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Reconstructed Phase Spaces of Intrinsic Mode Functions. Application to Postural Stability Analysis

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Abstract— **In this contribution, we propose an efficient nonlinear analysis method characterizing postural steadiness. The analyzed signal is the displacement of the centre of pressure (COP) collected from a force plate used for measuring postural sway. The proposed method consists of analyzing the nonlinear dynamics of the intrinsic mode functions (IMF) of the COP signal. The nonlinear properties are assessed through the reconstructed phase spaces of the different IMFs. This study shows some specific geometries of the attractors of some intrinsic modes. Moreover, the volume spanned by the geometric attractors in the reconstructed phase space represents an efficient indicator of the postural stability of the subject. Experimental results corroborate the effectiveness of the method to blindly discriminate young subjects, elderly subjects and subjects presenting a risk of falling.**

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. In France alone, falls cause more than 9000 deaths every year [1]. Many scientific studies have attempted to identify the risk factors [2]. The factors most commonly cited include balance disorders, previous falls, muscular weakness, visual problems, vestibular and proprioceptive problems. There are several clinical tests such as the Timed Get-up-and-go [3], the Berg Balance Scale [4] and the Tinetti Balance Scale [5] 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 (see Figure 1).

In order to study static equilibrium (when the subject is standing on the force plate), several parameters are extracted from the stabilogram signal. Classical parameters include temporal parameters (mean, standard deviation), spatiotemporal parameters (surface of the ellipse) and spectral parameters (median frequency, deciles). 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 [6], [7], while the Lyapunov exponent and entropy might also contain precious information about the static equilibrium of the subject [8].

In this paper, we propose a different approach to analyze the stabilogram signal. As can be seen in Figure 1, the ML and AP time series are non stationary and have non linear dynamics. Therefore, classical spectral signal decomposition fails to capture the nonlinear dynamics of the postural system. Moreover, the spectral parameters and estimated density of the stabilogram signal vary significantly for the same subject from an experiment to another. Thus, using the spectral representation does not allow the identification of a signature to characterize the risk of falling. The proposed approach relies on two successive signal-dependent decompositions of the stabilogram time series. The first applied decomposition is 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. Then, in order to study the non linear postural dynamics, each IMF is used to reconstruct an embedding phase space topologically equivalent to the original state space [10]. The reconstructed phase spaces (RPS) of the empirical modes allow the identification of specific attractor geometries of the postural system, which is not the case when the RPS is applied on the AP and ML signals without EMD decomposition. Our finding is that the surfaces of the attractors characterize the risk of falling. Moreover, representing the IMFs in the embedding space allows a simple visual inspection of the risk factor and can be thus a precious tool for clinicians.

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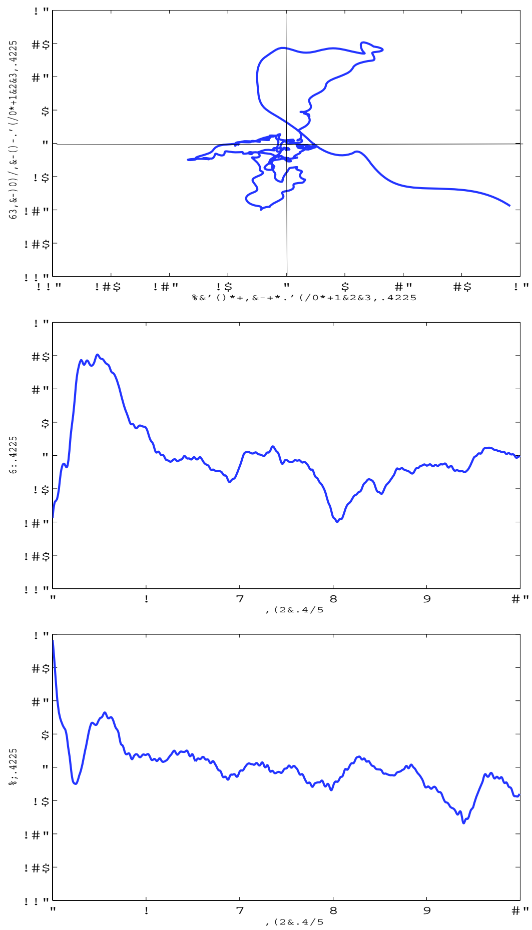

Fig. 1. Typical stabilogram of the displacement of the centre of pressure (COP). Data are from a healthy adult subject.

