Gait recognition by using Spectrum Analysis on state space reconstruction

Albert SAMÀ[a,1] Francisco J. RUIZ[a], Carlos PÉREZ-LÓPEZ[a] and Andreu CATALÀ[a]
[a] *Universitat Politècnica de Catalunya*

Abstract. This paper describes a method for identifying a person while walking by means of a triaxial accelerometer attached to the waist. Human gait is considered as a dynamical system whose attractor is reconstructed by time delay vectors. A Spectral Analysis on the state space reconstruction is used to characterize the attractor. The method is compared to other common methods used in gait recognition tasks through a preliminary test.

Keywords. Gait recognition, Spectral methods, Inertial sensors

Introduction

Human movement analysis is a research field with clinical and biometrics application. It has been shown useful in the objective measurement of gait, balance, falls risk assessment and mobility monitoring [1]. Biometric identification is also a field of great interest whose research covers security and access control applications. Typical identification systems analyze fingerprints, speech or iris. Recent studies try to perform it by more complex patterns like those obtained by gait [2]. The existing gait recognition methods can be grouped into three categories: vision based, floor sensor based and inertial sensor based. In this work, we focus our study in the third category.

Previous studies on biometric identification based on user's gait employed a mobile phone [4, 5] or a specifically developed device with an accelerometer [3,6]. The methodology used by those studies consists in segmenting the accelerometer signal in gait cycles and characterizing each cycle by some features (e.g. cumulants [4], histograms and correlations [3, 5 and 6]).

Dynamical systems give us a different approach to analyze human movement. It is based on Taken's theorem; thus sensor measures are treated as time series in order to reconstruct the attractor of the dynamical system being sensed. Then, reconstructed space is characterized by a spectral analysis. This approach is followed by this work, and it has been tested previously for extracting step length and velocity by using a triaxial accelerometer [8]. Similar methods have been previously used for human full-body pose tracking by means of six inertial sensors [9] and for activity classification [10]. The greatest advantage of the method over other methods is its ability to characterize an activity by using only a few number of features and regardless the orientation of the sensor.

[1] Corresponding Author: Albert Samà, Neàpolis Building, Rambla de l'Exposició, 59-69 08800 Vilanova i la Geltrú, Spain; E-mail: albert.sama@upc.edu

The paper is organized as follows: in the next Section, common gait recognition methods are described. Next, a brief introduction to the theory of state space reconstruction and spectrum analysis and some remarks on practical implementation are presented. Section 3 is devoted to introduce the approach used in this work, which is based on applying the described spectral method to the problem of gait identification. Experiments and the analysis of the results are described in section 4. Finally, section 5 includes the conclusion and future research issues.

1. Time-domain gait recognition methods

Most common gait recognition methods perform the identification of a person by using gait cycles [3, 4, 5, 6], i.e. one stride or two steps. For each user, a representative gait cycle must be constructed in a training phase. Then, the recognition process consists in comparing a new stride to the representative cycle of each user. The new stride is assigned to the most similar representative cycle, which provides the user.

The gait recognition methods described in this section are called as time-domain methods in order to differentiate them from those presented in section 2 that uses the reconstruction of the state space.

1.1. Segmentation process

The objective of segmenting is to divide accelerometer signal in gait cycles, i.e. each stride is isolated. This process can be performed by two different methods. On the one hand, a simple minimum peak detection based on lateral acceleration has been used in [4, 5, 6]. This kind of analysis is valid only when the accelerometer is located at the waist, a different analysis would be necessary if the sensor was attached to a different position. On the other hand, autocorrelation function of vertical acceleration may be used for step detection [3]. This method would be valid for almost any position the sensor can be attached. Figure 1 shows an example of a segmentation process result by using autocorrelation function.

