BULGARIAN ACADEMY OF SCIENCES

CYBERNETICS AND INFORMATION TECHNOLOGIES • Volume **12**, No 3

Sofia • 2012 Print ISSN: 1311-9702; Online ISSN: 1314-4081
DOI: 10.2478/cait-2012-0024

Individual Recognition from Gait Using Feature Value Method

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Abstract: *We propose a novel framework to recognize individuals from gait, in order to improve HRI. We collected the motion data of the torso from 13 persons' gait, using 2 IMU sensors. We developed Feature Value Method which is a PCA based classifier and we achieved an average individual recognition rate of 94% through cross-validation.*

Keywords: *Gait, Recognition, PCA, Feature vector, Exclusion method.*

1. Introduction

In order to develop truly intelligent systems for Human-Robot Interaction, it is necessary to improve their ability to understand non-verbal communication. When sharing the same space as humans, robots must know whom they are interacting with. The actions to take with a stranger or a known user are different. As well within a group of users, needs and information accessibility may differ. Motion based biometrics provide a unique contact-less and non-verbal way to recognize moving individuals. It is considered as soft biometrics as it preserves privacy; and it is relatively difficult to counterfeit. It is grounded in psychological studies that have shown that one can recognize known individuals in the absence of anatomical cues by looking solely at the motion [1-7].

Techniques to record motions using motion capture are already well spread [8-9]. However, post processes based on inverse kinematics and geometrical models to calculate the joint angles from marker positions' information are necessary. In this paper we replace optical motion capture by IMU sensors. IMU sensor measures the rotational velocity around the three axes and the accelerations in the three directions, which makes a total of 6 degrees of freedom (DOF) time-series data. Using 2 IMU attached on the lower and upper torso, we collect the data of motion from 13 candidates' gait, and we propose a recognition method based on feature vectors and PCA (Principle Component Analysis) that allows recognizing individuals. Further on, for a higher accuracy, we apply the idea of the exclusion method to our method.

The paper is structured as follows: first, we describe the experiments; second, we detail our method for recognition; third, we present the experimental results using motion data measured from 2 IMU sensors and test the performance through cross-validation. Finally, we apply the exclusion method to the recognition algorithm to enhance the performance.

2. Experiments

The experiments are conducted in our lab. 13 candidates (C1~C13) are chosen among students and faculties of ourcampus (6 males, 7 females). One IMU sensor is fixed on the lower torso (pelvis, centered) and the other one is fixed on the upper torso (sternum) of each candidate as Fig. 1 shows.

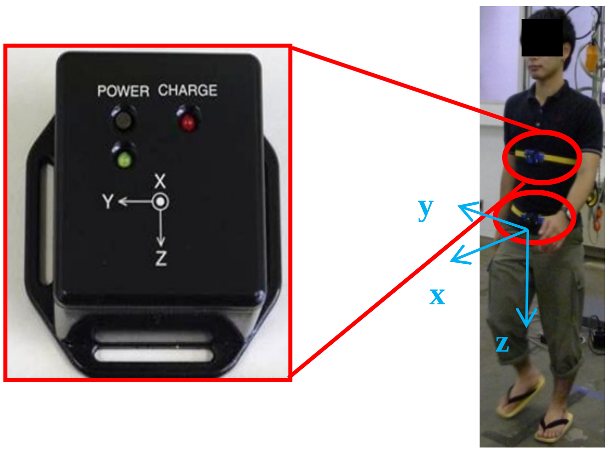

Fig. 1. A picture of the experiments and IMU we used

Literatures about inertial sensor-based gait database in this field are abundant. Comparing to arm swing or footstep, or footstep length [10-12], we believe that the torso is more stable and more robust to disturbance of clothes, shoes and even a hand luggage, during movement. [10, 12-15] did not consider cross-gender in their experiments. Others used cross-gender in their experiments [11, 16-24], especially [24] used 382 male and 354 females and constitute the largest inertial sensor-based database. However, they measured no more than 5 sequences per subject. It has been confirmed that gait can be dramatically affected by emotions such as joy, anger, sad and nervous [25-26].We think that 2 sequences are not enough to be used in gait analysis or performance evaluations since candidates might feel nervous at the first sequence which could affect their normal gait.

