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Nonlinear Chaotic Component Extraction for Postural Stability Analysis

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***Abstract*— This paper proposes a nonlinear analysis of the human postural steadiness system. The analyzed signal is the displacement of the centre of pressure (COP) collected from a force plate used for measuring postural sway. Instead of analyzing the classical nonlinear parameters on the whole signal, the proposed method consists of analyzing the nonlinear dynamics of the intrinsic mode functions (IMF) of the COP signal. Based on the computation of the IMFs Lyapunov exponents, it is shown that pre-processing the COP signal with the Empirical Mode Decomposition allows an efficient extraction of its chaotic component.**

I. Introduction

Recently, extensive research has been devoted to the study of postural steadiness. The attractiveness of this research field is essentially due to the importance of characterizing the fall risk and balance deficits among an elderly population. In fact, elderly may suffer from autonomy and independence loss after falling. In addition, for psychological reasons, fall risk increases after the first fall, leading to a severe deterioration of both the mental and physical health of the subject. Consequently, falls of the elderly is one of the main causes of death. Many scientific studies have attempted to identify the risk factors [1]. There are several clinical tests such as the Timed Get-up-and-go [2], the Berg Balance Scale [3] and the Tinetti Balance Scale [4] that can predict the risk of falling. The major drawback of these tests is the fact that they are not able to capture the time evolution of this risk and do not allow a daily evaluation of the balance status. Biomechanical tests of balance, however, circumvent these problems offering the possibility of predicting falls by extracting several parameters from the displacement of the centre of pressure. In fact, postural stability can be measured using a force plate, from which measures of centre of pressure (COP) displacement in anteroposterior (AP), mediolateral (ML), and resultant (RD) directions are obtained. The representation of the time series data of COP in AP and ML directions is known as the stabilogram. More recently, nonlinear methods have been proposed in order to extract new parameters linked to the underlying physiological systems. Among these parameters, the Hurst exponent provides information about the correlation and the auto similarity of the stabilogram [5], [6], while the Lyapunov exponent [7] and entropy [8] might also contain precious information about the static equilibrium of the subject.

In this paper, a different approach is proposed to analyze the stabilogram signal. The ML and AP time series are obviously non stationary and governed by nonlinear dynamics. Therefore, classical spectral signal decomposition fails to capture the nonlinear dynamics of the postural system. The proposed approach is based on applying the empirical mode decomposition (EMD) [9], which extracts the local oscillations composing the signal, referred to as the Intrinsic Mode Functions (IMF), as well as the residual representing the local trends. Estimation of the IMFs Lyapunov exponents makes evident the ability of the EMD decomposition to properly extract the chaotic component from the stabilogram signal contaminated by stochastic and deterministic quasi-periodic signals, confirming the conjecture made in our previous work [10].

II. Methods

A. Subjects

Ten healthy control subjects (three males and seven females), ten healthy elderly subjects (four males and six females) and one healthy faller elderly subject participated in the study. Control subjects' mean age, height and weight were $33.3 \pm 7.4y$, $168.0 \pm 6.5cm$, and $65.7 \pm 17.6kg$, respectively. Elderly subjects' mean age, height and weight were $80.5 \pm 4.7y$, $165.6 \pm 7.0cm$, and $71.9 \pm 9.9kg$, respectively. The faller subject had fallen twice in the previous 2 years (age 75 y). All subjects who participated gave their written informed consent. No subjects reported any musculoskeletal or neurological conditions that precluded their participation in the study.

B. Data Acquisition and Data Processing

Centre of pressure data were obtained from a Bertec 4060-08 force plate (Bertec Corporation, Columbus, OH, USA). The initial COP signals were calculated with respect to the centre of the force-plate before normalisation by subtraction of the mean value. Data were recorded using ProTags (Jean-Yves Hogrel, Institut de Myologie, Paris, France), which was developed in Labview (National Instruments Corporation, Austin TX, USA). Data were sampled at 100 Hz, using an 8th-order low-pass Butterworth filter with a cut-off frequency of 10Hz. All subsequent calculations were performed using Matlab (Mathworks Inc, Natick, MA, USA).

