	σ (N·m)	P (N·m/rad)	D (N·m·s/rad)	ρ
60	60	1	4.0	471	9.81	0.2	0.2	$\mathcal{U}_{[294;\,471]}$	$\mathcal{U}_{[0;\,400]}$	$\mathcal{U}_{[0.3;\,1]}$

2.2. Extended detrended fluctuation analysis

Given a time series $x(i)$ of length N, the DFA involves the transformation of $x(i)$ in its profile $y(i)$ through an integration after mean removal [26, 24]:

$$y(k) = \sum_{i=1}^{k}[x(i) - \langle x \rangle], \quad \langle x \rangle = \sum_{i=1}^{N} x(i) \tag{6}$$

The resulting profile or random walk undergoes to non-overlapping segmentations of equal length n. Then, for each segment of the profile, a local trend

$y_n(k)$ is computed through a linear fit in a least square sense [23]. When local trend is available, one can proceed by computing the fluctuation, or standard deviation of the signal profile around the local trend as:

$$F(n) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}[y(k) - y_n(k)]^2} \tag{7}$$

The process is iterated for different segment size (n) in order to obtain $F(n)$ over a possible large number of scales. In general, $F(n)$ presents a power law behavior of the type:

$$F(n) \sim n^{\alpha} \tag{8}$$

where the α-exponent can be estimated through the log-log representation of $F(n)$ versus n [24, 26].

What reported until now are the basic steps of the DFA. However, as highlighted in [23], the inhomogeneity of the data, which can be due to multiple dynamics interactions, can lead to a consistent variability of the profile fluctuations around the local trend among the different signal epoch sizes (n). This can produce a departure from model (8), rendering more challenging the interpretation of the classical DFA. To mitigate this aspect, in [22, 23] the authors proposed a DFA extension, namely EDFA, that takes care of the heterogeneity in the RMS fluctuations. Hence, in addition to the canonical DFA, one can consider the following quantity:

$$dF(n) = max[F_{loc}(n)] - min[F_{loc}(n)] \tag{9}$$

where $dF(n)$ is the difference between the maximum and minimum local RMS fluctuations $F_{loc}(n)$ [23]. Here, the local RMS fluctuations of the signal profile $y(k)$ from the trend $y_n(k)$ depends on the epoch length (n). As observed in [23], also $dF(n)$ could change with n, following a power-law dependence with another scaling exponent β:

$$dF(n) \sim n^{\beta} \tag{10}$$

The EDFA was applied to each COP trace generated as described in section 2.1, and both α and β were computed to evaluate how changes in the ICP impact on the simulated COP time-series.

3. Results and Discussion

In Figure 2 the mean trends among all the simulated time series of both F and dF are shown in the log-log scale. A greater variability is present at higher time scales and an inverse relation exists between (n) and the frequency, as underlined in [27]:

$$n(f) = \frac{f_s}{f} \tag{11}$$

where f_s is the sampling frequency and f is the considered frequency. This suggests that modifications of the active controller parameters lead to changes of balance response focused at the higher time scales and thus at the lower frequency ranges [10], aligning with [28], where the effects of neural control on COP data were observed in the lower bands (LB) frequency range of 0.5-0.1 Hz. Confirmations can be found also in [27], where part of such neural feedback due to the visuo-vestibular information should be mirrored in COP time-series at frequencies lower than 0.5 Hz [27]. This aspect supports the goodness of the intermittent motor control paradigm, since modifications of its parameters produce larger variations at the LB ranges (Fig. 3), thus in according with the regulatory activity of the CNS in the human balance maintenance, focused on the frequency LB [28, 10, 27]. For the above mentioned reasons, one can focus on the fluctuations at the higher time scales to observe the behavior of both F and dF in the LB.

The EDFA appears suitable for capturing variations in the active control policy: observing the F and dF fluctuations restricted at the LB (Fig. 3), one can appreciate that both type of fluctuations are affected by ICP variations and dF showed a greater level of variability at all the (n) with respect to F, likely indicating that dF responds to the same control parameters changes by greater modifications of its value (Fig. 3).