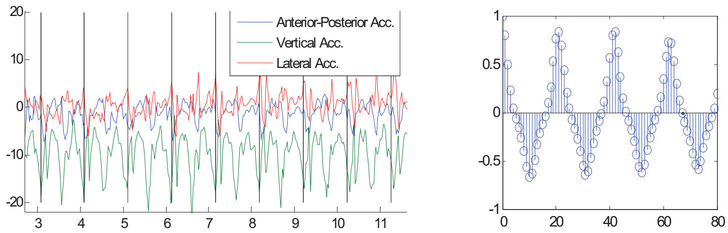

Figure 1. Gait segmentation on the left. Example of autocorrelation obtained on the right.

In this work, strides are detected by using the autocorrelation function. The minimum-peak-based detection does not perform well in every user since some gaits are irregular and produce occasional minimum peaks that result in a bad segmentation.

1.2. User representative cycle

Once cycles from training data have been extracted, it is necessary to construct a representative stride in order to compare new cycles to it. The simplest approach consists in normalizing the cycles by length and amplitude and then average them to obtain the representative stride by mean [6] or median [5]. The most common approach is to use a histogram with a fixed number of bins [3, 5, 6], where features comprise the number of values relying in each bin. Note that normalization in time and amplitude is needed. Correlation between axis [3, 5, 6] and cumulant coefficients of order 1 to 4 [5] has been also used for characterizing gait cycles. In this work, the combination of those possible features that maximize the gait recognition accuracy has been chosen.

Once representative strides for each user have been obtained, the identification would be performed in the following way. Given a signal whose user is needed to be recognized, first it is divided into strides by the method showed in the previous subsection. Then, each stride is characterized by the same features used to characterize the representative stride. The signal is assigned to the user whose representative stride is more similar to the new stride being analyzed.

2. State space reconstruction

In this Section, a brief introduction to the theory of state space reconstruction and some remarks on practical implementation is presented. State space reconstruction methods have been developed as a mean to obtain a topologically equivalent representation of the state space from one or more observed signals of a dynamical system.

2.1. Delay coordinates

A scalar time series can be considered as a one-dimensional observed measures obtained from a smooth *d*-dimensional dynamical system. The original *d*-dimensional state space of the dynamical system cannot be directly observed from the time series. However, it is possible to reconstruct this original state space or, at least, a topologically equivalent embedded space from the called *delay coordinates* [11].

Considering a single time series measured every time step Δt $\{s_{t'}, s_{t'+\Delta t},\ldots\}$ (where Δt is the inverse of the sampling frequency), the *delay coordinates set* with dimension m and time lag τ is formed by the time delayed values of the scalar measurements $\mathbf{r}_t=\{s_{t-\tau(m-1)\Delta t},\ldots, s_{t-\tau\Delta t}, s_t\}\in \mathrm{R}^m$. For notation simplicity, henceforth, time step Δt is avoided. Takens proved in 1980 the well known *Takens' embedding theorem* [12], which states that if the time series comes from a noiseless observation of a smooth dynamical system, the attractor recovered by delay coordinates is topologically equivalent to the original attractor in the state space. Even though Takens' theorem does not give guarantees of the success of the 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 [13]. In terms of the time lag τ, one of the most extended method to determine the optimal delay time was suggested by Fraser and Swinney [14]. They suggest using the first minimum in delayed average mutual information function. On the other hand, a method to determine the minimal sufficient embedding dimension m was proposed by Kennel et al. [15] [16]. The idea is related to topological properties of the embedding and consists of computing the percentage of false neighbors, i.e. closer points that are no longer neighbors if the embedding dimension increases, which allows the sufficient embedding dimension to be determined.

2.2. Singular Spectrum Analysis

If Taken's theorem requirements are accomplished, the time delay coordinates leads to an embedding of the original state's space. Then, every linear transformation of sufficient rank from the time delay coordinates also leads to an embedding. A good choice of linear transformation is known as *principal component analysis* (PCA). This technique is widely used, for example to reduce multivariate data to a few dimensional data. The idea is to introduce a new set of orthonormal basis vectors in embedding space such 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 orthogonal eigenvectors obtained from the autocovariance matrix determine the *principal directions*. By considering only a few of this directions (those with largest eigenvalues) is sufficient to represent most part of the embedded attractor.

