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On the Detection of Elderly Equilibrium Degradation Using Multivariate-EMD

Abdelkader Miraoui, Hichem Snoussi and Jacques Duchêne
Institut Charles Delaunay, LM2S
BP 2060 - 10010 TROYES Cedex, France
E-mail: abdelkader.miraoui@utt.fr

Nourddine Azzaoui
Laboratoire de Mathématiques
UMR 6620 UBP - CNRS
BP 80026 - 63177 Aubière cedex, France

***Abstract*—The aim of this paper is to provide a new methodology for the detection of an increased risk of falling in community-dwelling elderly. A new extended method of the empirical mode decomposition (EMD) called multivariate-EMD is employed in the proposed solution. This method will be mainly used to analyze the stabilogram center of pressure (COP) time series. In this paper, we describe also the remote non-invasive assessment method, which is suitable for static and dynamic balance. Balance was assessed using a miniature force plate, while gait was assessed using wireless sensors placed in a corridor of the home. The experimental results show the effectiveness of this indicator to identify the differences in standing posture between different groups of population.**

I. Introduction

Due to the resulting loss of the elderly autonomy, the deterioration of their balance is a major problem in biomedical. Thus, several risk factors have been identified to minimize the effects of the falls. The muscular weakness is recognized as the most commonly cited factor. Recent analysis [1]-[3] show that the economic cost of the falls is proportional to the elderly population. In France, for example, the annual number of deaths caused by the falls is estimated to be more than 9.000, with a resultant cost over than two billion euros [4].

To capture clinically relevant episodes accurately and reliably, in a pervasive healthcare monitoring system, multiple sensors are employed to measure, both physiological and contextual informations. The postural equilibrium is maintained by reacting information from all the sensory systems, including vestibular, visual, and proprioception systems.

To evaluate postural sway, a force plate is used which integrates wireless sensors recording data captured from the body mouvements. The force plate measures the displacement of the COP, which represents the location of the resultant force exerted on the surface of a force plateform. The COP, which can be used as a measure of postural stability, is defined in the horizontal plane in both anteroposterior (AP) and mediolateral (ML) directions [1]. The representation of the COP time series, in the AP and ML directions, is known as the stabilogram (see Fig. 1).

Authors in [5] and [6] have proved that the stabilogram signals are nonstationary. Hence, the use of these curves presents a lack of ability to decide whether the person has a risk of falling or not. Therefore, we need a more precise and powerful method to explore these signals and then extract the relevant parameter. In this paper, in order to extract informations from the stabilogram and to characterize the postural stability, we propose the use of a new version of empirical mode decomposition of bivariate signals. This is the stabilogram signal, which may be seen as a multi-component signal [7]. Fig. 1 depicts an example of real data scenario.

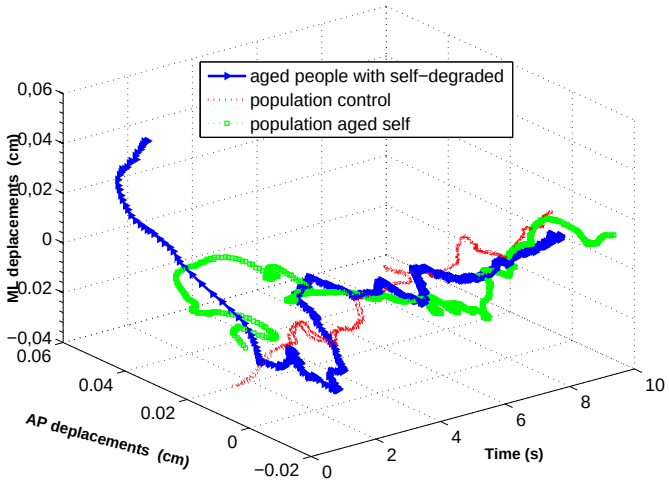

Fig. 1. Time evolution of ML and AP in young people and elderly

The proposed method ensures the decomposition of the signals into elementary rotating functions, oscillating functions and tendencies. The technique is based on recursive extraction of non planar and rapidly rotating functions, and then a recursive extraction of rapidly oscillating functions as in case of univariate-EMD. Our concept is based on a theoretical decomposition and is confirmed on simulated signals (see Fig. 2).