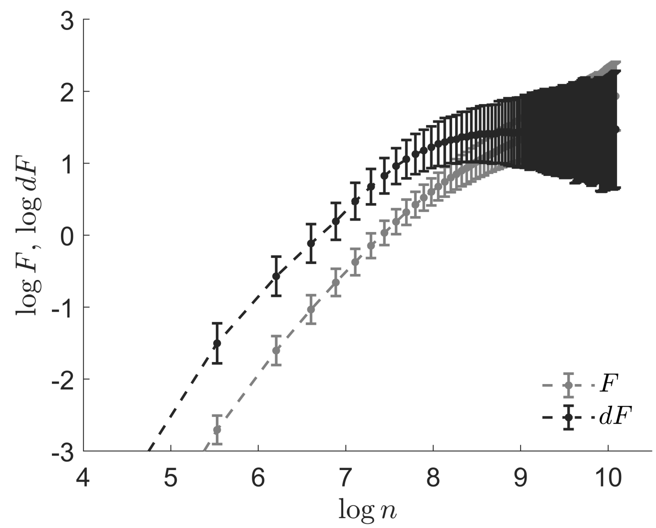

Figure 2: Log-log representation of the EDFA fluctuations in mean and standard deviation, the latter were computed over the 1000 synthetic COP time-series generated by the model.

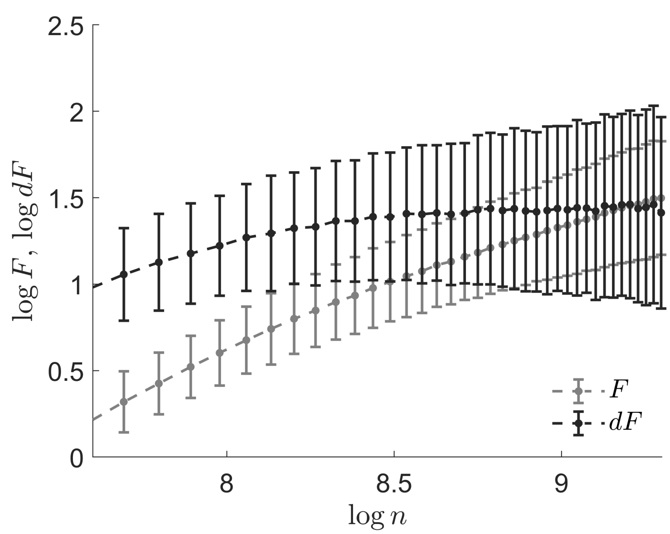

Figure 3: Log-log representation of the EDFA fluctuations in mean and standard deviation. Focus on the time scales that maps the frequency band 0.5-0.1 Hz.

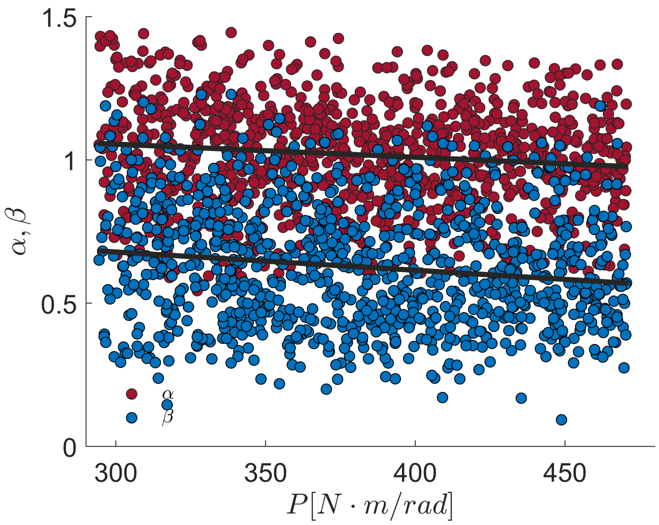

Figure 4: EDFA coefficients α and β obtained for the simulated COP time series and scattered in relation to P parameter. The correlation coefficients results $r = -0.12$ and -0.15, for α and β respectively. Figure shows also the linear trend between P and the coefficients.

