Neurocomputing 121 (2013) 79–88

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Gait identification by means of box approximation geometry of reconstructed attractors in latent space

Albert Samà [a,*], Francisco J. Ruiz [a], Núria Agell [b], Carlos Pérez-López [a], Andreu Català [a], Joan Cabestany [a]

[a] Technical Research Centre for Dependency Care and Autonomous Living – CETpD, Universitat Politècnica de Catalunya, Rambla de l'Exposició 59-69, 08800 Vilanova i la Geltrú, Spain

[b] Universitat Ramon Llull – ESADE, Av. de la Torre Blanca 59, 08172 Sant Cugat, Spain

ARTICLE INFO

Available online 26 February 2013

Keywords:
Singular spectrum analysis
Gait recognition
Inertial sensors
Box approximation geometry

ABSTRACT

This paper presents a novel gait recognition method which uses the signals measured by a single inertial sensor located on the waist. This method considers human gait as a dynamical system and employs a few singular values obtained by means of Singular Spectrum Analysis applied to scalar measurements from the inertial sensor. Singular values can be interpreted as the approximate edge length of the bounding box wrapping the attractor in the latent space. Effects of different parameters on the gait recognition performance using patterns from 20 different subjects are analysed.

1. Introduction

Human movement analysis is a wide research field with clinical and biometric applications. Monitoring human movement in a clinical setting has been shown useful for the objective measurement of gait, balance, and fall risk assessment [1]. Biometric identification is also a field of great interest whose research covers security and access control applications. Typical identification systems analyse fingerprints, face, hand and ear geometry, as well as speech or iris. Recent studies have performed human identification using more complex patterns such as those obtained from gait [2,3]. Biometric gait recognition, i.e. recognising people from the way they walk, is a recent topic in biometric research that can provide benefits in itself, as well as can improve the performance of other existing biometric systems [4].

Existing gait recognition methods can be categorised into three groups: vision-based; floor-sensor based; and inertial-sensor based. In the first category, a sequence of images or silhouettes is obtained using a camera. After that, image processing techniques are used to extract gait features for recognition [2]. The main advantage of vision methods is that identification can be performed from afar and without personal interaction. In floor sensor-based gait recognition, a set of force sensors are installed on the floor and recognition is performed using floor pressure data. These methods offer unobtrusive data collection and also provide location information, for instance within a building by using sensors that are unaffected by visual obstructions and light changes. The third category is based on measurements obtained from one or more inertial sensors, normally accelerometers although gyroscopes and magnetometers might be used as well. Gait identification based on accelerometers can be used to protect personal portable devices such as mobile phones, wearable computers, intelligent clothing and other smart devices from unauthorised usage [5]. In this work, we focus our study on the third category.

Most of the previous studies on inertial-based biometric gait recognition use a gait cycle model to represent the identification characteristic of every subject [5–9]. In these studies, gait recognition is performed by comparing gait cycles. Therefore, the identification is divided into two steps. First, training signals are segmented into gait cycles by detecting maximum values in the autocorrelation function [6] or some specific characteristics of the acceleration signal that, given the biomechanical behaviour of gait, provide the cycle detection [9,5,8]. Once signal has been divided, each cycle is represented by a feature vector. This vector might be composed of the cumulant coefficients [8] or histograms and correlations values [6,9,5]. A disadvantage of these methods is that they significantly depend on existing gait cycle detection methods, which have been proved to show poor performance in ambulatory conditions [10].

An interesting alternative which uses techniques from nonlinear time series analysis [11] is proposed by Frank et al. [12]. This method consists of considering the human gait as the result of a complex dynamical system influenced by muscles, cardiovascular system, skeleton and even by the frame of mind. The sensor measurements are treated as a time series that enable an attractor

* Corresponding author. Tel.: +34 93 8967276.
E-mail addresses: albert.sama@upc.edu, albert.sama@gmail.com (A. Samà), francisco.javier.ruiz@upc.edu (F.J. Ruiz), nuria.agell@esade.edu (N. Agell), carlos.perez-lopez@upc.edu (C. Pérez-López), andreu.catala@upc.edu (A. Català), joan.cabestany@upc.edu (J. Cabestany).

0925-2312/$ - see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.neucom.2012.12.042

reconstruction of the dynamical system. The reconstruction is based on the well-known Takens' embedding theorem [13] that establishes the conditions under which a dynamical system can be topologically reconstructed from a sequence of scalar observations. In [12] the recognition is performed using an algorithm named *Geometric Template Matching* that assesses how well the reconstructed time series obtained from a segment of an acceleration signal fit a particular model. Thus, this method requires to save the observed trajectory in the reconstructed state space in order to be able to be compared to new trajectories.

This paper also considers the dynamical system approach. However, it will be shown that identification tasks can be performed by taking into account only a reduced number of features obtained from the reconstructed attractor of a short segment of gait signals. The features considered are associated with the geometry of the *box* that contains a filtered version of the reconstructed attractor, i.e. the sizes of the hyperrectangle edges where the filtered attractor is embedded, which are the so-called *Box Approximation Geometry*. These features represent the amplitude of the reconstructed trajectory in each of the dimensions so, consequently, trajectories are not required to be saved as in [12]. The hyperrectangle edges measurements are related to the time series spectrum obtained through the well-known Singular Spectrum Analysis (SSA) methodology. SSA has been shown to be a very useful tool for noise-reduction and oscillatory components identification [14]. This reduction is achieved by selecting the eigenvalues and the associated principal components from the lagged-covariance matrix of the time series data [15]. In this work, we show that not only the components associated to small eigenvalues can be rejected, but also one component of each consecutive pair can be discarded due to the redundancy caused by strong correlation between components in phase-quadrature.

This paper is organised as follows: an introduction to the theory of state space reconstruction with some examples and a method for characterising a dynamical system are presented in Section 2. Section 3 is devoted to describe the application of the reconstructed attractor geometry features into gait recognition problem using inertial sensors. Experiments and analysis of the results are described in Section 4. Finally, Section 5 includes the conclusions and future research issues.

2. Dynamical system characterisation

In this section, a method for characterising a dynamical system based on Singular Spectrum Analysis is presented. Previously, a brief introduction to the theory of state space reconstruction and some remarks on practical implementation are presented. State space reconstruction methods have been developed to obtain a topologically equivalent representation of the state space from one or more observed signals of a dynamical system.

Let us suppose that we have a dynamical system that is both stationary and deterministic. At any time t the system is in a certain state z_t from the state space X. If we measure at any time t a single scalar quantity s_t from this system through an observation function g, the value $s_t = g(z_t)$ cannot offer a complete description of the system. However, according to Takens' embedding theorem, it is possible to reconstruct the evolution of the system in X through the so-called delay coordinates [16].

Considering a scalar time series measured at every time step Δt, $\{s_1, s_2, \ldots, s_N\}$ (where Δt is the inverse of the sampling frequency), the delay coordinate set with embedding dimension m and time lag $\tau \cdot \Delta t$ is formed by the time delayed values of the scalar measurements $\mathbf{r}_i = (s_i, s_{i+\tau}, \ldots, s_{i+(m-1)\cdot\tau}) \in \mathbb{R}^m$. Note that, for notation simplicity, time step Δt is avoided, i.e. we consider the time lag τ instead of $\tau \cdot \Delta t$.