In our experiments we measured 10 sequences per subject and it is enough to reflect their gaits. We can obtain a 12DOF model which is made of the joint angular velocities (lower torso 3DOF, upper torso 3DOF) and the accelerations (lower torso 3DOF, upper torso 3DOF) from the IMU sensors fixed on each candidate. The candidates are asked to walk about 6~8 steps' distance and the experiment is repeated 10 times for each candidate. Thus, a total of 130 time-series motion data that has 12DOF is recorded synchronously by the twoIMU sensors.

3. Feature Value Method

We propose a simple classifier that can classify the data directly in the feature vector space visualized by PCA. First, we calculate the feature vectors of the model we use for recognition [27]. The feature vector of a data-set is computed as the auto-correlation matrix for each component of the data-set. In our case, we use the data measured by the IMU, so that the data-set is composed of the time-sequence of angular velocities or accelerations for each of the N_{DOF} DOF of our model. Let us note $q_i[k] \in \mathrm{R}^{N_{\mathrm{DOF}}}$ the vector of measured data for the considered N_{DOF} for a motion i and at time k. We compute the auto-correlation matrix $M_i(l)$ as equation (1).l is a constant time difference, here we set l=2. Then we arrange the elements of $M_i(l)$ into a single columnvector. The result is the feature vector $m_i(l) \in R^{N_{\mathrm{DOF}}^2}$,

(1) $$M_i(l) = \frac{1}{T_i} \sum_{k=1}^{T_i} \dot{q}_\iota[k] \dot{q}_\iota{}^{\mathrm{T}}[k-l].$$

PCA of the obtained feature vector provides information of the clustering possibility of the training data-set. Consequently, it gives information on the possibility to discriminate a data-set from another. Applied to individual recognition, it means that itgives information on the differences and resemblances of different motion data-sets, thus different individuals. Depending on the resemblances, points create clusters of various shapes, in the space of principal components, which are dense or scattered. Often the 3D space of the first three principal components is used. The 2D space can also be used if the cluster structure is clear enough using only the first two components. The shape of a cluster highlightsdata-set with similarities, while scattered points representdata-set with little similarity to each other. Then the further processes of the algorithm are described as below.

- First, data were collected for each person we want to include in our database of known persons to create a minimal knowledge or training data.
- Feature vectors were computed for this data and generate the points $T_i^p(x_i^p, y_i^p, \ldots)$ in the PCA space for each person p and each experiment i as detailed in Section 2.
- We compute the barycentre of the class of each person p for the n training data by:

(2) $$A^p\left(x^p, y^p, \ldots\right) = \frac{1}{n} \sum_{i=1}^{n} (x_i^p, y_i^p, \ldots).$$

- The distance d_j^p to any new point j to the barycenter of person p is given by

(3) $$d_j^p = \sqrt{(x^p - x_j)^2 + (y^p - y_j)^2 + \cdots}.$$

- The least squares linear approximation for each class is then calculated. It gives for each person p, in the 2D case: $y = P_1^p x + P_2^p$, where P_1^p and P_2^p are two real constants obtained from least squares method. And the orthogonal projection h_j^p of any point j (x_j, y_j) to the straight line is given by (4) in 2D space. In case of 3D space, the linear approximation is $P_1^p x + (Q_1^p - 1)y - z + (P_2^p + Q_2^p) = 0$ and the orthogonal projection is thus given by (5). An example of feature vector space visualized by PCA with barycenters and linear approximations is shown in Fig. 2.

(4) $$h_j^p = \frac{\left|P_1^p x_j - y_j + P_2^p\right|}{\sqrt{P_1^{p^2} + 1}},$$

(5) $$h_j^p = \left(\left(\frac{\left|P_1^p x_j - y_j + P_2^p\right|}{\sqrt{P_1^{p^2} + 1}}\right)^2 + \left(\frac{\left|Q_1^p y_i - z_i + Q_2^p\right|}{\sqrt{Q_1^{p^2} + 1}}\right)^2\right)^{\frac{1}{2}}.$$