Singular Spectrum Analysis (SSA) [17] consists of applying a PCA, or other similar methods of spectra decomposition, to the set of delay coordinates, hereafter to be called *reconstructed attractor* or *reconstructed space*. This analysis is applied in this case as follows: given a time delayed vector $\mathbf{r}_t=(s_{t-\tau(m-1)},\ldots,s_t)$, which reconstructs the attractor for the actual state $\mathbf{x}_t$ at time t, a matrix which reconstructs the trajectory from time t to time $t+w$ is:

$$\mathbf{M}_t=[\ \mathbf{r}_t\ \mathbf{r}_{t+\tau}\ldots\mathbf{r}_{t+k\tau}\ ]^{\mathrm{T}} \tag{1}$$

where $k=w/\tau$.

Such matrix is first set to have zero mean (that leads to matrix $\mathbf{M}^0_t$) and then analyzed by applying a PCA process, so $\mathbf{M}^0_t$ is decomposed such that:

$$\mathbf{M}^0_t=\mathbf{U\Sigma V^*} \tag{2}$$

$\mathbf{V}$ represents a change of basis from the reconstruction space to the latent space. Thus, $\mathbf{VM}^0_t$ identifies the trajectory of the reconstruction of the states $\mathbf{x}_t$, $\mathbf{x}_{t+1},\ldots,\mathbf{x}_{t+w}$ in the latent space.

3. Gait identification approach

This section describes the approach used in this work, which is based on applying the spectral method described in the previous section on the state space reconstruction in order to perform gait identification.

The accelerometer signal is measured at each time t as a triplet composed of three accelerations from the three axes of the sensor. Its magnitude is used as the scalar measure that will lead to reconstruct the state space:

$$s_t=(x_t^2+y_t^2+z_t^2)^{1/2} \tag{3}$$

Thus, only magnitudes are going to be used which provide a method independent of the orientation.

Gait is a process of cyclic nature and its sequence of states is expected to be essentially periodic. Thus, trajectories in the state space reconstruction, i.e. the sequence of reconstructed states, should be also closed orbits and a cyclical behavior should be observed in the generated matrix $\mathbf{M}_t$. Different gaits are expected to provide different orbits, so the characterization of those orbits may allow us to identify which person belongs to. The orbit characterization from PCA is considered by two ways. Firstly, the directions where maximum variance is achieved are expected to characterize the dynamical system, as each trajectory should take a different form. Secondly, the eigenvalues are assumed to describe the transformation between latent and reconstruction space, so each transformation would be particular for each gait.

Embedding dimension m, time-lag τ and window size w are set through the characteristics of the dynamical system. Different values are tested for m and w considering both the attractor dimension and the number of states that a cycle takes. The time lag will be fixed by the results obtained by Average Mutual Information. This approach is different from classical spectral methods where an arbitrarily large value for m parameter is fixed without evaluating its effect [19].

4. Experiments

A database composed of 233 steps belonging to five users has been used for the experiments. The healthy volunteers walked 20 m at normal speed twice. A device containing a triaxial accelerometer developed at CETpD [8] and located at the lateral side of the waist logged accelerations in a sampling frequency of 200 Hz.

4.1. Time-domain gait recognition

A time-domain gait recognition method is applied to accelerometer signal in a lower sampling frequency in order to use the minimum number of samples required. Since frequency content is known to be below 20 Hz [18], signal is resampled from 200 Hz to 40 Hz.

Signal segmentation into steps is performed by detecting maxima in the autocorrelation function applied to the vertical acceleration. It has been observed that left and right steps of a user may be quite different. A classification based on steps should take into account those differences, but it has been also observed that the stride composed by both of them remain constant in a user. This observation was also remarked in [6]. Thus, the elements considered to be identified are the strides.