C. Experimental Protocol

Subjects were tested barefoot or wearing socks. Testing began with subjects standing upright with their arms by their sides in front of the force-plate while looking at a 10-cm cross fixed on the wall two meters in front of them. Upon verbal instruction, subjects stepped onto the force plate. Subjects were not required to use a pre-ordained foot position. Data recording lasted 15 seconds, during which time subjects maintained an upright posture. A second verbal command was given for subjects to step down from the force-plate.

D. Data analysis

Centre of pressure data were calculated from the instant that the second foot contacted the force plate (FC2). The time at which FC2 was considered to occur was calculated as the time at which the maximum value of the second derivative of the ML displacement signal occurred. This instant in time corresponded to the moment when the second foot touched the force plate, thus creating the largest acceleration of ML when the COP moved rapidly towards the second foot. This time was used for both AP and ML displacements. All analyses were done for the 10 s period starting 1 s after FC2, in order to give both AP and ML displacement time to return to near central values.

E. Empirical Mode Decomposition

The empirical mode decomposition is an intuitive signal-dependent decomposition of a time series into waveforms modulated in amplitude and frequency [9]. The iterative extraction of these components is based on the local representation of the signal as the sum of a local oscillating component and a local trend. The first iteration of the algorithm consists in extracting a component, referred to as the Intrinsic Mode Function (IMF), representing the oscillations of the entire signal. The difference between the original signal and the IMF time series is the residual. The IMF component is obtained by a sifting process such that it satisfies the requirement that it is zero-mean and that the number of extrema and the number of zero crossings are identical or differ by one. This same procedure is then applied on the residual to extract the second IMF. All the IMFs are therefore iteratively extracted. The nonstationary signal $x(t)$ is then represented as a sum of Intrinsic Mode Functions and the residual component:

$$x(t) = \sum_{k=1}^{K} d_k(t) + r_K(t) \quad (1)$$

where $\{d_k(t)\}_{k=1}^{K}$ denote the K extracted empirical modes and $r_K(t)$ the residual which is a monotonic function without extrema.

The EMD algorithm[1] can be summarized as follows:

1. *Extract all the extrema of* $x(t)$
2. *Interpolate between minima (resp. maxima) to obtain two envelopes* $e_{min}(t)$ *and* $e_{max}(t)$
3. *Compute the average:* $m(t) = (e_{min}(t) + e_{max}(t))/2$
4. *Extract the detail* $d(t) = x(t) - m(t)$
5. *Iterate on the residual* $m(t)$

In Figure 1, the intrinsic mode functions of a 10 s recording of the anteroposterior displacement of a healthy subject are shown.

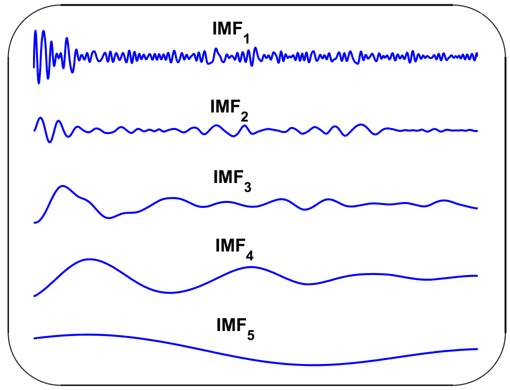

Fig. 1. EMD decomposition of a 10-s recording of the anteroposterior signal of a healthy young subject (age 19 y).

F. Lyapunov Exponents of Intrinsic Mode Functions

It was conjectured in [10] that the empirical mode decomposition allows the separation of the stochastic, chaotic and deterministic components composing the original stabilogram signal, based on a visual inspection on all the stabilogram signals in our data base. In this work, we resort to a quantative criteria to prove the ability of the EMD decomposition to properly extract the chaotic component from the remaining stochastic and deterministic components. The Largest Lyapunov Exponent (LLE) is a well defined tool to characterize the chaotic behavior of a given signal. In the following, we briefly recall the LLE definition and the numerical algorithm for its evaluation.