Takens' theorem states that, under certain conditions, the delay coordinates obtained using noiseless observations of a smooth dynamical system recover an attractor topologically equivalent to the original one in the state space X, i.e. there exists a diffeomorphism which maps the original attractor into $\mathbb{R}^m$. An important condition for obtaining a valid reconstruction is that the number of measurements used in the delay coordinates must be large enough to unfold the trajectories. The condition that has to be satisfied is

$$m > 2 \cdot D \tag{1}$$

where D is the dimension of the attractor in the state space X.

Although Takens' theorem does not give guarantees of a successful embedding procedure in the noisy case, the method has been found useful in practice.

There is a large literature of the 'optimal' choice of the embedding parameters m and τ. It turns out, however, that what constitutes the optimal choice largely depends on the application [11]. In terms of the time lag τ, one of the most common methods to determine the optimal delay time – using the first minimum in delayed Average Mutual Information function – was suggested by Fraser and Swinney [17]. A method to determine the minimal sufficient embedding dimension m was also proposed by Kennel et al. [18,19]. This idea relates to the topological properties of the embedding and involves computing the percentage of false neighbours, i.e. close points that are no longer neighbours if the embedding dimension increases. It was found by Kennel et al. that for noise-free time series the percentage of false neighbours will drop to zero when the optimal embedding dimension m is reached. A further increase in the embedding dimension will not affect the percentage since the attractor will be properly unfolded.

2.1. Singular spectrum analysis

Singular spectrum analysis (SSA) [20] is essentially a filtering method based on principal component analysis (PCA), although other spectra decomposition methods may be considered that extracts information from short and noisy time series without prior knowledge of its dynamics. SSA unravels the information embedded in the delay coordinate phase space by decomposing the time series into statistically independent components. The idea is to introduce a new set of orthonormal basis vectors in the embedding space so that projections onto a given number of these directions preserve the maximal fraction of the variance of the original vectors. Solving this problem leads to an eigenvalue problem. The orthonormal eigenvectors determine the *latent variables*. The consideration of only a few of these directions (those with largest eigenvalues) is sufficient to represent most of the embedded attractor. The selected directions are used to reconstruct the filtered signal.

The first stage of SSA consists of the embedding procedure that maps the original series to a sequence of $N-(m-1)\cdot\tau$ multi-dimensional m-lagged vectors $\mathbf{r}_i = (s_i, s_{i+\tau}, \ldots, s_{i+(m-1)\cdot\tau})$, where N is the length of the original time series. It is assumed that time series have been previously mean-corrected and normalised. The trajectory matrix of the time series is obtained by placing these vectors in rows:

$$M = (\mathbf{r}_1 \mathbf{r}_2 \ldots \mathbf{r}_{N-(m-1)\cdot\tau})^T = \begin{pmatrix} s_1 & s_{1+\tau} & \cdots & s_{1+(m-1)\cdot\tau} \\ s_2 & s_{2+\tau} & \cdots & s_{2+(m-1)\cdot\tau} \\ \vdots & \vdots & \ddots & \vdots \\ s_{N-(m-1)\cdot\tau} & s_{N-(m-2)\cdot\tau} & \cdots & s_N \end{pmatrix} \tag{2}$$

In general, this trajectory matrix is referred to as a Hankel matrix, which means that all the elements along the diagonal $i+j=k$ with k constant, are equal. However, this is true only when $\tau=1$.

The second stage of SSA consists of determining the eigenvalues and eigenvectors of the positive semidefinite matrix $M^T \cdot M$. Let us denote the eigenvalues by $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_m \geq 0$. For each eigenvalue λ_i there is a corresponding eigenvector $\mathbf{v}_i$ such as $(M^T \cdot M) \cdot \mathbf{v}_i = \lambda_i \cdot \mathbf{v}_i$. The eigenvalues of $M^T \cdot M$ are usually calculated by undertaking a singular value decomposition of M. The right singular vectors of M are identical with the eigenvectors of $M^T \cdot M$ and the eigenvalues are the squares of the corresponding singular values of M.

From the eigenvectors $\mathbf{v}_i$, new vectors $\mathbf{u}_i = M \cdot \mathbf{v}_i$ of length $N-(m-1)\cdot\tau$ are defined. These vectors are referred to as *latent variables* and are the projections of the embedded time series onto the eigenvectors. If the eigenvectors $\mathbf{v}_i$ are chosen orthonormal, i.e. $\mathbf{v}_i^T \cdot \mathbf{v}_j = 0$, $(i \neq j)$ and $\mathbf{v}_i^T \cdot \mathbf{v}_i = 1$, then the latent variables $\mathbf{u}_i$ are orthogonal, $\mathbf{u}_i^T \cdot \mathbf{u}_j = 0$, $(i \neq j)$, and $\mathbf{u}_i^T \cdot \mathbf{u}_i = \lambda_i$. The space formed by the union of consecutive k latent variables, $\mathbf{u}_1, \ldots, \mathbf{u}_k$ is denoted as *k-latent space*.

Finally, the third stage of SSA provides the filtered signal by means of reconstructing the original signal through the set of the selected k latent variables. The most important behaviour of a time series is found by taking into account only the first few latent variables. The *scree plot*, which is a plot of the eigenvalues versus the order, can be used to select the relevant latent variables. In Fig. 1, the scree plot and the representation of two pairs of latent dimensions, corresponding to dimensions (1, 2) and (1, 3), for white noise, sine series and the second variable of the well-known Lorenz attractor are shown. In all cases, a value of $m=20$ is considered. In the case of white noise, the scree plot is flat; all eigenvalues are approximately distributed around value 1, which means that the reconstruction needs a large number of dimensions (theoretically infinite). In the second case, the sine series, only two eigenvalues are significantly different from zero. Thus, the reconstruction can be made by using two dimensions. This reconstruction corresponds to the ellipse in the figure. Finally, one of the variables of the Lorenz series is considered. In this case, only three eigenvalues are significantly different to zero; although the third eigenvalue is much smaller than the first two of them.

Although the only relationship that can be theoretically proven between the original trajectory of the dynamical system and the reconstructed trajectory is the topological equivalence, some heuristics have found that this relationship goes further. This can be seen by observing, for example, the similarity of the original and reconstructed trajectory for the Lorenz series (Fig. 2).

2.2. Dynamical systems characterisation in the reconstructed space

Many works have attempted to characterise a dynamical system by obtaining some measurements from its reconstructed attractor. The approach is of special interest in human functions