Once a stride has been identified, features are extracted from it. The histogram technique is applied after normalizing in time and amplitude. As in [3, 6], each stride is interpolated into 100 values and the quantity remained in the 10 bins of the histogram are used to characterize the step. Correlation between axes, kurtosis and skewness are also used, similarly to [6].

4.2. State space reconstruction

Part of the results reported in this section has been published in a recent article [7]. Figure 2 shows average mutual information (AMI) applied to the signals obtained for each volunteer as a function of the time lag parameter. AMI measures the dependence among reconstructed states. A small value of time lag produces correlated states which may do not allow trajectories of the dynamical system appear, and a high value of time lag produces independent states, which may convert the sequence of states to a random process. However, time lag influences the attractor reconstruction by its order of magnitude but not by its specific value. A suitable value for time lag is considered to be the first minima when its value is observed against the AMI value. Observing Figure 2, a suitable time-lag value for all volunteers is 10 times the original time step. Therefore, as the original time step was 1/200 Hz = 5 ms, new time step is 50 ms and the resulting frequency sampling is 20 Hz.

As in the previous section is described, cyclical properties of gait must be shown in the reconstructed trajectories at $\mathbf{M}_{t.}$ Recurrence plots, which are a common technique helpful to visualize the recurrences of dynamical systems, may be used with this purpose. Given a sequence of reconstructed states $x_1,..,x_n$, a matrix $\mathbf{R}_\mathrm{n}$ is considered where each element m_{ij} may have two values: 1 when $x_i \approx x_j$ and 0 otherwise. Note that similarity is dened by ε-insensitivity. This matrix is plotted, so that recurrence plots are obtained, and periodic motions are reflected by long and non-interrupted diagonals. The vertical distance between these lines corresponds to the period of the oscillation. Figure 3 shows the recurrence plot for a volunteer when using embedding dimension 5 and 30. For the lower dimension, the periodic motion is not as clear as in the higher dimension where the cyclic motion appears obvious. This results agrees with Taken theorem.

From Figure 3 it is shown that the period of the orbit in the state space is the same for both embedding dimensions, and is reckoned to be ~30 reconstructed states. The rest of volunteers provide a similar period. FNN algorithm gives 5 as the minimum embedding dimension for all volunteers. Taking into account results from recurrence plots and FNN, *m* parameter is tested with values from 5 to 30.

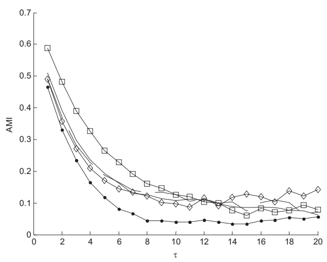

Figure 2. AMI results for all five signals. A time lag of 10 is suitable for all time series

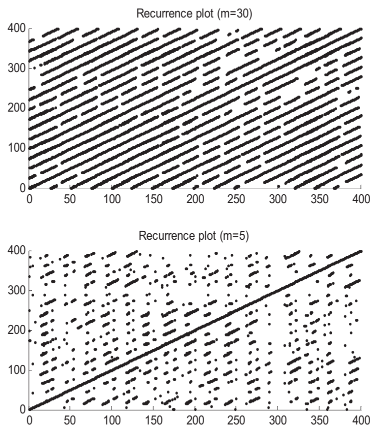

Figure 3. Recurrence plot when using embedding dimension 5 (up) and 30 (down).

Since orbits comprise 30 samples and sampling frequency was 200 Hz, a whole orbit takes $30\cdot\tau/200=1.5$ seconds approximately. In order to test whether half a period, one or two periods enable to recognize the system, window size values used are: w=0.75 s., w=1.5 s. and w=3 s.

