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Fractal Analysis of Lower Back Acceleration Profiles in balance tasks*

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***Abstract*— The body sway during standing displays fractal properties that can possibly describe motion complexity. This study aimed to use the Higuchi's fractal dimension (HFD) and Tortuosity on lower back accelerations recorded on younger (< 35 y) and older adults (> 64 y). One wearable sensor was secured on participants lower back (i.e., fifth lumbar vertebra), which were asked to perform three different postural tasks while standing barefoot as still as possible with and without performing a visual oddball task. Results of HFD and Tortuosity, applied to global anterior-posterior and medial-lateral accelerations of the body, were not dependent from signal amplitude, nor from any parametrization and allowed distinguishing between different postural tasks ($p < 0.001$). The proposed fractal analysis is promising to describe the complexity of postural control in both younger and older adults, paving the way to a wider use in pathological populations.**

I. INTRODUCTION

Walking and balance impairment associated either with ageing or neuro-musculoskeletal disorders are important markers of disability, loss of independence and depletion of individuals' quality of life [1]. Quality of walking and balance performances are generally evaluated by describing different motor skills: i.e., complexity, adaptability, smoothness, efficiency, symmetry and stability [2].

Although being a powerful tool to quantify motor impairment, conventional motion analysis is still limited to clinical environments and, thus, may not capture the relevant motor skills needed in everyday life [2], especially in pathological conditions. As an example, freezing of gait is associated with high risk of falls in people with Parkinson's disease and it does not necessarily occur during neurological examination [3]. Wearable technologies can possibly overcome such limitations and interest in their use is rising due also to their limited cost [2], [3]. Waist-mounted Inertial Measurement Units (IMUs), generally mounted between the third and fifth lumbar vertebrae and composed by accelerometers, gyroscopes and magnetometers, are often used to quantify the body Center of Mass (CoM) motion [4]. In particular, accelerometers are used to derive a set of measures that can serve as global indicators of walking [2] and balance performances [4]. A large variety of indicators obtained from lower back acceleration profiles have been proposed, but there is no clear agreement on the association of those measures with specific motor skills [2].

The body sway during standing is a non-stationary process that display fractal properties [5]. A signal has fractal properties when pieces of it can be found elsewhere in the signal at different time scales and have a relationship of similarity. Fractal analysis (FA) has advantage of not being restricted to study steady-state signals, but has the potential of characterising transients [6]. FA was used in the past to study the stride-to-stride variability and trunk acceleration profiles in both normal and pathological gait [7], [8]. A signal with fractal properties is a complex signal: in particular, the higher the fractal dimension (FD) the higher the complexity.

Many algorithms have been proposed to calculate fractal properties of signals, but some of them: call for (i) high computational cost [9], (ii) long-lasting data collections [5], (iii) high sampling frequency [10]; or (iv) have no clear definition [4]. As an example, the Detrended Fluctuation Analysis (DFA) was implemented to study the fractal properties of gait stride-interval in people with Huntignton's disease compared with younger and older adults [7]. DFA detected a more disordered signal in walking of people with Huntington's disease. However, results obtained via the DFA are difficult to interpret due to the lack of standardization in the algorithm definition itself [4].

Although the use of indices evaluating the fractal properties of lower back accelerations may pave the way to a new understanding of postural control in static and dynamic conditions, both in pathological and healthy individuals, at both transient and 'steady-state', the aforementioned drawbacks have hampered their implementation in research and clinical practice.
Among the available approaches, the Higuchi's Fractal Dimension (HFD) is frequently adopted to describe fractal properties in the non-linear analysis of electroencephalogram. HFD is clearly defined [11], has a low computational cost, does not call for any storage memory and, thus, overcomes the limitations that affect other approaches [6], [12], [9].

The aim of this study was (A) to perform a fractal analysis of lower back acceleration signals gathered from both younger and older adults using the HFD, and (B) to compare the measures obtained with this approach with a more common measure of signal complexity in motion analysis.

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II. MATHEMATICAL BACKGROUND

A. Higuchi's Fractal Dimension and Tortuosity

FD is a time domain analysis that provides a quantitative measure of signal dynamics [13]. In the last decades, many algorithms have been proposed to estimate FD. The most widely accepted are Higuchi's, Katz's and Petrosian's methods [11], [14], [15]. HFD is considered the most accurate [16].