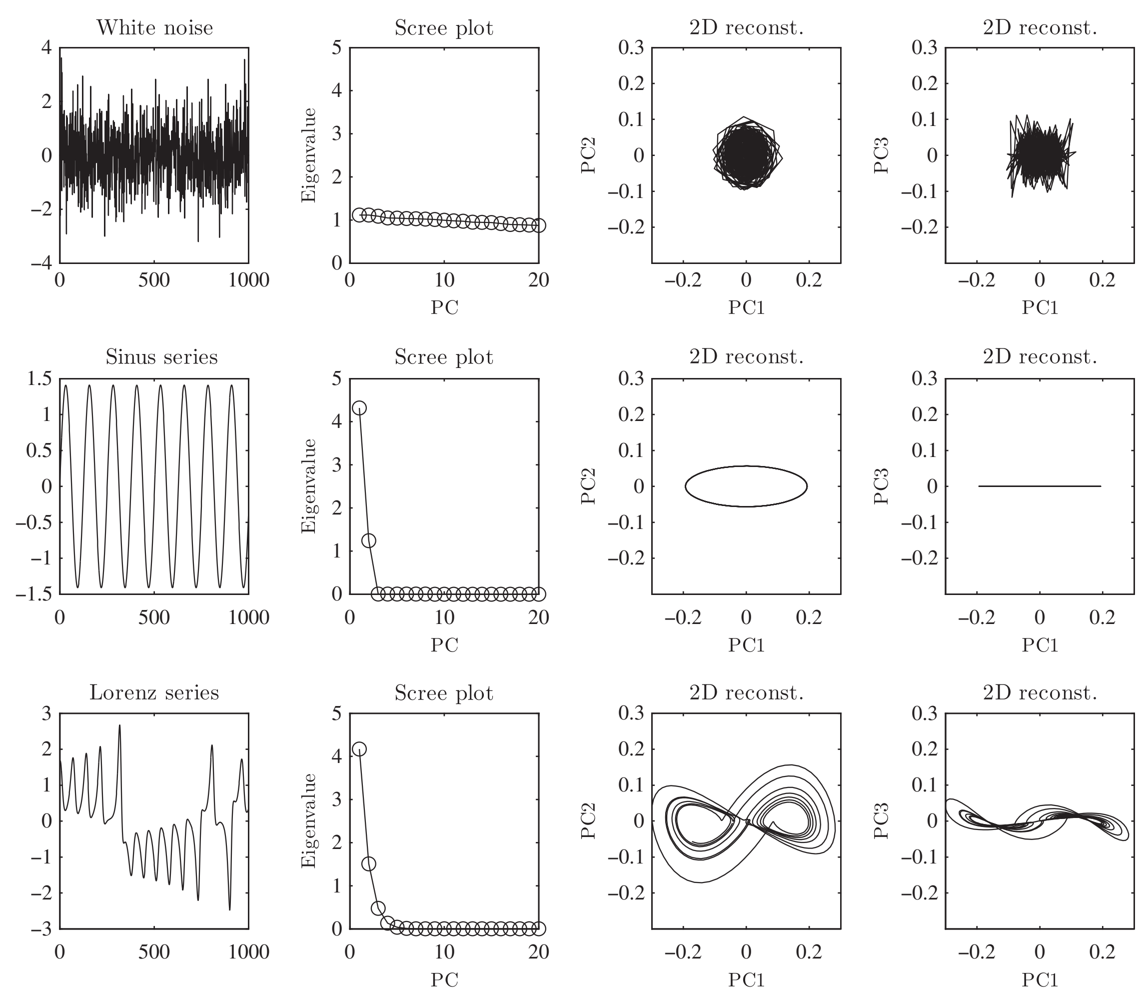

Fig. 1. Time series, scree plots and two-dimensional reconstruction for white noise, sine and Lorenz series.

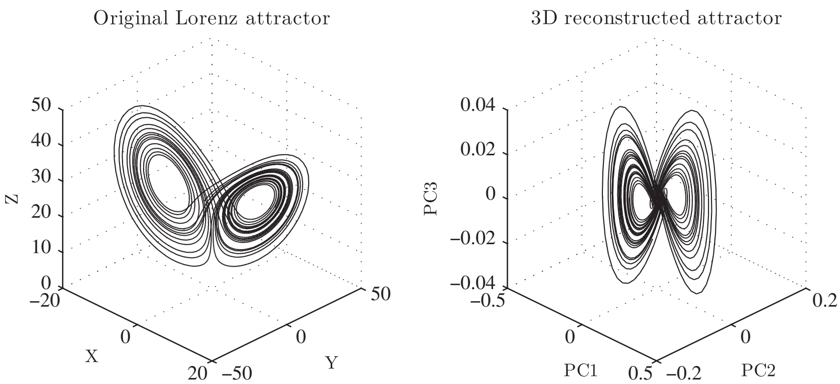

Fig. 2. Comparison between the original Lorenz attractor and the reconstructed attractor in the 3-latent space using the time series obtained when only considering the second variable.

description since characterising the state of a human physical system, like heart or brain, offers the possibility of characterizing malfunctions as heart failures [21].

Previous works have pointed that the evolution of the dynamical system in the reconstructed state space, which ideally consists of a periodic trajectory during stable conditions, only ensures to be topologically equivalent to the original trajectory. Thus, various methods have been developed to characterise a dynamical system by using topological measures that are invariant to delay coordinates. For instance, the correlation dimension, which aims to represent the dimensionality of the space occupied by the trajectory of a dynamical system, has been proved able to characterise various cardiac abnormalities [22]. In a similar manner, fractal dimension has been used to identify fluctuations in electroencephalography signals during heart failures [21].

Correlation dimension, as well as other fractal dimensions such as Hausdorff, box-counting, or information dimensions, is normally hard to calculate and require long time series to obtain accurate estimations. A more accessible measure that quantifies the dimensionality of an attractor was presented in [23]. It is called *Statistical Dimension* and gives a theoretical upper bound for the minimal number of degrees of freedom required to describe the attractor up to the accuracy of the data. SSA, which estimates the statistical dimension by counting the number of eigenvalues above the noise floor, has shown to characterize brain connectivity through functional magnetic resonance imaging [24].

2.3. Box approximation geometry

According to [23], the statistical dimension can be estimated by counting the eigenvalues above the noise floor after the trajectory matrix decomposition into orthogonal components. However, eigenvalues contain more information since they give an idea of the reconstructed attractor shape. Specifically, they represent a measure of the bounding box enclosing the attractor. The approach proposed in this work consists of characterising the dynamical system, i.e. identifying the personal gait, through what is termed as *Box Approximation Geometry* (BAG) of the attractor in the latent space obtained through the same trajectory matrix decomposition that SSA performs. The term Box Approximation Geometry is used to refer to the k-dimensional hyperrectangle containing most of the filtered trajectory in latent space. The dimension sizes of this hyperrectangle are closely related to the k-larger eigenvalues. This leads to define $BAG(k)$ as the vector:

$$BAG(k) = (\lambda_1, \ldots, \lambda_k) \tag{3}$$

$BAG(k)$ represents the quantity of information among the attractor dimensions. We will show later that taking into account only a subset of $BAG(k)$ is enough to accurately identify a person.

Another algorithm that uses the filtered reconstructed attractor for activity recognition and gait identification is *Geometric Template Matching* (GTM) [12]. This algorithm assesses how well a given time series projected onto the eigenvectors, obtained with other training examples, fit a particular model. Short segments of the projected data are then compared geometrically against their nearest neighbours and they are assigned to the model that obtains the highest average score. Thus, several elements of the latent space are compared against others, which is avoided when the geometry of the attractor is employed since only the amplitude of the trajectories are needed.

It has been shown that the projection of a quasi-periodic time series into the eigenvectors of the time-delayed matrix provides pairs of principal components which are in an approximated phase quadrature [25]. Vautard and Ghil [23] argued that, subject to certain statistical significance tests, such pairs correspond to the nonlinear counterpart of a sine–cosine pair in the standard Fourier analysis of linear problems. However, the advantage over sines and cosines is that the components obtained from SSA are not necessarily harmonic functions and they can capture highly anharmonic oscillation shapes. Considering this, BAG method is designed to use only the eigenvalues corresponding to odd principal components so that redundant information is avoided.