- We define the ‘‘feature value” S of point j with respect to person p by

(6) $$S_j^p = d_j^p + h_j^p.$$

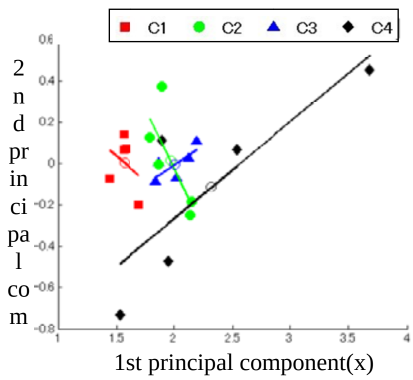

Fig. 2. Feature vector space with barycenters and linear approximations

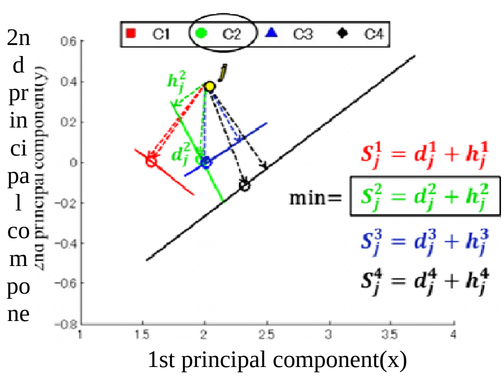

Fig. 3. Concept of the proposed algorithm

When implementing a recognition algorithm, we use PCA to analyze the feature vector, then in the 2D or 3D space configured by the 1st ~ 2nd, 3rd principal component, if a minimum feature value S_j^p is found by utilizing a random data point j, we conclude that this data point fits the person p, as Fig. 3 shows [28]. If a data is too different from the data in the database, a threshold on S_j^p can be set to return a *“non-recognized candidate”* result. The algorithm flowchart is shown in Fig. 4.

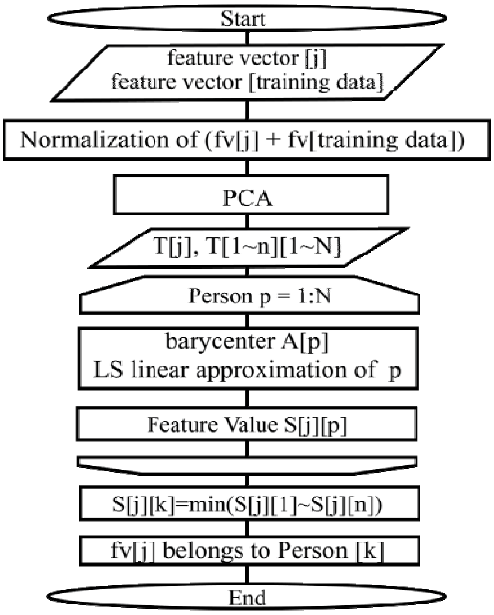

Fig. 4. Flowchart of the proposed Feature Value Method

The feature value chosen as above has some properties. First, with that configuration, both the clusters that have a high degree ofconcentration and the ones that have a clear linear distribution are considered at the same time. In Fig. 2, if the feature value S_j^p is only calculated by the barycenter, the test data j would be wrongly identified as the class of C2. Further, according to the shape of theclusters, we can balance the order of priority by adding weight coefficient to d_j^p and h_j^p. However, a data point far away from the cluster of its class can be regarded as an accidental error and it is not considered into the calculation of the barycenter and linear approximation. In this paper we just use equation (6) without adding any weight coefficient to see the algorithm original performance.

4. Experimental results and evaluation

First, to ensure that the data are unaffected by the starting and stopping phases, we extracted only the real walking part from the recorded data of each sequence. Then feature vectors are computed from the motion data of only joint angular velocity collected by the 2 IMU (3×2 DOF). Thus, $m_i(l) \in R^{N_6^2}$. The obtained result is shown in Fig. 5.

In order to verify the validity of the recognition method, we use 130-fold cross validation, which means a systematic rotation of 129 of the collected data to train our system and then plot the $T_i^p(x_i^p, y_i^p, z_i^p)$ in the feature vector space successively, and use the remaining ones as the trial data. Therefore, the trial data is not included in the training data.