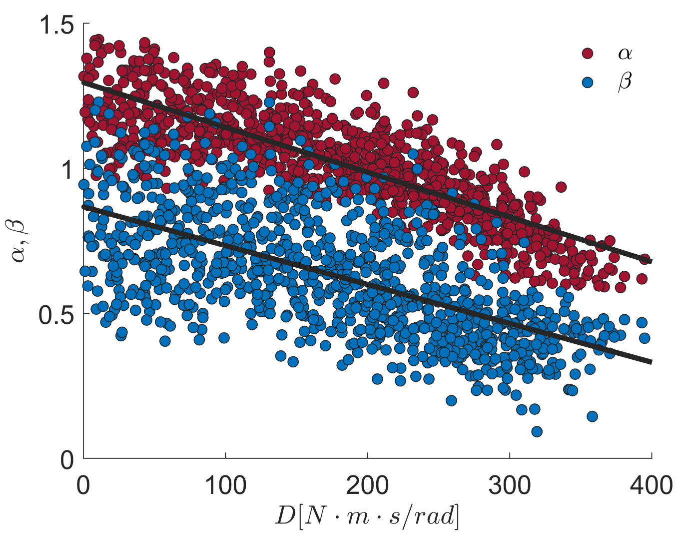

Figure 5: EDFA coefficients α and β obtained for the simulated COP time series and scattered in relation to D parameter. The correlation coefficients results $r = -0.83$ and -0.63, for α and β respectively. Figure shows also the linear trend between D and the coefficients.

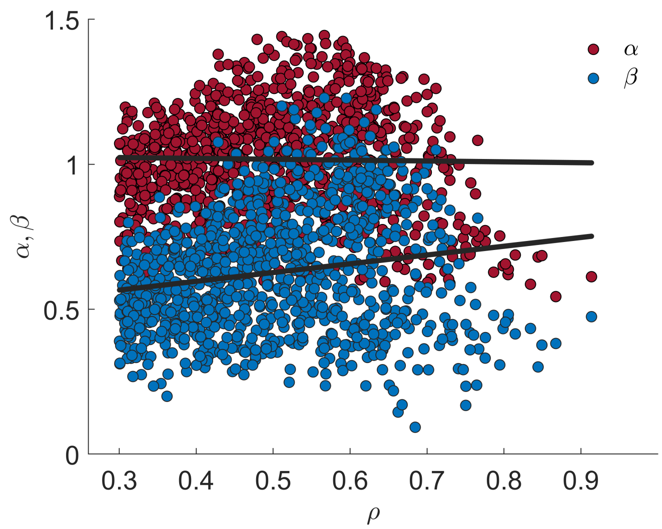

Figure 6: EDFA coefficients α and β obtained for the simulated COP time series and scattered in relation to ρ parameter. The correlation coefficients results $r = -0.019$ and 0.17, for α and β respectively. Figure shows also the linear trend between ρ and the coefficients.

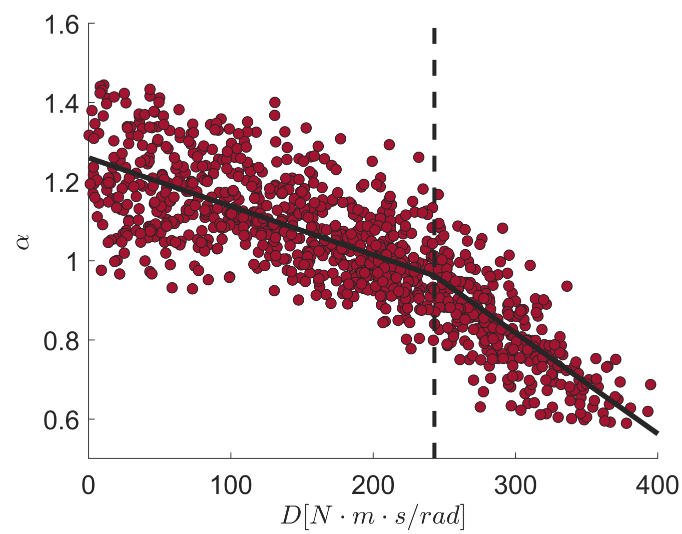

Figure 7: EDFA α coefficient scattered against D parameter. The two lines of the best fitting model are reported in black and the knot point is indicated with the dashed, vertical line.