3. Gait identification by means of box approximation geometry

Accelerometers are the most common inertial sensors used in movement analysis. They can be used to measure vibration on cars, machines, building, process control systems and safety installations. Nowadays, they are integrated on laptops, tablets, digital cameras and mobile phones providing a new opportunity to protect these devices from unauthorised usage. Triaxial accelerometers sense linear acceleration along three orthogonal directions.

In the current application, the magnitude of the acceleration is used as the scalar measure to reconstruct the state space, thereby providing a method that is independent of the orientation:

$$s_t = (x_t^2 + y_t^2 + z_t^2)^{1/2} \tag{4}$$

where x_t, y_t and z_t are, respectively, the acceleration along x, y and z axis of the accelerometer at time t.

Gait is a cyclical process which can be divided into two main phases: *swing phase*, during which the foot is in the air for limb advancement, and *stance phase* when the foot is resting on the ground. Cycles of the human gait should appear as quasi-periodic trajectories in the reconstruction space. These trajectories are

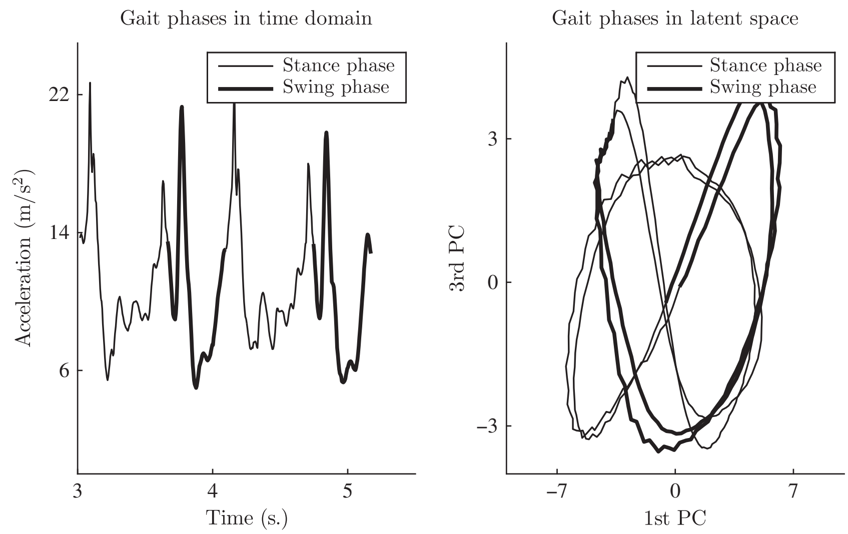

Fig. 3. Acceleration magnitude measurements and their reconstruction into 2-latent space by using the first and third dimensions, $m=20$ and a sampling frequency of 200 Hz.

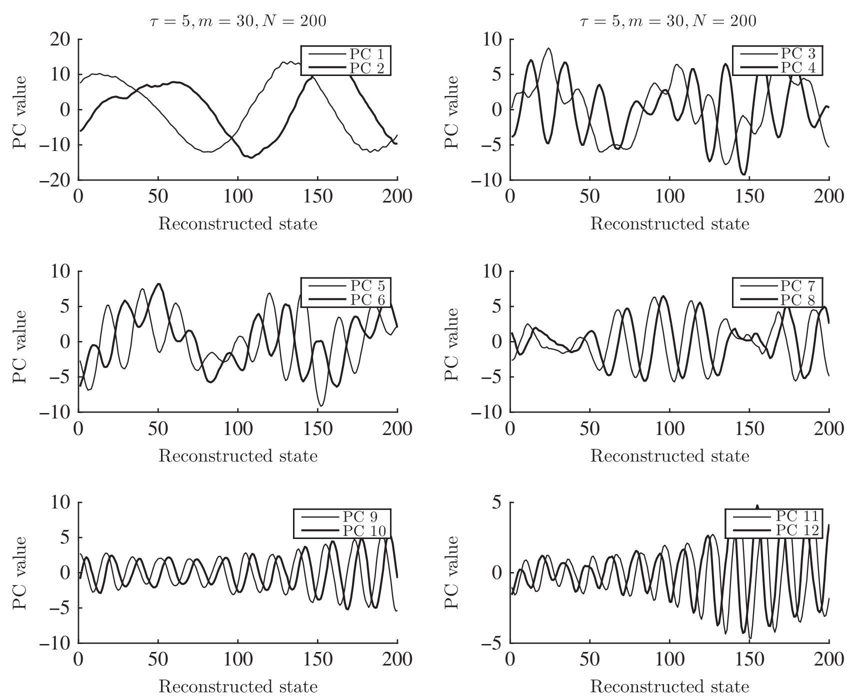

Fig. 4. Latent variables in approximately phase quadrature.

slightly different for each person and form a type of a 'gait signature' that is expected to enable identification.

Fig. 3 shows the typical walking acceleration measures obtained by an accelerometer located on the waist during stance and swing phases. Gait phases have been estimated by the lateral acceleration obtained from the waist according to [26]. Fig. 3 also shows the reconstruction obtained by using $\tau=5$, $m=10$ and a sampling frequency of 200 Hz. Stance and swing phases are shown to be different parts of the trajectory and they clearly form a complete gait cycle. Since a correctly reconstructed trajectory in the phase space cannot intersect itself along an orbit, it turns out that the reconstruction observed needs more than just two latent variables in order to be valid, so the statistical dimension is greater than two.

As mentioned before, components associated to consecutive eigenvalues in the spectrum are approximately in phase quadrature. This behaviour is illustrated in Fig. 4, where the first 12 principal components are represented in pairs (1–2, 3–4,…, 11–12). This behaviour confirms that considering only one component from each consecutive pair enables us to avoid redundant information. Consequently, only odd eigenvalues are taken into account, improving the efficiency of the method. Thus, a new *BAG* denoted as $BAG^*(k)$ is defined in the context of gait identification as follows:

$$BAG^*(k) = (\lambda_1, \lambda_3, \ldots, \lambda_{\lceil k/2 \rceil}) \tag{5}$$

The characterisation of the human gait is dependent on the time lag τ, the number of measures used in the delay coordinates m, and the number of latent variables employed, which should be lower than its statistical dimension. For instance, the time lag effect is shown in Figs. 5 and 6 by observing the eigenvalues for three different time lags in two individuals. These figures have been obtained by using $m=10$ and a sampling frequency of 200 Hz.