We propose to exploit the stabilogram to extract a relevant indicator that allows diagnosing a risk of falling and monitoring of the evolution of imbalance quality in the elderly.

The remaining of the paper is organized as follows. Firstly, the experimental protocol, mv-EMD, and the data processing are presented in Section II. Section III summarizes the main result, obtained by applying our proposed method on the stabilogram. Finally, Section IV concludes the paper.

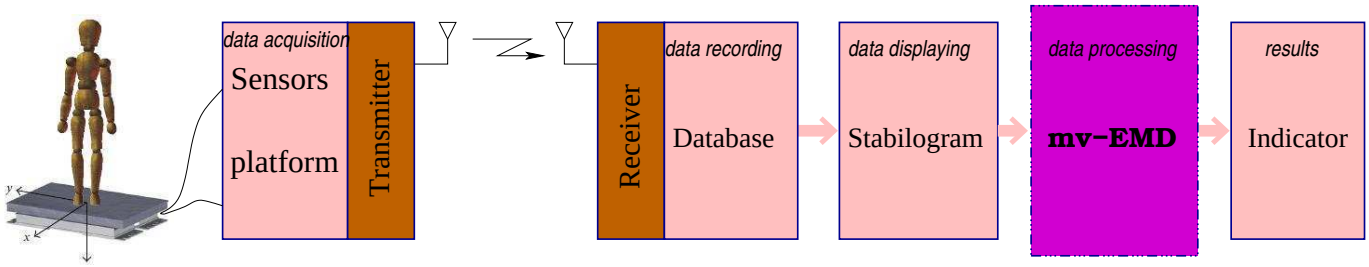

Fig. 2. Schematic diagram of a remote monitoring system for balance assessment

II. Materials and Method

In this section, we give a detailed description of the proposed method and the materials employed for signal acquisition and data analysis.

A. Population Groups and data Acquisition

During all manipulations, we assume that all measurements are taken from two classes of people: the first class is composed of ten healthy control subjects (three males and seven females) while the second includes ten healthy elderly subjects (four males and six females).

Control subjects mean age, height, and weight are 33.3 ± 7.4 years, 168.0 ± 6.5 cm, and 65.7 ± 17.6 kg, respectively. Elderly subjects mean age, height and weight are 80.5 ± 4.7 years, 165.6 ± 7.0 cm and 71.9 ± 9.9 kg, respectively.

We notice here, that the data related to center of pressure (COP) are obtained from a Bertec $4060-08$ force plate (Bertec Corporation, Columbus, Ohio, USA). The initial COP signals are recorded for several non-normalized values of the center of force plate and by subtracting the mean value. The data is sampled at the rate of 100 Hz and then filtered using an 8th-order lowpass Butterworth filter with a cutoff frequency of 10 Hz. Then the data are recorded and treated using ProTags and Labview (National Instruments Corporation, Austin, Tex, USA). Finally, all subsequent calculations are performed using MATLAB.

B. Experimental protocol

Subjects are tested barefoot or wearing socks. The test starts 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 in 2 meters in front of them. Upon verbal instructions, subjects stepped onto the force plate and they are not required to use a preordained foot position. Data recording lasted 15 seconds, during which subjects maintain an upright posture.

C. Data processing

1) Overview of the mv-EMD: The EMD concept was first introduced by Huang et al. [7]. It is based on the simple assumption that any data may have many different coexisting modes of oscillations one superimposing on the others. It is a signal processing decomposition technique that decomposes each signal into waveforms modulated in both amplitude and frequency by extracting all modes that the signal contains [7].

The decomposition is an intuitive and adaptive signal-dependent and does not require any conditions about the stationarity and linearity of the signal. The waveforms extracted by EMD are named IMFs (Intrinsic Mode Functions). Each IMF is symmetric, assumed to yield a meaningful local frequency, while different IMFs do not exhibit the same frequency at the same time. In other words, each IMF satisfies the two following constraints:

- the number of extrema and the number of zero crossings are identical or differ at most by one;
- the mean value between the upper and the lower envelope is equal to zero at any time.