4.3. Results and discussion

Both time-domain gait recognition and state space reconstruction training processes are performed by Classification and Regression Trees (CART) using the first 20 m. walked by volunteers. Accuracies are obtained classifying the second 20 m. walk. CART methodology used is the standard cross-validation prune, where the optimal tree is the one with least nodes whose accuracy is within 1 standard error of the minimum cost tree.

Time-domain gait identification achieves 82% of accuracy for the 5 users. This percentage is similar to described in [5] (86%), and quite below than the percentage in [3], which was 95% although this paper located the accelerometer at the leg. Accelerations from leg show clearer the behavior of gait than those obtained when the sensor is at the waist, which may explain the higher performance.

Gait identification results using State Space Reconstruction approach are shown in figure 4. A sequence of reconstructed states, i.e. matrix $\mathbf{M}_{t_i}$ is characterized by using the eigenvalues of the matrix as features. The coefficients of the Principal Components (PC), which determine their direction, may be used but they were found to obtain poorer results [7]. Accuracies are shown as a function of the window size w, embedding dimension m and the number of eigenvalues used.

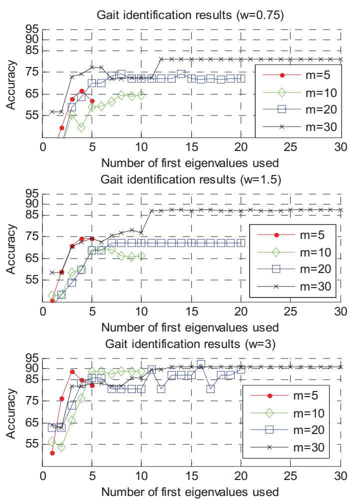

Figure 4. Gait identification results

Results show that it is possible to identify a person from a gait classifier with an overall accuracy of 90%.

When gait identification is performed by means of eigenvalues, a better identification is also obtained for larger window sizes. A window size containing half a period (w=0.75) provides a maximum accuracy of 82%, for a whole period (w=1.5) achieves 88% of accuracy, and for two-periods size (w=3) obtains the highest accuracy: 92.3%. Best classification results are obtained for m=30 when window sizes are w=0.75 and w=1.5. For w=3 such value of m also provides the highest accuracy, but m=20 does as well. Thus, it can be concluded that, in general, unfolding whole orbits provide good results.

However, it may be used lower embedding dimensions for some windows sizes, which would save computational costs. Observing the number of eigenvalues needed to achieve the maximum accuracy for m=30, it may be seen that less than a half of them is needed. Thus, the embedding approach used is able to characterize the dynamical system with a number of parameters which is lower than the half of the dimensions used to reconstruct it with the highest accuracy.

State space reconstruction method outperforms the time-domain gait method used: best accuracies were 92% and 82%, respectively. Although the approach presented in this paper obtains a performance much higher than common gait identification methods, results should be taken as a preliminary study since database is composed of only 5 users and are not representative enough to be generalized. A more extensive database should be tested in order to confirm the abilities of the method. However, results show that relevant characteristics of gait can be obtained from the reconstructed space.

It should be noted that the algorithm is computationally expensive compared to the time-domain method. A real-time implementation of the algorithm would require a significant effort since large amounts of memory and computational capacity are used.

5. Conclusions

A methodology to identify people by gait has been tested and compared against a standard gait recognition method. It considers human gait as a dynamical system, whose attractor is reconstructed and characterized in order to recognize it. The characterization is performed by a spectral analysis of the reconstruction space, and it is tested into a small database of 5 people achieving an overall accuracy of 92.3%. A triaxial accelerometer located in the waist is needed to perform it.

Attractor's reconstruction is based on Taken's theorem. The different parameters involved in the reconstruction and the characterization are tested in order to evaluate the effect in gait identification. It is concluded from results that unfolding a whole orbit seems to provide the best identification, though in some cases unfolding a part of the orbit may be enough. Suitable window sizes for identification are those equal or larger than the orbit duration.