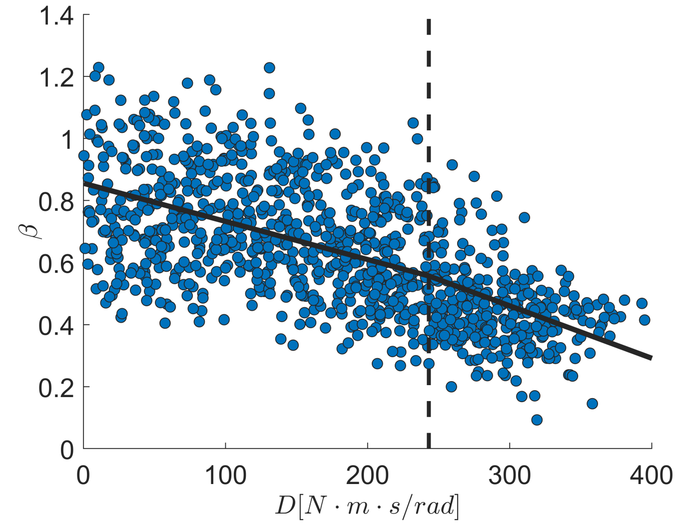

Figure 8: EDFA β coefficient scattered against D parameter. The two lines of the best fitting model are reported in black and the knot point is indicated with the dashed, vertical line.

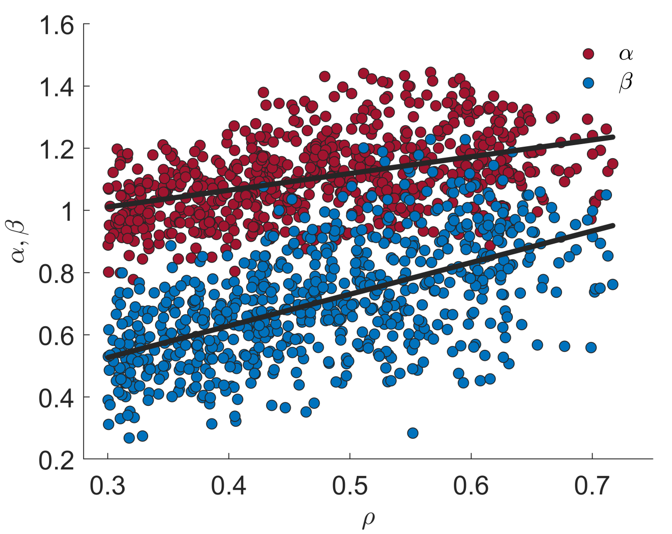

Figure 9: EDFA coefficients α and β obtained for the simulated COP time series and scattered in relation to ρ parameter for D <243 $N \cdot m \cdot s \cdot rad^{-1}$. Figure shows also the linear trend between ρ and the coefficients.