The difference between the original signal and the IMF time series is the residual. The first IMF component is obtained by a sifting process. This procedure is then applied on the residual in order to extract the second IMF, and so forth. Thus all the IMFs are iteratively extracted. The nonstationary signal $x(t)$ is then represented as a linear sum of IMFs and the residual component.
After the convergence of this algorithm the signal $x(t)$ can then be written as:

$$x(t) = \sum_{k} c_k(t) + r(t), \tag{1}$$

where $r(t)$ is a residual tendency and $c_k(t)$ are the intrinsic modes IMFs. (IMF : intrinsic mode function) It relies heavily on the calculation of the extrema that do not have any meaning in such multidimensional signals.

The originality of our method lies in the fact that it drops the step of sifting and consequently its drawbacks. In contrast to the classical EMD, our proposed method uses the convexity changes of the signal instead of its extrema. These new adaptations are easy to deal with, since they have no natural significance for vectorial or complex functions. Some research works related to the applications of EMD, in the case of vectorial and complex signals, are provided by authors in [8], [9] respectively .

Our proposition is to be able to decompose any signal into elementary bivariate IMFs which is a bivariate function characterized having the following forms :

- **Rotating IMFs:** are non-planar curves which are turning around the time axis (they have a spiral shape). In addition, they are "locally symmetric" as explained bellow. For example $(\sin(t), \cos(t))$ is a non planar rotating IMF.

- **Oscillating IMFs:** are planar curves having many changes of the convexity and have a "local symmetry" as well. In their containing plan, they can be seen as a univariate IMFs. For example, the function $(\sin(t), 2\sin(t))$ is a simple planar oscillating IMF.
- **Tendencies:** are planar or non planar curves which have no inflexion.

What will be considered as tendency is any function which has no change in the sense of its convexity. Somehow, a tendency may be seen as a piece of an IMF that one cannot observe entirely because of the relative short time of observations. In order to decompose the signal into elementary IMFs, the procedure consists on identifying the inflexion points by searching the points for which the convexity of the curve changes. These inflexions give an idea about the apparent rotation and oscillatory nature of the studied signal.

2) Model motivation and physical explanation: The balance of a person, moving or in a static state, can be described by the fundamental rule of dynamics, illustrated by a differential equation of Langevin type:

$$\frac{d\vec{v}(t)}{dt}(t) = -k(t)\ .\ \vec{v}(t) + \vec{n}(t), \tag{2}$$

where $\vec{v} = (\dot{x}, \dot{y})$ is the velocity vector, and $\vec{n}(t)$ is the resultant of forces applied by the muscles to maintain the balance. The term $k(t)\vec{v}(t)$ represents the resultant forces responsible for the imbalance. In [7], it was shown that the empirical mode decomposition is more suited to this kind of system (2) in its one-dimensional version. It breaks down the movement into elementary displacement which can be described by intrinsic components (IMFs). In this paper we use the bi-dimensional version of the EMD introduced in [10] which will consider the mutual link between x and y and their combined influence on the balance. We are aware that the EMD will not necessary find exactly the real elementary behaviors that gave rise to the movement. However, it will give exploitable intrinsic mode functions summarized through their instantaneous amplitudes and frequencies. These instantaneous components will allow the construction of an accurate indicator permitting to point out the state of balance degradation of a given patient.

3) An indicator for precarious imbalance detection: The idea is based on a physiological explanation of the equilibrium. Firstly, in order to maintain equilibrium, muscles must deploy more energy proportionally to the gap between the COP and the center of gravity (COG). This means that equilibrium becomes more precarious as well as this gap is larger. This distance between the COP and COG will manifest as an *amplitude* in the stabilogram. On the other hand, the precarious state of the equilibrium worsens when the patient spends more time in this situation of imbalance. This fact will be seen as a the time *period* to return to the state where the COP coincides with the COG. The idea of the indicator we introduce here consists in exploiting these periods and amplitudes. These last quantities cannot be directly extracted from the stabilogram but only from its corresponding IMFs. For this reason, we begin first by decomposing the stabilogram using the mv-EMD and then extract instantaneous amplitudes and frequencies. The indicator that allows to quantify the risk of falling is introduced as a deviation from the equilibrium amplified by the time spent in this imbalance state.