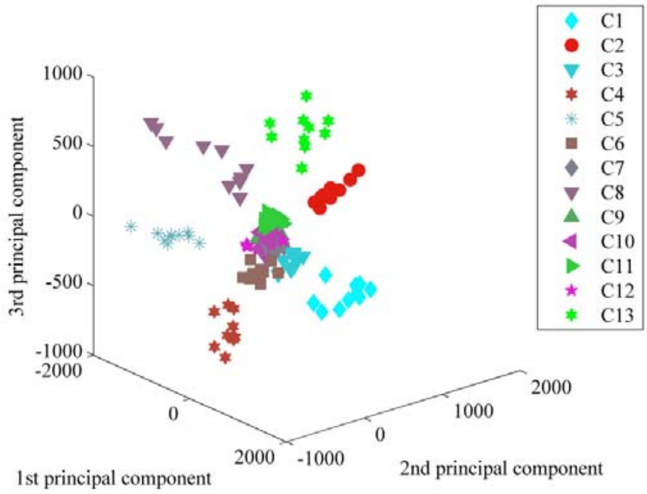

Fig. 5. Feature vector space calculated from joint angular velocitydata in 6 DOF

The recognition rate is shown in Table 1. The results show that using the proposed method we achieved an average recognition rate of 77% for each candidate, which is significantly higher than chance: around 8%.

Table. 1. Recognition rates from Fig. 5

Candidate	C1	C2	C3	C4	C5	C6	C7
Rate(%)	100	100	80	100	100	80	10
Candidate	C8	C9	C10	C11	C12	C13	Average
Rate(%)	100	70	40	80	50	90	77%

5. Exclusion method

The direction of the 1st principle component that reflects the largest variance is generally dependent on the data normalization. Thus the direction of the 1st principle componentmay be influenced even when the data are partly changed and then the cluster structure in feature vector space could change at the same time. Considering this property of PCA, we propose an exclusion method specifically for our Feature Value Method to improve the recognition performance.

The key point of the exclusion method is that, when there are some cluster of classes far away from others, such as clusters of C1, C2, C4, C5, C8 and C13 in Fig. 5, we can identify whether the test data belongs to one of them first, if not, we can run a second PCA only on the remaining feature vectors, thus a new structure made of the remaining data will appear in which the cluster structure is usually more distinct.

We use Fig. 6 to highlight the structure of Fig. 5. We can see the clusters of C3,C6,C7,C9 to C12 are concentrated together while C1, C2, C4, C5,C8 and C13's clusters are distributed far away from each other.

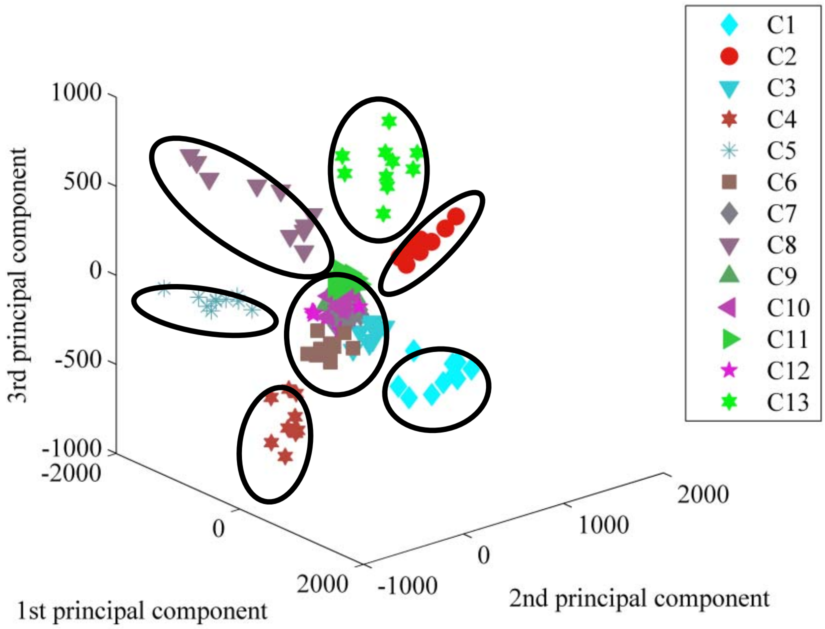

Fig. 6. Feature vector space calculated from 2 IMU's joint angular velocity data in 6DOF

Taking both the cluster distribution and the high recognition rate of C1, C2, C4, C5, C8 and C13 from Fig. 6 and Table 1, we exclude their data and run the PCA from normalization only to the remaining data containing C3, C6, C7, C9 to C12. The result is shown in Fig. 7. Also, we run cross-validation on only C3, C6, C7, C9 to C12, checking if they are easier to be recognized in this range and the result is shown in Table 2.