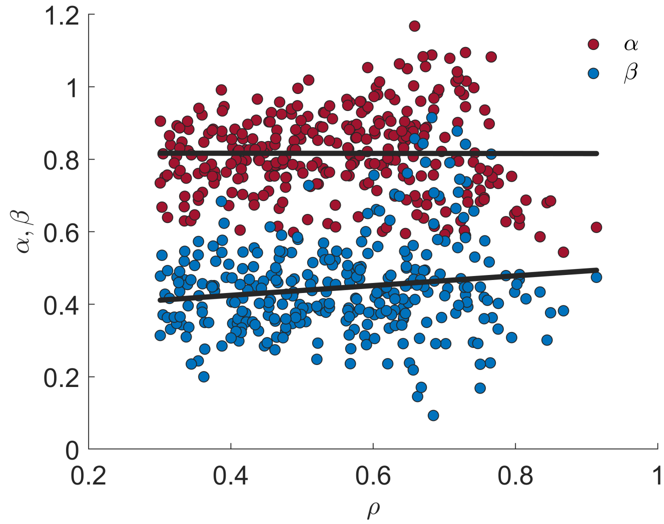

Figure 10: EDFA coefficients α and β obtained for the simulated COP time series and scattered in relation to ρ parameter for $D \geq 243\ N \cdot m \cdot s \cdot rad^{-1}$. Figure shows also the linear trend between ρ and the coefficients.

As highlighted in section 2.1, the motor control paradigm examined in this study depends upon ρ, P, and D. The EDFA coefficients showed different relationship with the above mentioned parameters when considered over their whole range of variation (Table 1). Globally, the P parameter did not appear related to neither the long term correlation properties, nor to the inhomogeneity of the simulated COP time-series, as showed by the poor correlation between P, α, and β (Fig. 4). This confirms that when P is large enough to compensate the portion of the gravitational toppling torque not counteracted by the passive muscles properties (K and B), a wide range of values is admissible for P and thus, with respect to D, its role becomes less crucial for the control model [6, 10]. The latter aspect aligns with the strong relation observed between both EDFA coefficients and D (Fig. 5), highlighted by the significant correlations of the derivative gain with α and β ($r = -0.83$ and $r = -0.63$, $p < 0.0001$). In passing, the $\alpha - D$ relation (Fig. 5) points out that the higher is D, the lower is the long-term correlation of the COP timeseries, in agreement with previous studies that reported lower values of α in elderly populations, where a degraded motor control can be assumed [19, 29]. This was confirmed also in [7], where it was observed that patients affected by Parkinson's disease showed higher D values if compared to healthy elderly. Indeed, control schemes with large derivative gain constitutes an energetically inefficient control strategy, with inflexible and non-reactive stabilizing mechanism, marked by lower α values [7].

As happened for P, also ρ did not show any significant correlation with α and β coefficients (Fig. 6), indicating that, despite the significant role of ρ in defining the exchange between the ON and OFF sub-dynamics (see section 2.1), it appears to be not directly related with the stochastic properties of COP timeseries quantified through the EDFA. In addition, it deserves to be noted that, within the range of P and D values selected in this study (Table 1), stable simulations were obtained for ρ up to $\simeq$0.9, although ρ was free to vary with the upper bound set to 1 (Table 1). This indicates that the condition for a fully continuous control (ρ =1) was not reached and thus findings of this study hold when an intermittent control takes place.

For what concerns the β coefficient, it can be observed that the inhomogeneity of the COP timeseries decreases for progressively higher values of D (Fig. 5). The coefficient β was defined to indicate departure from the power law behavior (8), since the standard deviation of the profile from the local trend (7) can vary significantly among the different segments [22]. A reduction of inhomogeneity implies COP timeseries characterized by regular oscillatory fluctuations, closer to a stationary behavior. Hence, the β coefficient can provide additive information regarding the organization of biological signals in terms of complexity, since it provides a quantitative measure of local transients [22]. The lower β values observed for increasing derivative gains appears in agreement also with the *loss of complexity* paradigm [30]. This hypothesis essentially states that healthy physiological systems produce responses that are complex in the sense of non linear correlations and long-term dynamics, while a functions' breakdown, due to aging or disease, leads to less complex outputs that mirror a reduced ability in producing an adaptive set of responses when facing motor, cognitive or neurological needs [31, 32]. Thus, the reduction of β coefficient highlights a loss of fine-structures in COP epochs and it suggests a reduced capability to cope with balance demands, relying on a set of few and repeatable postural patterns with a limited physiological adaptability. Hence, a lower degree of inhomogeneity could reflect a rearrangement in the CNS motor control schemes due to certain pathologies, resembling an inefficient tuning of the IP active controller [7, 33].