Indeed, for each IMF extracted from the stabilogram and each simple oscillation, the parameter we propose is given by $I = A.T$, where A is the amplitude of a given local oscillation and T its corresponding period. The amplitude A, weighted by the period T, quantifies the influence of the deviation from equilibrium which is amplified by the duration of the imbalance. In practice, especially when it comes to rapid oscillation IMFs, it is unnecessary to process the data for all periods but rather at fixed laps of time that we choose. The indicator has been extracted using the forthcoming rules:

- Data acquisition and extraction of the stabilogram.
- Signal decomposition using the mv-EMD and extraction of all the IMFs and trends (Suppose we obtain K IMFs).
- The indicator $I_k, k = 1 \ldots, K$ is calculated for all the IMFs and for every local oscillation.
- The interval of 10 seconds is fractionated into small intervals. Then, we calculate $I_k^{\max}$ the maximum value of the indicator over an interval of 2 seconds corresponding to the k^{th} IMF.
- The final indicator, represented in figure (Fig.9), is equal to $I = \sum_{k=1}^{K} I_k^{\max}$.
- We repeat the same process for each subject and for each category.

III. Simulation results

The idea of control (or visual performance) is inspired from technique of management and quality control which are classically used in manufacturing processes and systems reliability. This is achieved by establishing a control chart (Fig. 9) which is composed of a curve representing the evolution of the indicator for ten seconds over three regions: a normal, alert and risk zones. The bounds of these regions are obtained from a large control population. This control chart reflects the ability of an older person to maintain his balance and eventually detect the risk of fall.

A. Signal decomposition

For the implementation of our technique, we illustrate its ability to separate our data. For this purpose, we propose to study an interval of 2 seconds of the real signal.
In Fig. 3 to 8, we give the curve shape of an example and its components respectively. We see clearly that the technique introduced in this paper is able to decompose the signal into IMFs and separate rapidly rotating and oscillating components.

B. Extraction of the indicator

Taking curve corresponding to a representative population of young controls as a reference and a large number of autonomous and non autonomous older persons; we have established the chart given in Fig. 9. In this chart we