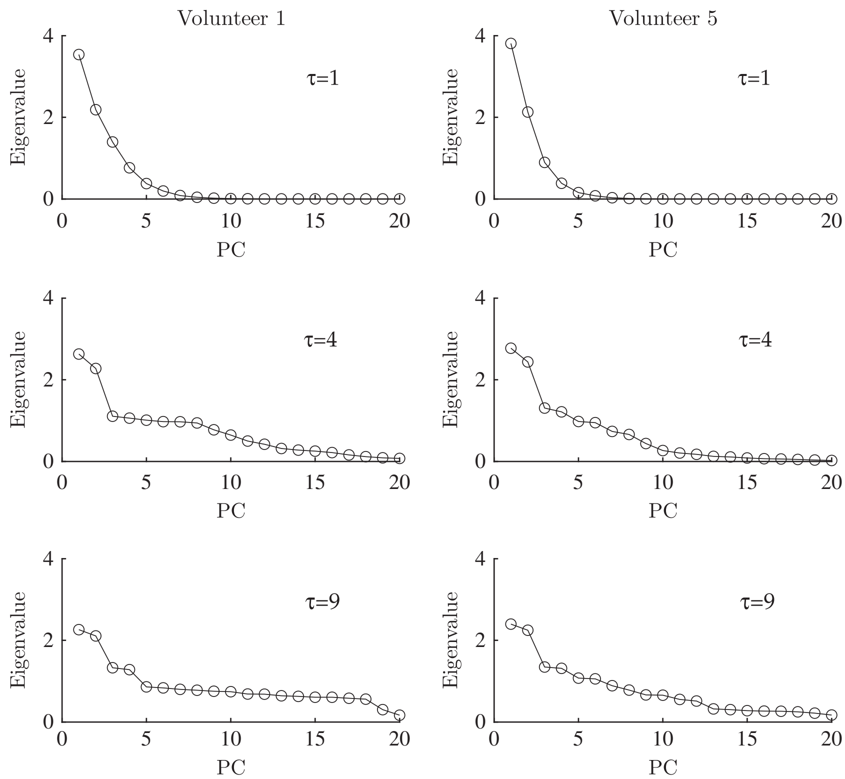

Fig. 5. Scree plots for two different volunteers using three different time lag values.

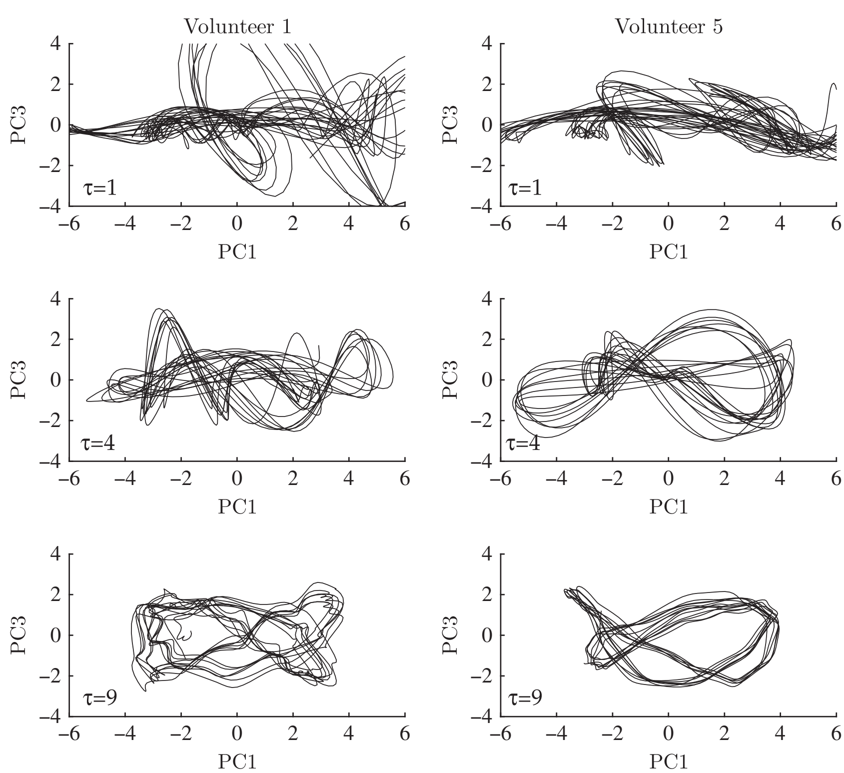

Fig. 6. Reconstruction of the trajectory in the first and third dimensions of the latent space for two individuals (m=20; N=2000, N=500 and N=222 for $\tau=1$,$\tau=4$ and $\tau=9$, respectively).

4. Experiments

Experiments have been performed using a data-acquisition device developed at the *Technical Research Centre for Dependency Care and Autonomous Living* in Barcelona (Spain) as a prototype device used specifically in research projects. The device enables inertial data from an accelerometer, a gyroscope, and a magnetometer in the three axes of space to be obtained. The system can obtain samples at 200 Hz with an autonomy of 15–18 h by using a Li-ion battery and storing inertial data in a μSD card. Circuit and battery are protected with an encapsulation of $77 \times 37 \times 21$ mm to avoid external agents; and the entire system is managed by a dsPIC microcontroller. A triaxial LIS3LV02DQ accelerometer was used. The sensor was worn by the volunteers attached to a belt that was located on the left side of the hip. The sampling frequency ($\tau = 1$) used was 200 Hz.

Twenty volunteers participated in this study. Each volunteer walked at a normal speed twice along a straight corridor that was approximately 20 m long. Between both walks, the belt was taken off completely and then put it on again so that the device was located in, at least, a slightly different position. The first walk was used for training the gait recognition algorithm and the second walk for testing.

Different values for the parameters that affect the characterisation method have been tested: the time-lag; the embedding dimension; and the feature dimension vector k, i.e. the number of the hyperrectangle edges considered in $BAG^*(k)$ defined by Eq. (5). Another important tested parameter that affects gait identification is the window length measured in seconds into which the reconstruction is performed, henceforth denoted by w, where $N = w \cdot F_s$ and F_s is the sampling frequency. It is expected that larger windows provide more accurate gait recognitions since a larger state space trajectory enables better reconstruction. Optimal values of τ and m are commonly estimated according to Average Mutual Information and False Nearest Neighbours. In this work, they have been calculated to establish whether the optimal values provide the best recognition rate or not.

4.1. Results

BAG patterns, which are composed of eigenvalues according to Eq. (5), were extracted by means of overlapped windows of w seconds obtained from the accelerometer. Every $w/2$ s a new window was started. The number of patterns obtained depends on w, τ and m (from 25 to 52 patterns per each individual). Thus, a classification problem of 20 classes and a maximum of 1025 patterns has been obtained. BAG values from the first walk have been used to train a Support Vector Machine (SVM) with a Gaussian kernel. The resulting SVM was tested using values obtained from the second 20 m walk.

The parameters that affect the method have been tested with several values. More concretely, w and τ tested values are 1, …,10. Regarding the other parameters, m=5,7,9, …,29 and k=1,3,5, …,29 were used, since only odd latent variables are considered. The number of features used is $(k+1)/2$.

The maximum accuracy obtained fixing the value of a pair of parameters among (τ, m, w and k) and testing the previously mentioned values for the rest of them are shown in Figs. 7–10. The highest accuracy is 96.4% with $\tau = 3$, w=7, m=23 and k=23. Fig. 11 shows the impact of increasing k in the accuracy of four given examples. The False Nearest Neighbours and the Average Mutual Information results are shown in Figs. 12 and 13, respectively.

4.2. Discussion

A gait cycle, i.e. two steps, usually takes more than one second at normal speed, so a window length of 1 s does not enable the whole trajectory to be unfolded. This could explain that accuracies obtained for w=1 s. do not exceed 80%, as Fig. 7 presents. Larger window lengths reach accuracies over 90%. On the other hand, gait recognition performance is also affected by the embedding dimension m, as Fig. 8 shows. For instance, m=5 leads to accuracies below 80%. This is an expected result according to the False Nearest Neighbours scheme since, as Fig. 12 shows, the attractor is not yet unfolded when an embedded dimension below 10 is used. Regarding time lag τ, good results can be obtained by any value as long as it is lower than 10, i.e. samples must be taken at a frequency sampling greater than 20 Hz.