The Lyapunov exponent is a nonlinear parameter measuring the rate of loss of information from a chaotic time series. It characterizes the sensitivity to initial conditions, which one of the main features of chaotic dynamical systems. In fact, a chaotic signal is very sensitive to the initial condition so that two trajectories, governed by the same deterministic time evolution equations and starting from two nearby initial states, diverge at an exponential rate. The Largest Lyapunov Exponent is indeed a measure of this rate, defined by the following expression:

$$\lambda = \lim_{\Delta t \longrightarrow \infty} (1/\Delta t) \log\{\|\delta\boldsymbol{x}(\Delta t)\| / \|\delta\boldsymbol{x}(0)\|\},$$

where $\delta\boldsymbol{x}(0)$ is an infinitesimal initial state difference and $\delta\boldsymbol{x}(\Delta t)$ is the difference between the two trajectories at a later time. A positive value of λ indicates the presence of a deterministic chaos in the system dynamics, a negative

[1] Matlab codes are available at : http://perso.ens-lyon.fr/patrick.flandrin/emd.html

value suggests the existence of a stable fixed point and a zero value is found when the trajectory converges to a limit cycle. Although its definition is simple and intuitive, the computation of LLE in practical situations requires much care. An efficient numerical algorithm, robust to noise and to the limited data samples, has been proposed in [11] and in [12]. It consists in computing averaged divergences over different reference points $\boldsymbol{x}_{n_0}$, for a given embedding dimension m and a neighborhood volume ϵ:

$$D_{m,\epsilon}(\Delta t) = \frac{1}{N}\sum_{n_0}^{N} ln \frac{1}{|\mathcal{U}(\boldsymbol{x}_{n_0})|} \sum_{\boldsymbol{x}_n \in \mathcal{U}(\boldsymbol{x}_{n_0})} |\boldsymbol{x}_{n_0+\Delta t} - \boldsymbol{x}_{n+\Delta t}| \quad (2)$$

where $\mathcal{U}(\boldsymbol{x}_{n_0})$ is the neighborhood of $\boldsymbol{x}_{n_0}$ with diameter ϵ.

Expression (2) yields a family of curves indexed by two parameters m and ϵ. In general, ϵ is fixed as small as possible but large enough in order to ensure a minimum of neighbors around the reference point $\boldsymbol{x}_{n_0}$. However, the embedding dimension must be varied in order to check if the curves have a stable linear increase for a certain range of Δt. If the slope remains stable after a certain value of m (in general the Takens dimension), it yields an estimate of the largest Lyapunov exponent. Otherwise, if the curves (2) do not exhibit a linear behavior, it is difficult to evaluate the chaotic behavior of the signal and even misleading to apply a linear regression on the curves to calculate a value of the Lyapunov exponent.

III. Results

Figure 2 shows the computed log-divergences $D_{m,\epsilon}(\Delta t)$ for a filtered stabilogram signal in the AP direction and for its Intrinsic Mode Functions, for a control healthy subject. The embedding dimension m is ranging between 2 and 20 with an increment of 2. It can be noted that AP signal has linear log-divergence curves, for a long region. The small positive slope of the log-divergence curves suggests the existence of a low-level deterministic chaos in the stabilogram signal. However, plotting the log-divergence curves of the intrinsic mode functions confirms the ability of the EMD decomposition to separate the stochastic, the chaotic and the deterministic periodic components of the stabilogram signal. In fact, the log-divergence plots of the first and second IMFs are typical plots for a random noise (see figure 2), where it is difficult and misleading to estimate the Lyapunov exponent as no long enough linear region exist. However, the third IMF exhibits a long enough linear region with a slope equal to 0.26. The remaining IMFs have low Lyapunov exponents proving their quasi-periodic motions. The most interesting result is the fact that the Lyapunov exponent of the third IMF is higher than that of the whole AP signal. Decomposing the AP signal with the EMD method allows thus the extraction of the chaotic component (third IMF) and a better estimation of the Lyapunov exponent. In fact, the non-chaotic components contaminating the whole stabilogram signal are the main origin of the poor estimation of the Lyapunov exponent.

IV. Conclusion

The nonlinear time series analysis of the intrinsic mode functions is a novel interesting tool to understand the empirical mode decomposition. Based on experiments on stabilogram signals, we have shown the ability of the empirical mode decomposition to properly extract the chaotic component. Motivated by these promising results, the next step is a more extensive statistical study of the this finding. An experimental protocol, consisting in providing elderly people with stabilogram measuring system at home, has been recently deployed. By this protocol, we aim to build the first consistent database for the postural analysis and the risk of falling. Also, finding a global indicator allowing to follow the evolution of the postural steadiness status is among our perspectives.