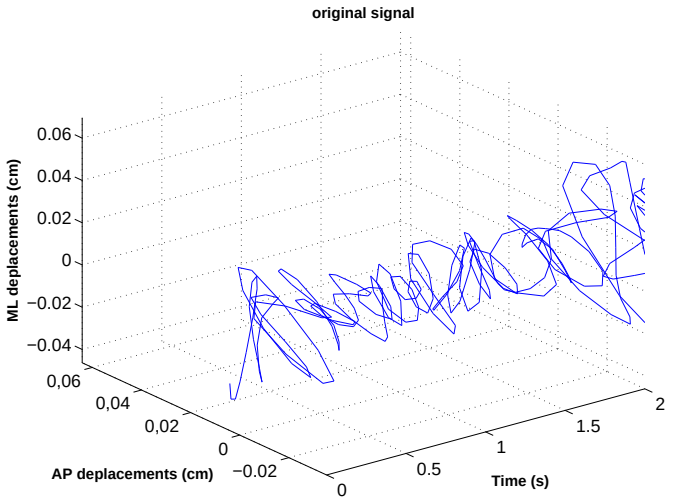

Fig. 3. stabilogram signal lasting 2 seconds before the decomposition

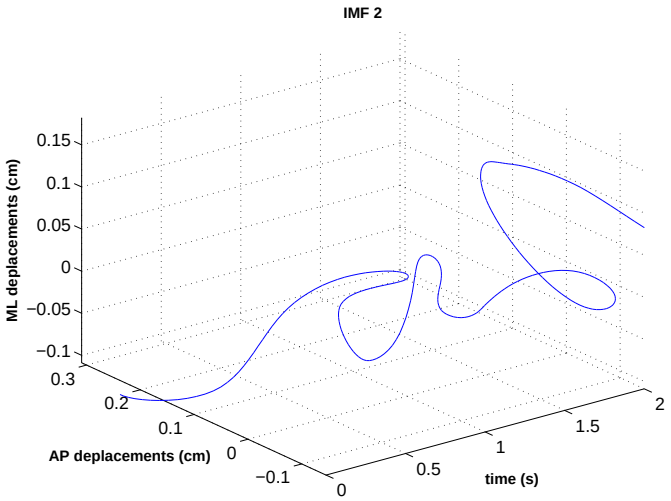

Fig. 5. the shape of the extracted second IMF

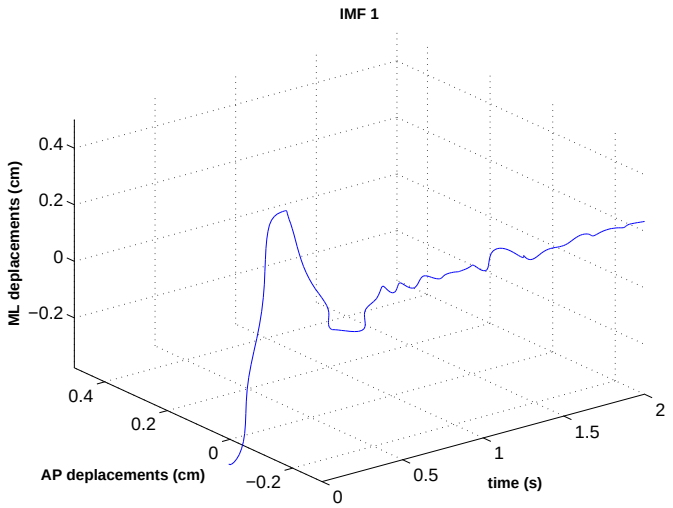

Fig. 4. the shape of the extracted first IMF

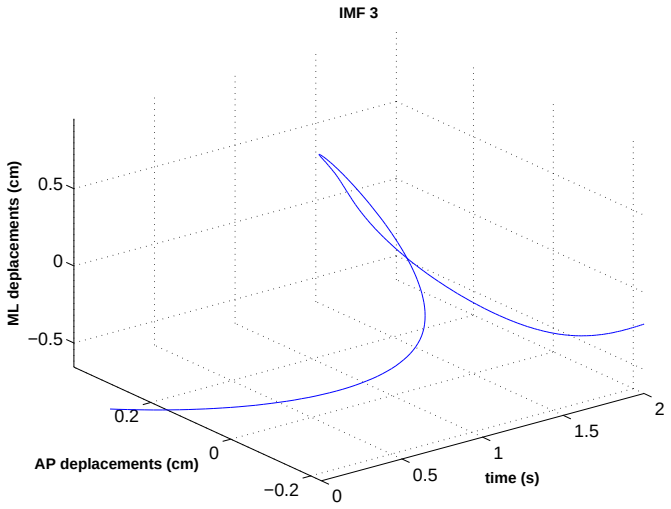

Fig. 6. the shape of the extracted third IMF

distinguish three zones delimited by two bounds: the lower limit corresponds to the the maximum value of the indicator corresponding to the worst situation of young subjects. The dashed line corresponding to the limit of the risk zone is obtained from the worst case corresponding to autonomous but older persons. This way we have sketched a reference graph that shows the variation bounds of the indicator versus time. Fig. 9, shows the temporal evolution of the indicator. It clearly shows that the curve corresponding to the young controls is less chaotic than the elderly. This is quite logical because of the limited autonomy of the latter.

Furthermore, the difference of behavior between elderly and autonomous persons is clearly highlighted by our indicator. The detection of a fall risk is reflected simply by the fact of finding a points outside these limits.