The above mentioned analysis indicates that, among the three ICP, D gain alone reflects changes in the long-term correlation and inhomogeneity properties of the whole COP timeseries. This aspect is strengthened also by considering separately $\alpha - D$ and $\beta - D$ relations (Figs. 7 and 8). In both cases, it appeared that the inter-dependence between D and EDFA coefficients can be fitted with two straight lines characterized by different slopes, highlighting the possible existence of two different relationships, depending upon D values. In order to test this hypothesis, both the $\alpha - D$ and $\beta - D$ were fitted through a least-square spline approach [34], testing respectively the existence of three models, described by one, two, and three polynomials of order 1. The criterion used for assessing the best model was the normalized Akaike's information criterion (nAIC) [35], for which the most accurate model presents the lowest nAIC. For both $\alpha - D$ and $\beta - D$ data distributions, the best fitting model was that with a single knot point and thus with two lines: in this case the nAIC resulted equal to -4.67 versus -4.57 (one line) and -4.40 (three lines) for $\alpha - D$. Similarly, for $\beta - D$ the two-lines model presented a nAIC of -3.67 versus -3.60 (one line) and -3.52 (three lines). In addition, in both cases the crossing point between the two lines (the knot), presented the same value, i.e. D =243 $N \cdot m \cdot s \cdot rad^{-1}$ (Figs. 7 and 8).

Given the presence of two different kind of relations between D and EDFA coefficients, a further analysis was performed regarding the correlation between α and β with the other two control parameters, i.e. P and ρ. Hence, those P and ρ values for which the correspondent D gain was respectively <243 $N \cdot m \cdot s \cdot rad^{-1}$ and ≥243 $N \cdot m \cdot s \cdot rad^{-1}$ were separately taken into account. To be noted, such D value was obtained directly from the above mentioned data-driven analysis and thus it cannot be claimed that it represents a critical value for the intermittent control scheme. Its possible physical meaning, however, deserves to be carefully investigated in future studies, also in relation to the other ICP.

Regarding the proportional gain, as happened when the $\alpha - P$ and $\beta - P$ correlations were examined over the entire range of the proportional gain (Fig. 4), neither α nor β showed any direct relation with P ($r = -0.36$ and -0.32 for $D < 243N \cdot m \cdot s \cdot rad^{-1}$ and $r = -0.19$ and -0.11 for $D \geq 243N \cdot m \cdot s \cdot rad^{-1}$). This supports once more that within the range of values assumed by P in this study, its variations seem to not consistently affect the COP fractal properties measured by EDFA.

On the other hand, the ρ parameter showed a different behavior with respect to α and β depending upon the values assumed by the derivative gain. When D is lower than 243 $N \cdot m \cdot s \cdot rad^{-1}$, both α and β showed a significant (p <0.0001) correlation with ρ (r =0.44 and 0.61, respectively, Fig. 9). This suggests that the stochastic behavior and the inhomogeneity of a timeseries, quantified by the EDFA coefficients, manifest a direct relationship with the intermittent nature of balance control when D assumes typical values for this control strategy [7]. Incidentally, this is also in agreement with ρ values that not overcome $\simeq 0.7$, which permits to exploit the two main features of the intermittent control: the stable manifold belonging to the OFF-dynamics and the spiraling state steering induced by the delayed unstable dynamic of the ON-subsystem. This eventually permits to obtain limit cycle stability without the need of greater control efforts [7]. In addition, the correlation between α and two control parameters (D and ρ) aligns with the findings by Yamamoto et al. [28], who reported that the slope of the COP power spectrum at the LB, which is directly related to α [36], is a universal characteristic of postural sway, associated to neural control strategies. Considering that, despite both trends are significant, β highlights a greater capability in detecting changes in ρ, if compared to α, and thus it further supports the use of the extended version of the DFA for analyzing posturographic data.