In brief, the Higuchi's FD calls for: (i) the definition of a set of k sub-signals s of length N, defined sampling the original time series at regular time interval k and starting from the sample m, with $m = 1, ..., k$; (ii) the calculus of the absolute distance between subsequent samples of each s-signal (i.e., samples at distance k in the original time series); (iii) the normalization of these absolute distances for a term that accounts for sub-signals length; (iv) the construction of the length curve

$$L_m(k) = \frac{1}{k}\Big[\sum_{i=1}^{q}\big|s(m+i\cdot k) - s(m+(i-1)\cdot k)\big|\Big]\cdot\frac{N-1}{q\cdot k}, \tag{1}$$

with $q = \text{integer}[(N-m)/k]$; and (v) the calculus of the average distance $L(k)$ for $m = 1, ..., k$ and $k = 1, ..., k_{max}$. The curve $L(k)$ is fractal with dimension D if $L(k) \propto k^{-D}$. Using a log-log plot, D can be estimated via a least square of the linear part of the ℓ_k curve:

$$\ell_k := \Big\{log(k), log\big(L(k)\big)\Big\},\ k = 1, ..., k_{lin},\ k_{lin} < k_{max}. \tag{2}$$

The so calculated fractal dimension D will be hereinafter addressed with H_{ℓ_k}.

The non-linear part of the ℓ_k curve presents oscillatory behaviours (i.e., for $k \in (k_{lin}, k_{max}]$), whose characteristics depend on the periodicity of the original signal [12]. The tortuosity (τ_{ℓ_k}) is a measure of the changes in the first ($\Delta(\cdot)$) and second partial differences ($\Delta^2(\cdot)$) of ℓ_k and, thus, is a measure of signal periodicity [17]:

$$\tau_{\ell_k} = \sum_{n=3}^{k_{max}}\left|\frac{\Delta x(n)\Delta^2 y(n) - \Delta^2 x(n)\Delta y(n)}{\big[(\Delta x(n))^2 + (\Delta y(n))^2\big]^{\frac{3}{2}}}\right|, \tag{3}$$

with $x = log(k)$ and $y = log(L(k))$. The higher the tortuosity, the more the signal is reach of oscillatory components. For this study, k_{lin} and k_{max} were defined by inspecting the first derivative of the constructed ℓ_k and were set at 6 (i.e, first change of value of the first derivative) and 100 (i.e, including ℓ_k ripples), respectively.

B. Sample Entropy

The sample entropy ($SampEn$) examines time series of length N for similar epochs [18]. In particular, the $SampEn$ is the negative natural logarithm of the conditional probability that two sequences that are similar for m points remain similar at the next point with a tolerance r, having excluded self-matches. The lower the $SampEn$, the higher the self-similarity and, thus, the lower the complexity.

III. MATERIALS AND METHODS

Data used in this research were collected as part of a larger project, which includes electroencephalography, electromyography and motion data. The detailed protocol used for data collection and processing is described elsewhere [19], whereas only relevant details are briefly reported here.

A. Participants and Ethics statement

Nine healthy older (ELD, 64-76 y) and 8 healthy younger adults (CTRL, 24-34 y) were recruited [19]. All subjects signed an informed consent prior data collection (ethical approval granted by the Ethics Committee for Clinical Trials of the Province of Padova, n.AOP2025).

B. Data collection

One IMU (Cometa WaveTrack Waterproof, Cometa srl, Italy) was secured on participants fifth lumbar vertebra (L5) with a double-sided adhesive tape (sampling frequency 142.85 Hz). See also Fig. 1a. Participants were asked to perform three different postural tasks while standing barefoot as still as possible for 3 minutes, keeping their feet at shoulder width, and staring at a screen at 1 m distance and at their eye-level.

Postural tasks were: 1) static and single-task (sST) – i.e., participants were standing on the floor and the screen was switched off; 2) static and dual-task (sDT) – i.e., participants were standing on the floor while performing a visual oddball task; and 3) dynamic and dual-task (dDT) – i.e., participants were standing on a 1 degree of freedom balance board that was free to rotate around a medio-lateral axis (i.e., pitch angle) while performing the visual oddball task (Fig. 1b). Tasks were presented in random order to the participants.

The visual oddball task consisted in the presentation of a sequence of repetitive ($\sim$ 80/100) stimuli (i.e., a 3 cm^2 red square in the center of the black screen) that were infrequently ($\sim$ 20/100) interrupted by a deviant stimulus (i.e., a 3 cm^2 yellow square in the center of the black screen). Participants were asked to count the deviant stimuli only.

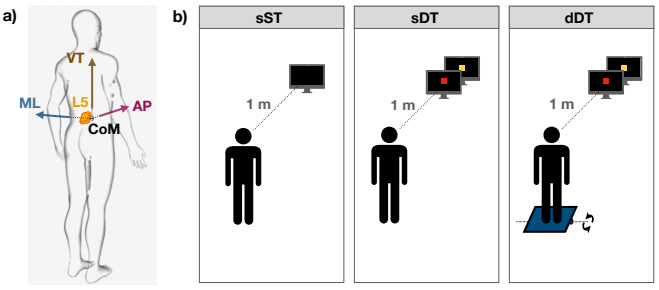

Fig. 1. Data collection protocol: a) participant equipped with the IMU on L5 and the antero-posterior, medio-lateral and vertical directions of movement (AP, ML and VT respectively); b) the three postural tasks (static and single task – sST; static with dual task – DT; and dynamic with dual task – dDT).