Further research is needed in order to validate in a more extensive database. Recently, a database of 50 people has been obtained and the abilities of the methodology are going to be validated. Future work will also try to use the same methodology for rehabilitation applications in order to detect, for example, the gait progress in a patient after a clinical intervention by measuring whether the attractor changes.

Acknowledgments
This work is supported by the Spanish project SENSORIAL (TIN2010-20966-C02-02) Spanish Ministry of Education and Science.

References

[1] K.M. Culhane, M. O'Connor, D. Lyons, G.M. Lyons. Accelerometers in rehabilitation medicine for older adults, *Age and Ageing* **34**-6 (2005), 556-560.
[2] A.P. Yazdanpanah, F. Faez, R. Amirfattahi, Multimodal biometric system using face, ear and gait biometrics, *Information Sciences Signal Processing and their Applications* (ISSPA), 2010 10th International Conference on.
[3] D. Gafurov, K. Helkala, and T. Søndrol, Biometric Gait Authentication Using Accelerometer Sensor, *Journal of Computers*, **1**-7 (2006), 51-59

[4] S. Sprager, D. Zazula, Gait Identification Using Cumulants of Accelerometer Data, *Proceedings of the 2nd WSEAS International Conference on Sensors, and Signals and Visualization, Imaging and Simulation and Materials Science* (2009)

[5] D. Gafurov, E. Snekkenes and P. Bours, Gait Authentication and Identification Using Wearable Accelerometer Sensor, *IEEE Workshop on Automatic Identification Advanced Technologies*, (2007)

[6] J. Mäntyjärvi, M. Lindholm, E. Vildjiounaite, S. Mäkelä, H. Ailisto, Identifying users of portable devices from gait pattern with accelerometers, *IEEE International Conference on Acoustics, Speech, and Signal Processing* (2005)

[7] A. Samà, F. J Ruiz , C. Perez, A. Catala, Gait identification by using Spectrum Analysis on state space reconstruction, *International Work-Conference on Artificial Neural Networks*, (2011)

[8] A. Samà, D. Pardo, J. Cabestany, A. Rodríguez-Molinero. Time Series Analysis of inertial-body signals for the extraction of dynamic properties from human gait. *Proceedings of IJCANN Conference*, (2010)

[9] L. A. Schwarz, D. Mateus and N. Navab, Multiple-Activity Human Body Tracking in Unconstrained Environments, *Lecture Notes in Computer Science*, **6169** (2010), 192-202

[10] J. Frank, Learning state space models from time series data, *Multidisciplinary Symposium on Reinforcement Learning,* 2009, Quebec

[11] T. Sauer, J. A. Yorke, M. Casdagli. Embedology. *Journal of Statistical Physics*, **65**-3/4 (1991) 579-616

[12] F. Takens, Detecting strange attractors in turbulence, *Dynamical systems and turbulence* **898** (1981) 366-381.

[13] H. Kantz, T. Schreiber. Nonlinear Time Series Analysis. Cambridge University Press; 2 edition (January 26, 2004)

[14] A. M. Fraser and H. L. Swinney, Independent coordinates for strange attractors from mutual information, Phys. Rev. A 33, 1134 (1986)

[15] M. B. Kennel, R. Brown, and H. D. I. Abarbanel, Determining embedding dimension for phase-space reconstruction using a geometrical construction, Phys. Rev. A 45, 3403 (1992).

[16] D. R Fredkin, and J. A. Rice. (1995), Method of false nearest neighbors: A cautionary note, Physical Review E, 51(4), 2950–2954.

[17] R. Vautard, Pascal Yiou, Michael Ghil, Singular Spectrum Analysis: A toolkit for short, noisy chaotic signals. Physica D 58 (1992), 95-126

[18] E. K. Antonsson and R. W. Mann, The frequency content of gait, *Journal of Biomechanics* **18**-1 (1985), 39-47.