II. Methods

A. Subjects

Three groups of subjects participated in this study: ninety healthy young subjects (mean age 19.7 ± 0.8 y), ten healthy non-faller elderly subjects (mean age 73.3 ± 1.5 y) and one healthy faller elderly subject, who had fallen twice in the previous 3 months (age 75 y). All subjects gave their informed consent.

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:

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

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

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

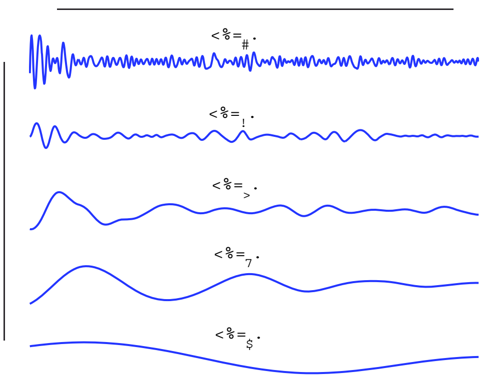

Fig. 2. EMD decomposition of a 10-s recording of the anteroposterior signal of a healthy young subject (age 19 y).

F. Reconstructed Phase Space

In order to extract the nonlinear dynamics of the stabilogram signal, we use the reconstructed phase spaces (RPS) of the empirical modes. We will argue later why this nonlinear analysis is more suitably performed on the empirical modes.

The RPS method is a time-delay embedding, a basic tool for nonlinear time series analysis. It consists of constructing a vector space for the system such that the dynamics of the system can be characterized by studying the dynamics of the corresponding phase space points. In particular, for dissipative systems, the set of points in the RPS is attracted to some sub-set, referred to as the attractor of the system. The geometry of the attractor characterizes the dynamics of the system and offers a visual inspection tool.

The RPS method requires the estimation of the delay time and the embedding dimension m. Given the measured time series $\{x_n\}_{n=1}^{N}$, the phase space vectors $\{x_n\}_{n=1}^{N}$ are then simply constructed in the following way:

$$x_n = [x_{n-(m-1)}, \ldots, x_{n-}, x_n]$$

where $n \; \{(1+(m-1)),\ldots,N\}$.

In the original work of Taken [10], the time delay is fixed to $= 1$. However, it has been shown that an optimal choice of this parameter reduces the required embedding dimension m. A well known method to determine the optimal time delay is to use the first minimum of the automutual information function[2] [11].

The embedding dimension m must be larger than twice the box counting dimension of the attractor (the number of active degrees of freedom). The optimal embedding dimension is determined by the false nearest neighbor technique [11]. This technique consists of increasing the embedding dimension m to $m+1$, in order to determine if the nearest neighbor to a data point in m dimension is the result of system dynamics or the result of projection due to an underestimation of the embedding dimension. The optimal dimension is found when the number of nearest neighbors do not significantly change.

Figure 3 shows the phase space reconstruction of a 10-s recording of an anteroposterior signal. Even though the trajectory of the phase space vectors has a similar form for all the recorded subjects (young, elderly, faller), it does not yield a specific geometry. However, when the RPS embedding is applied on the intrinsic mode functions of the same time series, specific geometries are obtained (see Figure 4). The attractor of the first IMF is completely unfolded in the phase space. This is the typical behavior of a stochastic noise. The attractor of the second IMF is a more complicated geometrical object (a strange attractor), which proves the existence of a chaotic structure in the stabilogram signal. The remaining third and fourth IMFs have simpler attractor geometries with spiral forms. The spiral form is a limit cycle suggesting the presence of a periodic non-chaotic motion in the stabilogram. We thus conjecture that the empirical mode decomposition allows the separation of the stochastic, chaotic and deterministic components composing the original signal. We have checked this conjecture on all the stabilogram signals in our data base. As the EMD is an empirical decomposition without an analytic expression, an ongoing research using extensive simulations on synthetic data is being done.