The number of the BAG hyperrectangle edges used greatly influences the gait recognition performance. Although the maximum accuracy is obtained by means of 12 features, accuracies over 90% can be obtained with only five features (k=9) and over 95% with seven features (k=13). In Figs. 10 and 11 it is clearly shown that if the number of edges used is increased, the performance also augments. This is obviously explained because the more dimensions used, the more information from the attractor is considered and higher accuracies are obtained. However, according to Fig. 11, there is a value of k after which the performance does not significantly increase since the last variables only correspond to noise [25,14].

The result of the Average Mutual Information applied to different time lags is shown in Fig. 13. This function measures

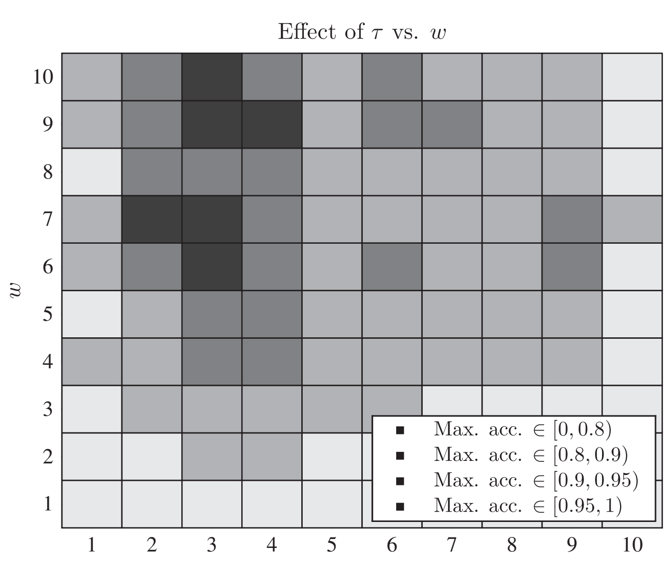

Fig. 7. Effect of τ and w in the accuracy.

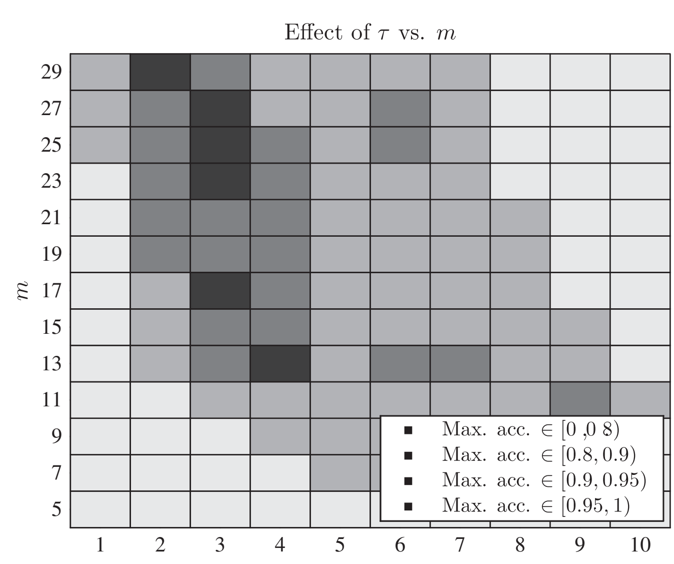

Fig. 8. Effect of τ and m in the accuracy.

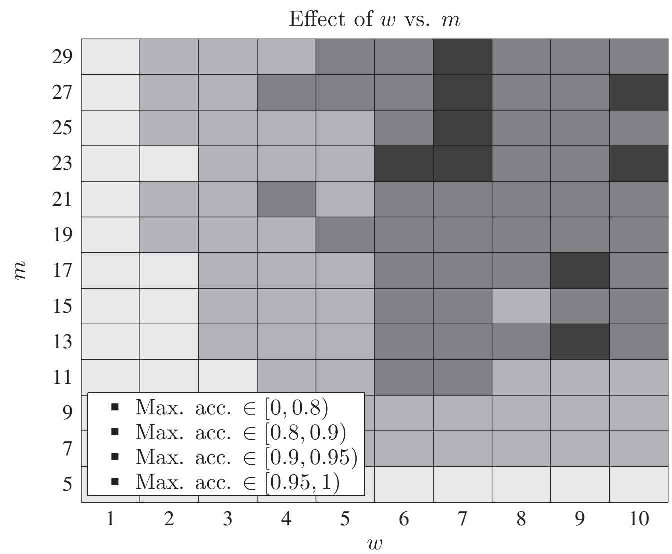

Fig. 9. Effect of w and m in the accuracy.

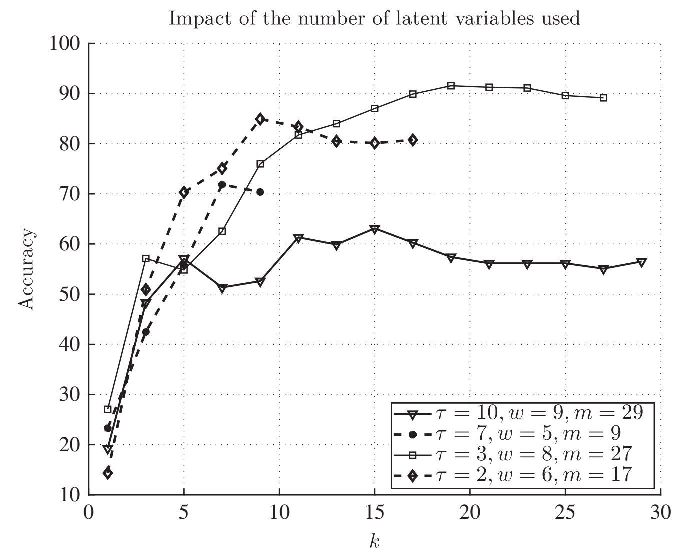

Fig. 11. Effect of k in the accuracy for four given examples.

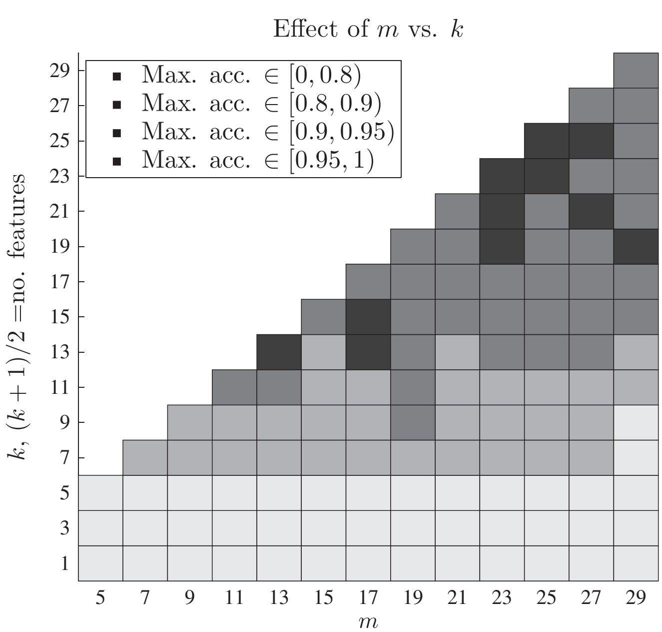

Fig. 10. Effect of k and m in the accuracy.