Finally, it is interesting to note that the α coefficient maintains in any case values quite close to 1 (Fig. 9), possibly referring to an attempt to maintain the output of the balance regularization, i.e. the COP, close to a $^1/_f$ process. Indeed, the latter is frequently encountered in different physiological time-series, characterizing a healthy motor control [27, 37, 38]. On the other hand, the β coefficient covered a larger set of values (Fig. 9), pointing out that the simulated COP timeseries exhibited different degrees of irregularity in their local structures [23, 22]. The latter can be associated with the complexity of the physiological system generating the data[22], which in healthy conditions is commonly characterized by a higher complexity [38, 39], leading in turn to an enhanced robustness and adaptability of the response [39, 40].

Present results indicate that, when relatively low D values are used in the active controller, the ρ parameter is connected to the degree of inhomogeneity of the COP and thus to the complexity of the balance regulation. This can motivate additional studies aimed at investigating how the tuning of the S_{on} and S_{off} regions impacts on the irregularity and complexity of the COP fluctuations. It should be noted that the EDFA investigated in this study provides a single-scale analysis, accounting for a global description of the data [23, 22], whereas many previous studies demonstrated the value of a multi-scale approach for COP timeseries [14, 19, 27, 32, 40]. This is also supported by present results, which highlighted different dynamics over different temporal scales (Fig. 2). Therefore, future works should be devoted to apply EDFA in a multi-scale analysis, in order to gain insights regarding the inhomogeneity of COP timeseries over different sub-dynamics.

When the derivative gain assumes values higher than 243 $N \cdot m \cdot s \cdot rad^{-1}$, the P gain remains unrelated to both α and β, as highlighted by the poor correlation coefficients ($r = -0.19$ and -0.11, respectively). In this case the same holds also for the ρ parameter (Fig. 10), for which the correlations observed in the previous case completely disappeared ($r = -0.0021$ for $\alpha - \rho$ and $r = -0.14$ for $\beta - \rho$). A possible explanation for this behavior can be proposed considering that, for such range of D values, the S_{on} dynamics can stabilize the IP process *per se* [7], without the need for switching between sub-dynamics, since with this range of D values ($\geq$243 $N \cdot m \cdot s \cdot rad^{-1}$) the (P, D) of the ON-subsystem is located inside the stability region reported by Suzuki et al. [7]. In this context, the control policy mimics a stabilizing delayed continuous control [7] and thus it is reasonable to assume that ρ becomes less crucial within this control scheme, loosing its relations with EDFA coefficients.

Outcomes of this study indicate that the α and β coefficients introduced by the EDFA provides additional information on local COP structures, which in turns are related to the parameters of the intermittent control model. Further, EDFA resulted able to highlight subtle properties of sway fluctuation data which can be observed if different ranges of control parameters' values are separately taken into account. Hence, EDFA can be used together with the classical DFA exponent to better characterize the upright balance maintenance under the intermittent control regime, since inhomogeneity and long term correlations can be useful descriptors of the hidden postural control paradigm.

4. Conclusion

In this study, the EDFA was used to investigate the COP time-series generated by using an IP model, intermittently controlled at the ankle. The IP model was used to simulate the dynamics of the human balance maintenance in the anterior-posterior direction [10]. The intermittent motor control paradigm confirmed to be adequate to simulate COP that presented characteristics of long-term correlation, as those observed for real data [4]. Moreover, the concept of inhomogeneity introduced in the EDFA turned out to be suitable for characterizing inner properties of the balance regulation output. The β coefficient was coupled to the hidden controller parameter D and ρ, showing different relations depending upon the derivative gain values investigated.

In addition, the modeling approach here employed resulted useful to highlight possible interpretation that the EDFA analysis can provide when applied to real data. Indeed, in a real scenario, functional rearrangements of the CNS can be identified in changes in the controller parameters, using opportune identification procedures [33, 7]. Hence, EDFA, embedding the concept of inhomogeneity, can be particularly suitable in posturography to highlight differences in balance strategies between healthy and pathological groups. Lastly, the choice of using COP rather than other time series, i.e., COM and joints angles, lies on an important practical consideration, since COP is directly measurable from force-plate and it does not require any patient instrumentation or estimation procedure.

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