C. Data processing

A time-window of 40 s (i.e., the minimum duration for transient extinction of stability parameters [20]) of the L5-acceleration was considered for the analysis for each task and was low-pass filtered with a zero-lag 2nd-order Butterworth filter (cut-off 15 Hz) [19]. A roll-pitch correction was then estimated from the sST condition and applied to all trials (sST, sDT, dDT) to correct for possible misalignment of the sensor axes with the global anterior-posterior (AP) and medial-lateral (ML) directions of the body [21]. Acceleration signals were then reoriented on the AP (pointing forward), ML (right-to-left) and vertical (VT parallel to $-g$, the negative gravity acceleration vector) directions (see Fig. 1a). Considering that VT signals are most likely to be considered as noise in sST and sDT conditions, VT component was retained for further analysis for the dDT condition only.

Data were processed in MATLAB (r2020a, Mathworks Inc., Natick, USA). H_{ℓ_k} and τ_{ℓ_k} were calculated using the codes published along with [9], whereas the $SampEn$ was calculated with [22], [18].

D. Statistics

All variables were tested via a two-tailed Wilcoxon rank test to check for significant differences between ELD and CTRL groups ($\alpha = 0.05$). Differences across balance conditions were also tested via a Kruskal-Wallis test ($\alpha = 0.05$), with a Wilcoxon rank test as post-hoc. A Bonferroni correction was applied to account for multiple comparison. Acceleration signals display different magnitude among conditions as assessed via Root Mean Square (RMS). Thus, the linear regression was calculated for H_{ℓ_k}, τ_{ℓ_k} and $SampEn$ against the RMS to test for possible dependence of those indices from signal amplitude ($R^2 > 0.70$ and $p < 0.05$ indicate a meaningful linear relationship). Statistical analyses were performed in RStudio (v1.4.1106, RStudio, Boston, USA).

IV. RESULTS

Fig. 2 and Fig. 3 respectively show the results obtained for H_{ℓ_k} and τ_{ℓ_k}, and $SampEn$.

H_{ℓ_k} and τ_{ℓ_k} allow distinguishing between floor standing and balance board postural test (dDT), see Fig. 2. Both H_{ℓ_k} and τ_{ℓ_k} are lower in dDT for both CTRL and ELD (Kruskal-Wallis $p < 0.001$). Post-hoc analyses revealed significant differences in H_{ℓ_k} and τ_{ℓ_k} when comparing sST with dDT and sDT with dDT, both in AP and ML directions in CTRL ($p < 0.001$) and ELD ($p < 0.0001$).

$SampEn$ is dependent from signal amplitude. Indeed, a linear relationship with the signal RMS was found only for the $SampEn$ in AP and sST (CTRL: $R^2 = 0.80$ and $p < 0.01$; ELD: $R^2 = 0.90$ and $p < 0.001$), in ML and sST (CTRL: $R^2 = 0.89$ and $p < 0.001$; ELD: $R^2 = 0.77$ and $p < 0.01$) and dDT (CTRL: $R^2 = 0.80$ and $p < 0.01$). For both H_{ℓ_k} and τ_{ℓ_k} a weak relationship was found in AP for the dDT condition only in the CTRL group ($R^2 < 0.70$ and $p < 0.05$). Moreover, $SampEn$ is not able to distinguish between different postural tasks (i.e., it is not sensitive to