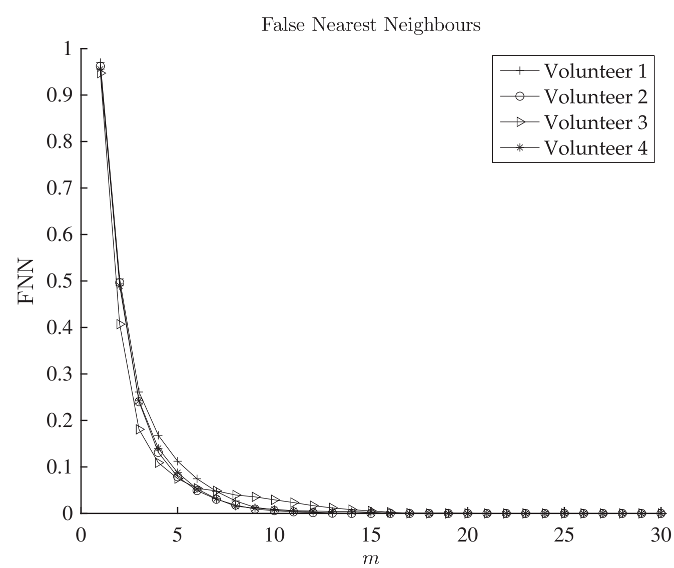

Fig. 12. False nearest neighbors results for different embedding dimensions. *Y*-axis represents the proportion of false nearest neighbours.

the dependence between a signal and its corresponding τ-lagged delayed signal. Thus, $\tau = 1$, provides the highest dependence of a sample and the following one, which is obtained after 0.005 ms. Time lag values greater than 10 provide similar results. This value is the optimal one according to the Average Mutual Information criterion. However, the best gait recognition accuracies are obtained for lower time lag values ($\tau = 2$, 3 and 4) according to Fig. 7. Thus, the optimal τ estimated through AMI does not provide in this case the best accuracy, confirming that there is no any universal approach to select the optimal τ and that the optimal choice depends on the application [11].

In terms of accuracy, provided results are similar to those obtained by other methods. For instance, in [9] an accuracy of 86% was reported and 95% was achieved in [6]. However, these methods use more features than the five used by BAG and, in addition, they depend on existing gait cycle detection methods, which have been proved to show poor performance in ambulatory conditions [10]. In [12] a similar recognition rate is achieved without detecting gait cycles. However, in that work, successive elements in the latent space that compose a trajectory were used as features, instead of just the rough shape of the attractor as the method introduced in this paper does. Using BAG, less and easier interpretable features are employed in the recognition task.

In this work, a specifically developed device was used while in [8,9,12] a mobile phone was employed instead. Using a specifically developed device may reduce the difficulty of our task since a stable frequency sampling is obtained. Regarding the sensor position, the belt-worn location corresponding to this work is the same than in [12] but different to the one used in other works. For instance, in [9] the sensor was in a trouser pocket and in [6] it was located on the leg.

In summary, results show that identifying a person through the dynamical system characterisation approach proposed is possible by using a standard SVM-classifier with an overall accuracy of 95%. The most suitable time lag values are from 2 to 4 when a sampling frequency of 200 Hz is employed, which are below the optimal value considered by Average Mutual Information. The necessary reconstruction dimension to achieve these results is at least 10, although higher values may be used, and

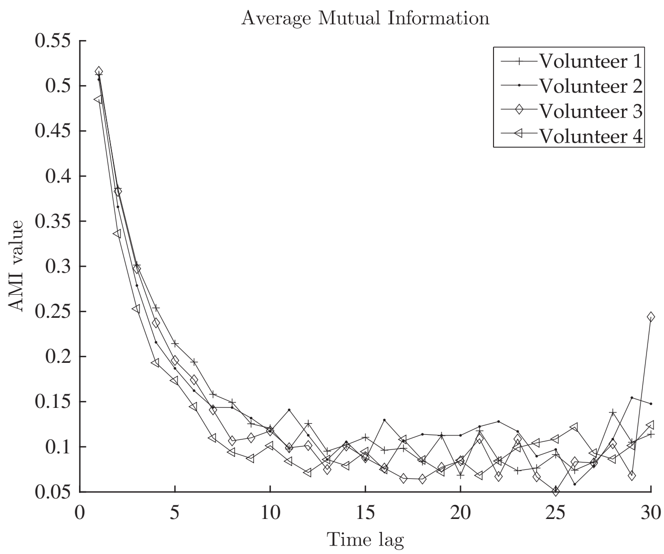

Fig. 13. Average mutual information results for all 12 training signals.

three or more seconds are needed as window length. The quantity of eigenvalues necessary to achieve 90% accuracy, and therefore the number of features, is just 5.

5. Conclusions and future research

In this paper, it has been shown that, taking into account only a reduced number of features obtained from a short walking signal segment, it is possible to perform gait identification with high accuracy. The features considered in our approach are the eigenvalues of the reconstructed attractor in the odd principal dimensions obtained using the Singular Spectrum Analysis methodology. These values can be interpreted as the edge lengths of the bounding box that approximately encloses the reconstructed attractor in the latent space.

Gait recognition has been performed by wearing a single triaxial accelerometer located on the waist and by means of different training and testing sets. The testing set values were obtained after removing and reallocating the sensor, thus ensuring a slightly different position for the sensor and so increasing the difficulty of the task.

Some insights have been achieved into the reconstruction of a gait attractor. The influence of the parameters time lag, embedding dimension, and BAG dimension has been discussed. It has been shown that the optimal value for time lag and embedding dimension according to False Nearest Neighbours and Average Mutual Information does not provide the best gait recognition performance. Furthermore, although the experiments have been performed using a prototype used specifically in research projects, the increasing number of gadgets that incorporate accelerometers should lead to further developments that may take advantage of the characteristics of these devices.

The methodology presented may be also applied to other purposes, such as clinical tasks, where instead of recognising individuals it is necessary to detect a pathological or healthy gait. For instance, Parkinson's Disease patients suffer various movement disorders that make them fluctuate into the so-called On and Off motor states. During On state, patients move normally but during Off states they have a slowness of movement and some symptoms that affect gait [27]. Thus, different attractors must be obtained in different motor states. As future research, BAG will be tested on recognising the motor state of Parkinson's Disease patients.

Acknowledgements

This work is supported by the Spanish project SENSORIAL (TIN2010-20966-C02-02) Spanish Ministry of Education and Science. Authors want to thank all volunteers for their participation and CETpD members that helped in the data gathering.