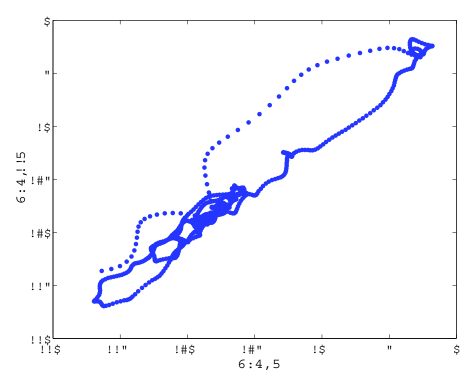

Fig. 3. Reconstructed phase space of 10 s recording of the anteroposterior signal, the optimal delay time is $= 0.4$ s and the optimal embedding dimension is $m = 5$. Signal magnitude at time $t-$ is plotted against signal magnitude at time t

III. Results

The reconstructed phase space analysis of the intrinsic mode functions is applied on 10-s recording segments of

[2] Matlab code for the RPS method is available at: http://povinelli.eece.mu.edu/itr-speech/download/index.html

AP and ML displacements for the three groups of subjects (young, elderly and faller). The optimal time delay and the embedding dimension are automatically generated for each intrinsic mode function. As evidenced in Figures 5, 6 and 7, a visual inspection of the phase vector trajectories allows the characterization of postural steadiness: the surfaces spanned by the trajectories increase as the postural stability deteriorates. In experiments reported in Figures 5 and 6, we have tried to study the RPS properties of the faller subject and how to differentiate it from the first two groups. In the first Figure 5, a typical comparison between the RPS of all the IMFs of a healthy young subject and a subject presenting a risk of falling is shown. It is visually clear that the surfaces spanned by the IMFs of the faller are much greater than those of the young person. In order to quantify this visual inspection, we have reported, in table I, the areas of the ellipses covering 95% of the data set in the phase spaces of the IMFs. Note the remarkable difference between the ellipse areas, characterizing the postural stability status. Similar plots, in Figure 6, confirm that the phase vector trajectories of the faller subject lie in higher volumes. In the experiment reported in Figure 7, the RPS of the young group is compared to the RPS of the non-faller elderly group. One can notice that postural stability can be easily characterized by the phase spaces surfaces.

	Young	Elderly non faller	Elderly faller
IMF-1	0.50	1.33	14.10
IMF-2	4.90	9.62	91.72
IMF-3	85.23	274.19	748.17
IMF-4	121.76	274.34	1066.87
IMF-5	58.55	68.61	347.55

TABLE I

ELLIPSE AREAS COVERING 95% OF THE PHASE SPACE VECTORS, FOR DIFFERENT IMFS.

IV. CONCLUSION

The nonlinear time series analysis of the intrinsic mode functions, by means of the reconstructed phase spaces, is a novel interesting tool to understand the empirical mode decomposition. Based on experiments on stabilogram signals, we have conjectured that the EMD allows an automatic separation of the stochastic, chaotic and simple deterministic components of the analyzed signal. An ongoing research consists in implementing extensive simulations on synthetic data in order to confirm the conjecture.

Concerning the postural steadiness analysis, the reconstructed phase spaces of the empirical modes of the stabilogram signal highlight the existence of specific geometries of some IMFs attractors. Moreover, the surfaces spanned by the phase vector trajectories yields a precious information about postural stability. In particular, blind discrimination of healthy young, elderly adults and faller groups is easily performed by either visual inspection or ellipse area computation.

Motivated by these promising results, the next step consists in a more extensive statistical study of the proposed discriminating criteria. Also, finding a global indicator allowing to follow the evolution of the postural steadiness status is among our perspectives.