IV. CONCLUSION

In this paper we give a simple indicator which can put in evidence the state of equilibrium of vulnerable or older persons. This is based on a novel technique of signal processing using multivariate EMD. This signal decomposition method is applied to the stabilogram whose goal is to give a classical tool that allows diagnosing a risk of falling. Besides its simplicity, the proposed indicator alow monitoring the evolution of balance quality in the elderly. This is important since it can be used to detect or prevent some pathology linked to equilibrium in elderly populations. Another advantage is that this indicator can be adapted to a real-time tracking of the state of the equilibrium and can be incorporated into prosthesis systems for real time monitoring.

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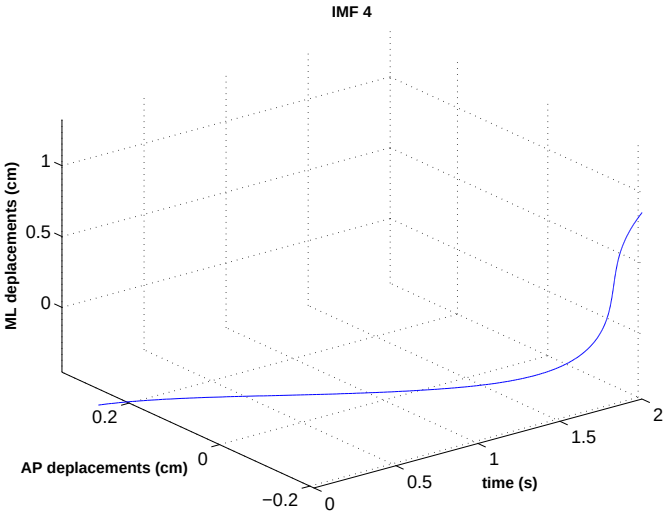

Fig. 7. the shape of the extracted fourth IMF

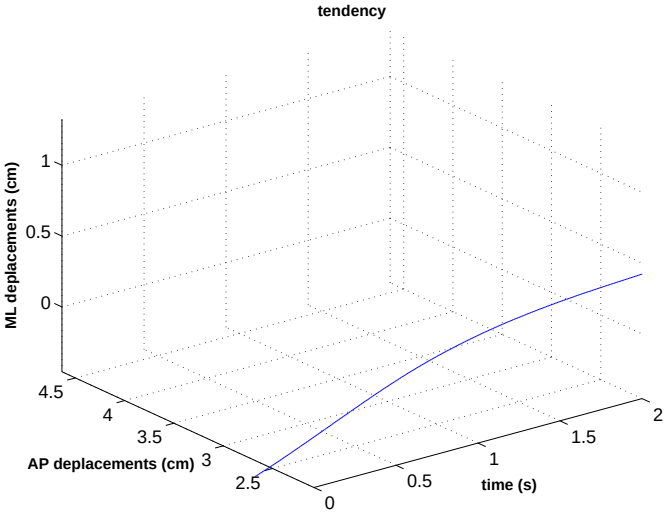

Fig. 8. the shape of the extracted tendency

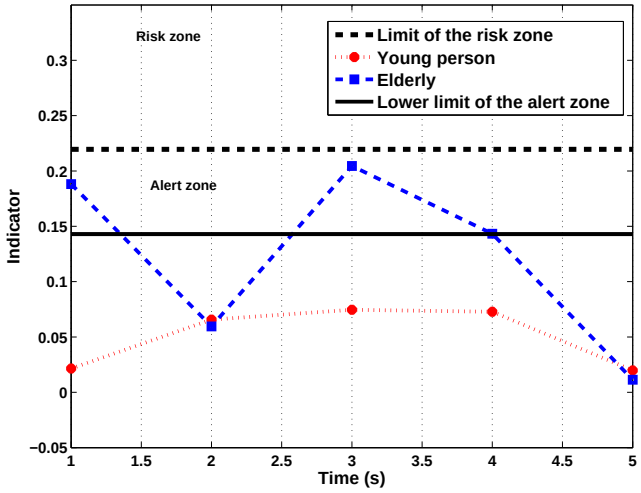

Fig. 9. Illustration of the index for a young person and an elderly person

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