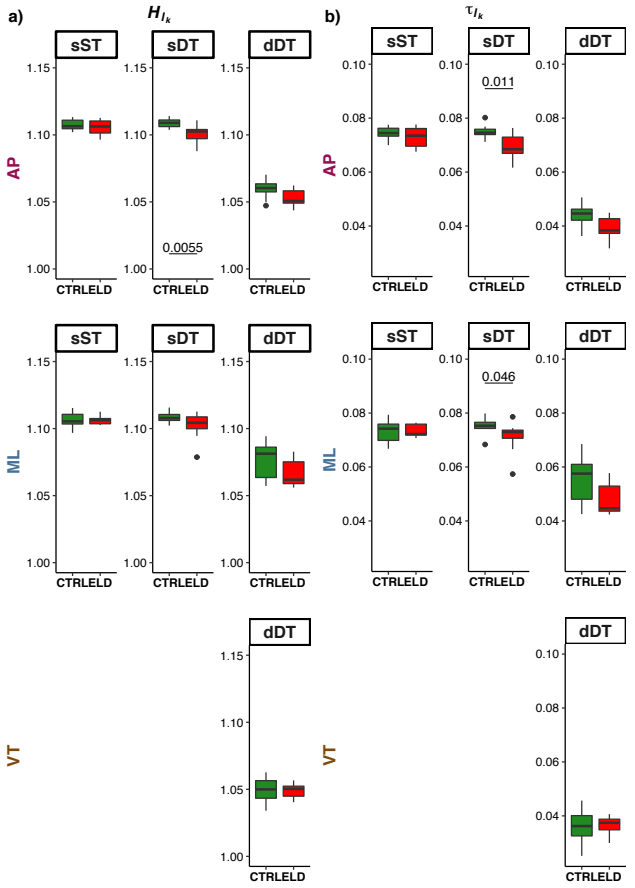

Fig. 2. Higuchi's fractal dimension H_{ℓ_k} (a) and tortuosity τ_{ℓ_k} (b) calculated for younger (CTRL) and older (ELD) adults (in green and red, respectively) for static single-task (sST), static dual-task (sDT) and dynamic dual-task (dDT) conditions in the three directions (antero-posterior – AP, medio-lateral – ML, and vertical directions – VT). CTRL vs ELD p-values are reported on each sub-panel for significant comparisons.

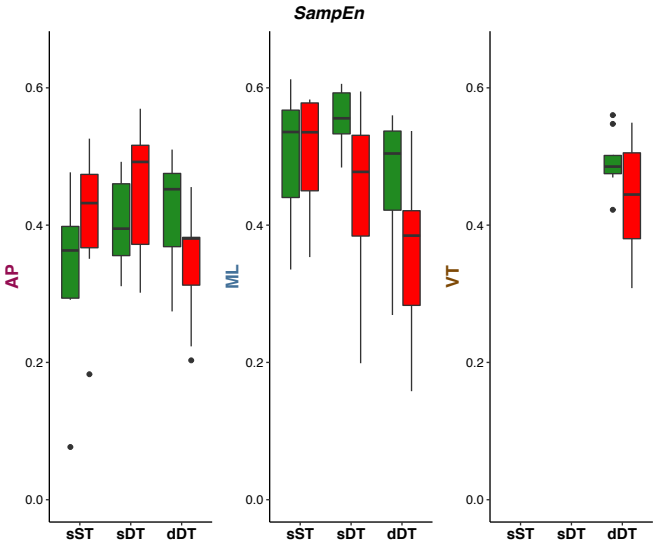

Fig. 3. $SampEn$ for younger (CTRL) and older (ELD) adults (in green and red, respectively) for the static single-task (sST), static dual-task (sDT) and dynamic dual-task (dDT) conditions in the three directions (antero-posterior – AP, medio-lateral – ML, and vertical directions – VT).

different conditions of movement), see Fig. 3 (Kruskal-Wallis $p > 0.05$).

V. DISCUSSION

Considering that 1) $SampEn$ is dependent from signal amplitude and 2) it requires to be evaluated on multiple scales (i.e., multiscale approach) being sensible to algorithm parameters [23], H_{ℓ_k} and τ_{ℓ_k} are more reliable nonlinear approaches to evaluate complexity of acceleration profiles in balance tasks.

Complexity is lower in dDT for both CTRL and ELD (see Fig. 2), most likely because the balance board constrained the movement to be oscillatory around one axes only. Thus, even though it is a more unstable condition, dDT introduces a periodicity in the postural adjustments that consequently increases the signal regularity (i.e., reduces the complexity). Despite non-evident differences are obtained comparing CTRL vs ELD in all conditions and for all acceleration components (AP, ML and VT), a trend of lower H_{ℓ_k} and τ_{ℓ_k} in the ELD group is visible. This may be associated with a gross and periodical balance adjustment due to a reduced ability of older adults of continuously adjusting their balance with respect to younger adults. This conclusion is also supported by results previously obtained on the same data set and published in [19], which highlighted a larger body sway in older adults, than in younger adults.

It is worth considering that these conclusions should be further explored on a larger sample of younger and older individuals, also considering analyses aiming to test the reliability of the Higuchi's FD and Tortuosity applied on lower back accelerations gathered from different balance tasks. Indeed, further analyses may either confirm our interpretation of the results, or reveal that sST and sDT tasks may be more reliable when studying body balance with the Higuchi's FD and Tortuosity.

VI. CONCLUSIONS

The results of present study encourage the use of the Higuchi's fractal dimension to describe the complexity of postural control in both younger and older adults, paving the way to a wider use even in pathological populations, e.g., in people with Parkinson's disease.

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