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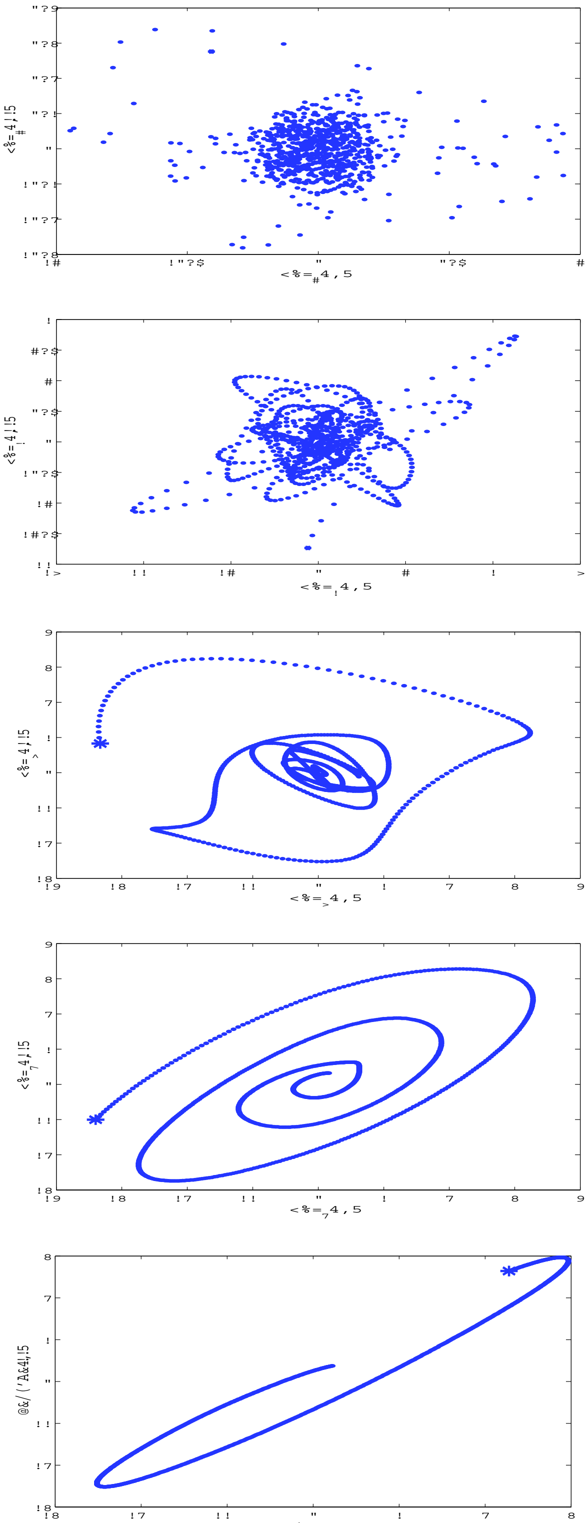

Fig. 4. Reconstructed phase spaces of the IMFs of the same signal in Figure 3. For each IMF, the signal magnitude at time t− is plotted against signal magnitude at time t. The first IMF characterizes the stochastic behavior, the second IMF highlights the chaotic behavior and the remaining IMFs characterizes the deterministic aspect of the stabilogram signal.