References

[1] K.M. Culhane, M. O'Connor, D. Lyons, G.M. Lyons, Accelerometers in rehabilitation medicine for older adults, Age Ageing 34 (6) (2005) 556–560.
[2] M.S. Nixon, T.N. Tan, R. Chellappa, Human Identification based on Gait. International Series on Biometrics, Springer, 2005.
[3] A.P. Yazdanpanah, K. Faez, R. Amirfattahi, Multimodal biometric system using face, ear and gait biometrics, in: Tenth International Conference on Information Sciences Signal Processing and their Applications (ISSPA), 2010, pp. 251–254.
[4] X. Zhou, B. Bhanu, Integrating face and gait for human recognition at a distance in video, IEEE Trans. Syst. Man Cybern. B: Cybern. 37 (5) (2007) 1119–1137.
[5] J. Mäntyjärvi, M. Lindholm, E. Vildjiounaite, S. Marja Mäkelä, H. Ailisto, Identifying users of portable devices from gait pattern with accelerometers, in: IEEE International Conference on Acoustics, Speech, and Signal Processing, 2005, Proceedings (ICASSP '05), vol. 2, 2005, pp. ii/973–ii/976.
[6] D. Gafurov, K. Helkala, T. Søndrol, Biometric gait authentication using accelerometer sensor, J. Comput. 1 (7) (2006) 51–59.
[7] M. Derawi, P. Bours, K. Holien, Improved cycle detection for accelerometer based gait authentication, in: Sixth International Conference on Intelligent Information Hiding and Multimedia Signal Processing (IIH-MSP), 2010, pp. 312–317.
[8] S. Sprager, D. Zazula, Gait identification using cumulants of accelerometer data, in: Proceedings of the Second WSEAS International Conference on Sensors, and Signals and Visualization, Imaging and Simulation and Materials Science, SENSIG'09/VIS'09/MATERIALS'09, World Scientific and Engineering Academy and Society (WSEAS), 2009, pp. 94–99.
[9] D. Gafurov, E. Snekkenes, P. Bours, Gait Authentication and Identification Using Wearable Accelerometer Sensor, 2007, pp. 220–225.
[10] M. Marschollek, M. Goevercin, K.H. Wolf, B. Song, M. Gietzelt, R. Haux, et al., A performance comparison of accelerometry-based step detection algorithms on a large, non-laboratory sample of healthy and mobility-impaired persons, in: Conference Proceedings – IEEE Engineering in Medicine and Biology Society, 2008, pp. 1319–1322.
[11] H. Kantz, T. Schreiber, Nonlinear Time Series Analysis, vol. 7, Cambridge University Press, 1997.
[12] J. Frank, S. Mannor, D. Precup, Activity and gait recognition with time-delay embeddings, in: Twenty-Fourth AAAI Conference on Artificial Intelligence, 2010.
[13] F. Takens, Detecting strange attractors in turbulence, in: D.A. Rand, L. Young (Eds.), Dynamical Systems and Turbulence, Warwick, Lecture Notes in Mathematics, vol. 898, Springer, Berlin, 1981, pp. 366–381.
[14] T. Harris, H. Yuan, Filtering and frequency interpretations of singular spectrum analysis, Physica D: Nonlinear Phenom. 239 (20–22) (2010) 1958–1967.
[15] B. Hu, Q. Li, A. Smith, Noise reduction of hyperspectral data using singular spectral analysis, Int. J. Remote Sensing 30 (2009) 2277–2296.
[16] T. Sauer, J. Yorke, M. Casdagli, Embedology, J. Stat. Phys. 65 (1991) 579–616.
[17] A.M. Fraser, H.L. Swinney, Independent coordinates for strange attractors from mutual information, Phys. Rev. A 33 (1986) 1134–1140.
[18] M.B. Kennel, R. Brown, H.D.I. Abarbanel, Determining embedding dimension for phase-space reconstruction using a geometrical construction, Phys. Rev. A 45 (1992) 3403–3411.
[19] D.R. Fredkin, J.A. Rice, Method of false nearest neighbors: a cautionary note, Phys. Rev. E Stat. Phys. Plasmas Fluids Relat. Interdiscip. Topics 51 (4) (1995) 2950–2954.
[20] R. Vautard, P. Yiou, M. Ghil, Singular-spectrum analysis: a toolkit for short, noisy chaotic signals, Physica D: Nonlinear Phenom. 58 (1-4) (1992) 95–126.
[21] R. Maestri, M.T.L. Rovere, E. Robbi, G.D. Pinna, Fluctuations of the fractal dimension of the electroencephalogram during periodic breathing in heart failure patients, J. Comput. Neurosci. 28 (3) (2010) 557–565.
[22] T. Harris, H. Yuan, Heart rate variability analysis using correlation dimension and detrended fluctuation analysis, ITBM-RBM 23 (6) (2002) 333–339.
[23] R. Vautard, M. Ghil, Singular spectrum analysis in nonlinear dynamics with applications to paleoclimatic time series, Physica D 35 (1989) 395.
[24] A.K. Seghouane, A. Shah, Functional brain connectivity as revealed by singular spectrum analysis, in: International Conference of the IEEE Engineering in Medicine and Biology Society, 2012.
[25] M. Ghil, M.R. Allen, M.D. Dettinger, K. Ide, D. Kondrashov, M.E. Mann, et al., Advanced spectral methods for climatic time series, Rev. Geophys. 40 (1) (2002) 1–41.
[26] W. Zijlstra, A.L. Hof, Assessment of spatio-temporal gait parameters from trunk accelerations during human walking, Gait Posture 18 (2) (2003) 1–10.
[27] A. Schrag, N. Quinn, Dyskinesias and motor fluctuations in parkinson's disease. A community-based study, Brain 123 (Part 11) (2000) 2297–2305.

Albert Samà (Barcelona, Spain, 1985) received his M.Sc. degree in control and robotics in 2009. He is currently pursuing his Ph.D. in control, vision and robotics at the Automatic Control Department of the Technical University of Catalonia. His research interests include machine learning, signal processing and qualitative reasoning.

Francisco J. Ruiz received the M.Sc degree in Physics in 1988 from the University of Barcelona, and the Ph.D. degree from the Technical University of Catalonia in 2006. Currently, he is an assistant professor in the Automatic Control Department at the Technical University of Catalonia. His research interests are in Qualitative Reasoning and Kernel Methods with applications in control systems and finances. He is a member of the Knowledge Engineering Research Group (GREC).

Núria Agell received the Ph.D. degree in applied mathematics from the Technical University of Catalonia. She is a professor in the Quantitative Methods Department, ESADE, University Ramon Llull. Her main research activities are currently related to the (1) development of softcomputing models and technologies based on qualitative and fuzzy reasoning and (2) application of artificial intelligence techniques to finances, marketing, and knowledge management. She is a member of the Knowledge Engineering Research Group (GREC).

Carlos Pérez-López (Barcelona, Spain, 1977) received his degree in Electronic Engineering in 2004. He is currently working as coordinator of research projects at the Technical Research Centre for Dependency Care and Autonomous Living of Universitat Politecnica de catalunya. His research interests include Embedded devices, Online Algorithms and Inertial Sensors.

Andreu Català received the M.Sc. degree in Physics from the University of Barcelona (1980) and a Ph.D. in Sciences from the Department of Automatic Control of the Technical University of Catalonia (1993) and serve as Associated professor at the same university from 1997. Head of the Knowledge Engineering Research Group (GREC) and co-director of the Technological Research Centre for Dependency Care and Autonomous Living (CETpD). Main research interests are computational intelligence and qualitative reasoning applied to the improvement of the quality of life of people and communities (http://www.upc.edu/cetpd).

Joan Cabestany holds currently a Professor position at the Department of Electronic Engineering of the Universitat Politécnica de Catalunya (UPC). He obtained the M.Sc. degree and Ph.D. degrees in Telecommunication Engineering in 1976 and 1982, respectively, both from the Universitat Politécnica de Catalunya. His research interests include analog and digital electronic systems design, configurable and programmable electronic systems, and neural networks models and applications.