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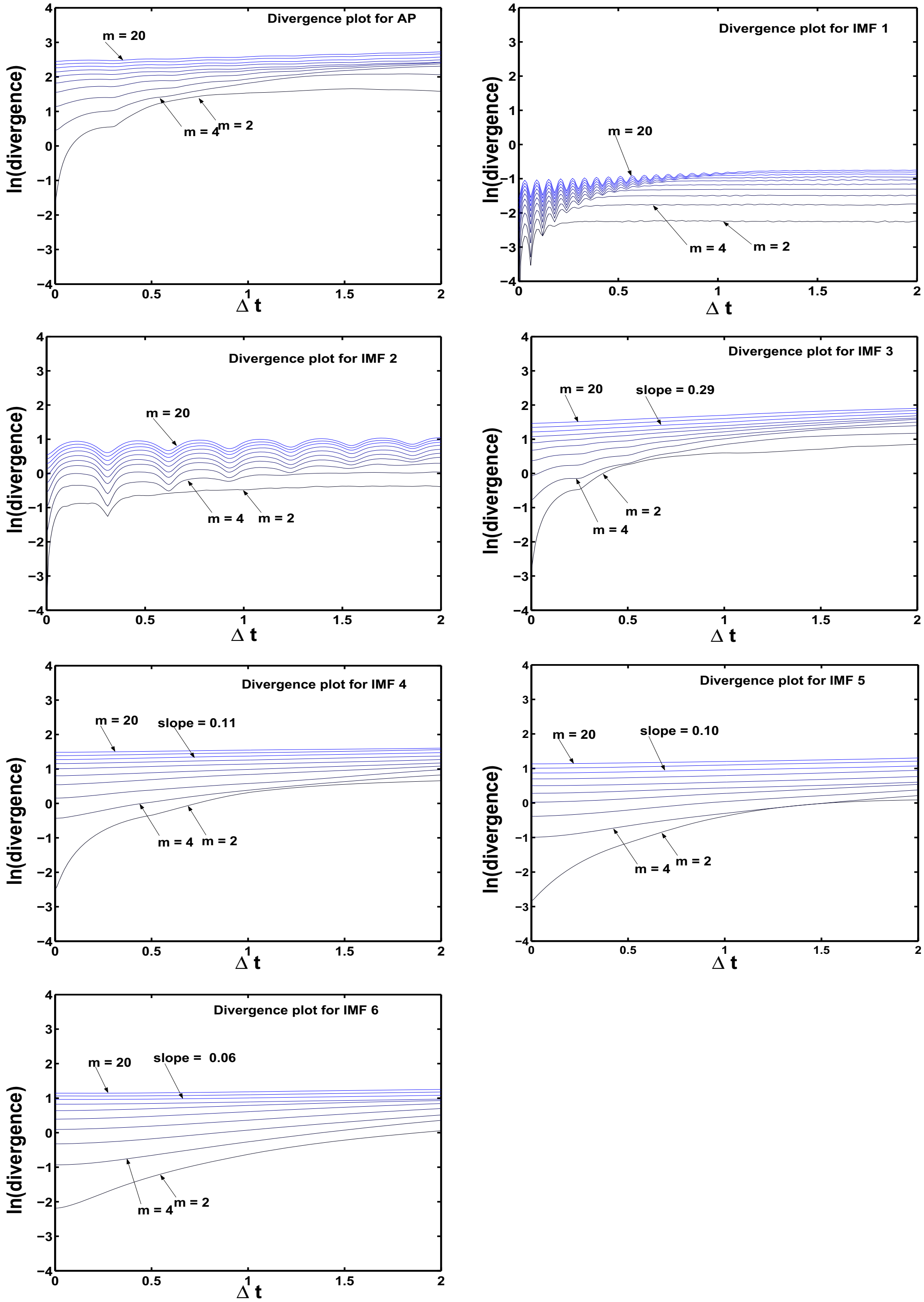

Fig. 2. Log-Divergence curves of a healthy control subject for the AP direction and all its IMFs.