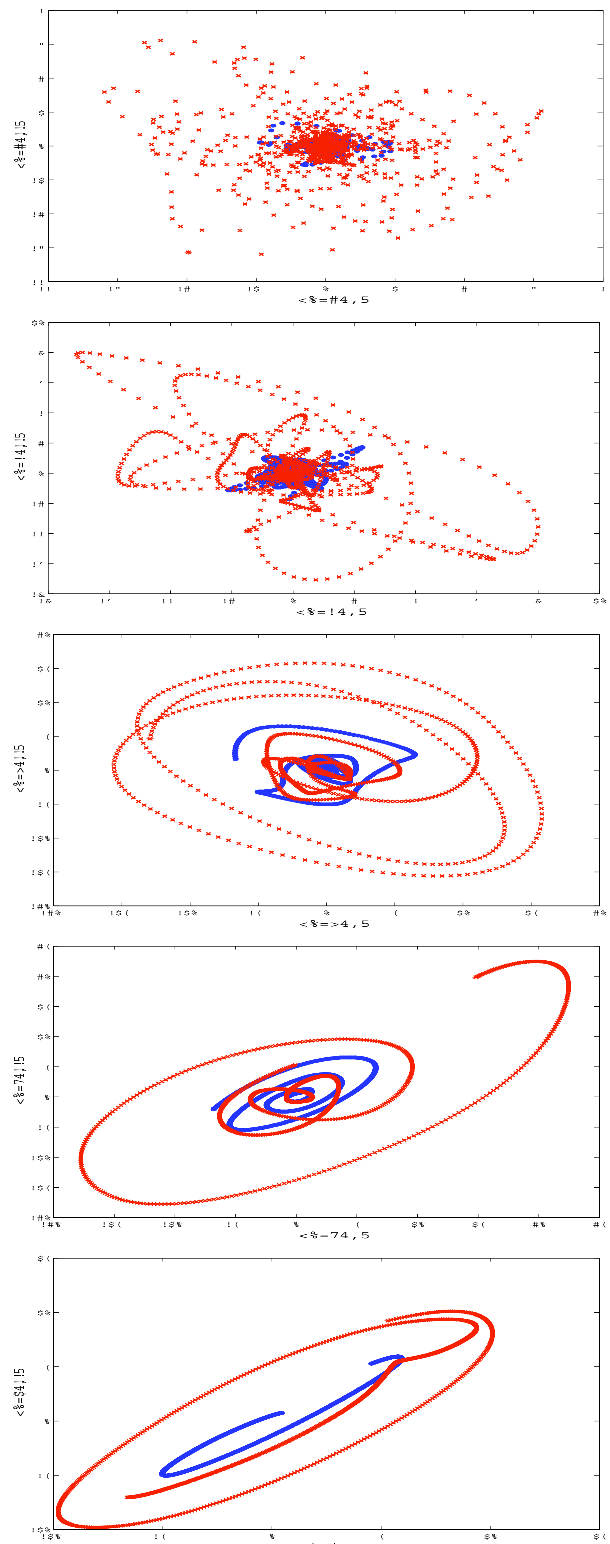

Fig. 5. Reconstructed phase spaces of the IMFs of a healthy young person (age 19) (blue points), superimposed to the RPS of the IMFs of an elderly faller (red cross).

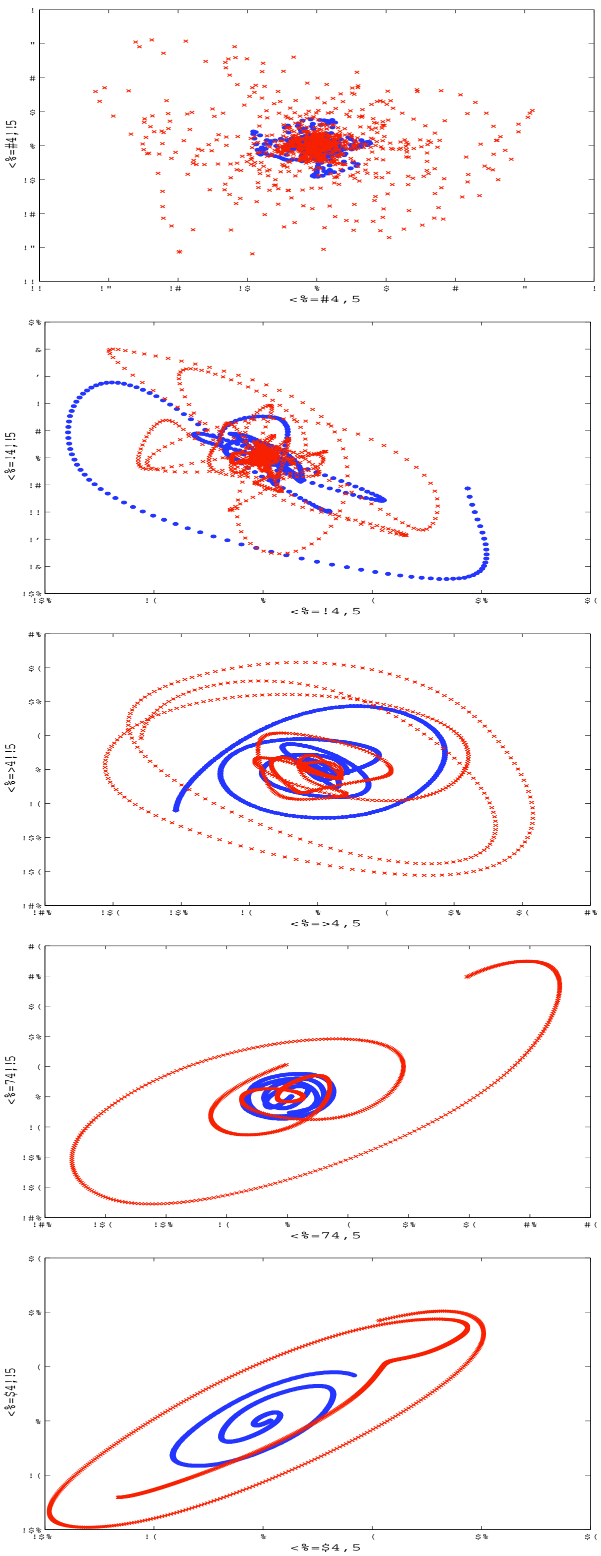

Fig. 6. Reconstructed phase spaces of the IMFs of a healthy elderly non-faller (age 74) (blue points), superimposed on the RPS of the IMFs of an elderly faller (red cross).

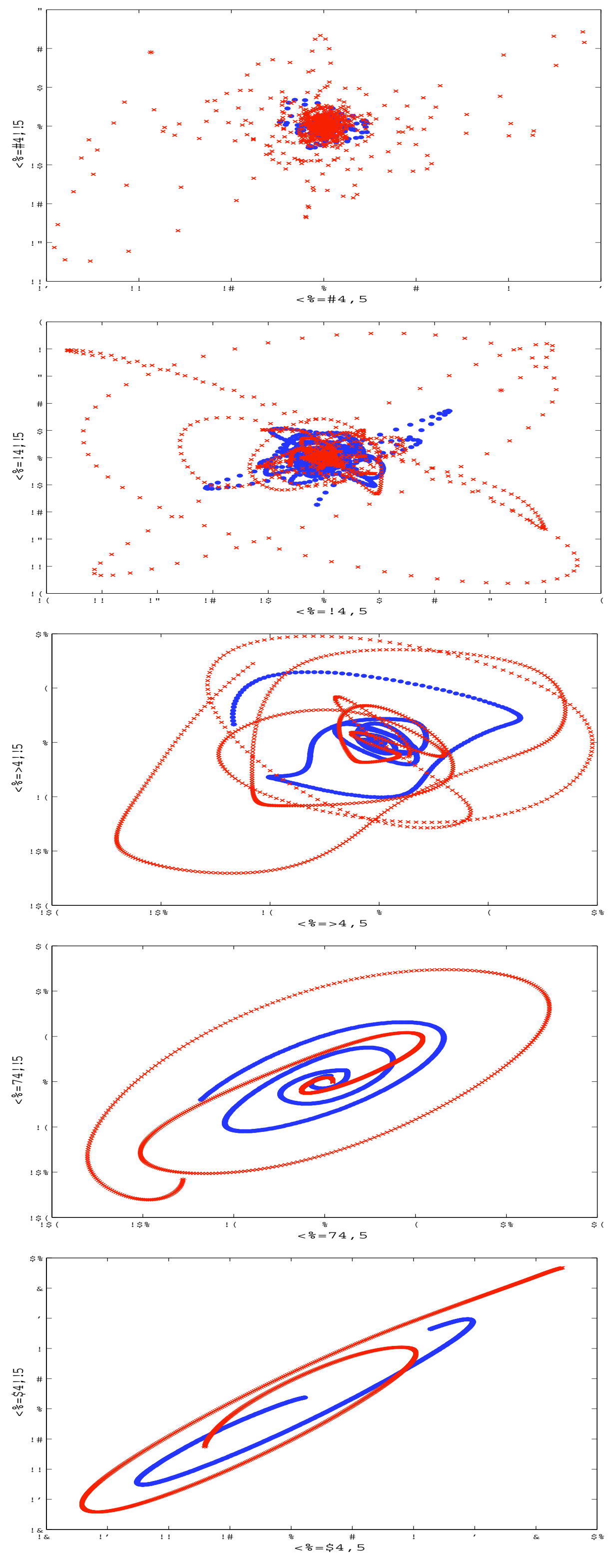

Fig. 7. Reconstructed phase spaces of the IMFs of a healthy young person (age 19) (blue points), superimposed on the RPS of the IMFs of a healthy elderly non-faller (age 74) (red cross).