Table 2 confirmed that each of C3, C6, C7, C9 to C12 can be recognized with a higher rate in the feature vector space build without C1, C2, C4, C5, C8 and C13. Even though C3, C6, C7, C9 to C12 almost concentrate in one cluster in Fig. 6, they can be separated after the exclusion process because the directions of the principle components are reset. Especially the rate of C7 rises from 10% to 90% so that we are able todistinguish the gait of C7 from others.

Next we combine the two processes into one by identifying the C1, C2, C4, C5, C8 and C13 first and C3, C6, C7, C9 to C12 next. In other words, if it is proven that the trial data is not belong to any class of C1, C2, C4, C5, C8 and C13 in space showed in Fig. 5, the trial data will automatically fall into the smaller range space showed in Fig. 7. At last, recognition rates obtained from 130 cross validationsare shown in Table. 3. By using the proposed Feature Value Method and the exclusion method we finally achieved an average recognition rate of 94% for 13 persons.

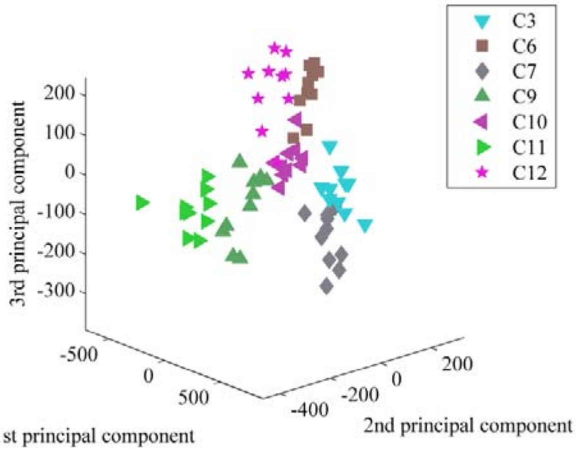

Fig. 7. Feature vector space constructed without C1, C2, C4, C5, C8 and C13

Table. 2. Recognition rate from Fig. 7

Candidate	C3	C6	C7	C9	C10	C11	C12	Average
Rate(%)	90	90	90	90	90	100	80	90

Table. 3. Recognition rates after applying exclusion method

Candidate	C1	C2	C3	C4	C5	C6	C7
Rate(%)	100	100	90	100	100	90	90
Candidate	C8	C9	C10	C11	C12	C13	Average
Rate(%)	100	90	90	100	80	90	94%

6. Conclusions

In this paper we have used the motion data of the lower torso and upper torso to recognize individuals. Our method is based on the use of PCA on feature vectors. The gait data was collected with 2 IMU sensors. The gait patterns of 13 candidates are recorded, with a repetition of 10 times. This data forms 130 motions' database with 129 training data, and the remaining one is used for recognition (trial data). Our classifier is based on the computation of the barycenter and the linear regression of the cluster for each candidate in the database. The feature value is computed as a linear combination of the distance to the barycenter and the straight line obtained previously. The smallest feature value designates the recognized candidate. The results show that:

- It is possible to recognize the person from gait within a 13 persons' database, with an average rate (94%) significantly higher than (8%) rate from the joint angular velocity data of the lower and upper torso measured by 2 IMU sensors.
- Cross-gender is used in our experiments and the result confirmed the individual diversity is far clearer than the gender diversity in gait so that the influence of gender can be left out.
- The results also confirmed the performance of the proposed method for classification. The exclusion method for our algorithm is used to improve the

accuracy. When there are some clusters of training data's classes far away from the others and obviously easy to be classified in the feature vector space, we can identify whether the target is belong to them first. If the target does not belong to any of them, we can run the PCA only on the remaining feature vectors, thus a new cluster structure made of these remaining data will work more effectively for recognition.

• Compared to Supporting Vector Machine (SVM) [29-31], the proposed algorithm for recognition is simpler and requires less computation since its recognition results are acquired by simply summing two distances calculated by the barycenter and linear regression between the targets and clusters made of training data, in the feature vector space. Further, SVM is a classifier to identify two classes theoretically. Therefore, SVM is not able to be applied to identify a multi-class at the same time in the form as it is, unless in the form of combination of multiple discriminant functions. However, Feature Value Method is a classifier that can identify a multi-class at one time.

The method is promising in developing biometric systems based on gait in order to enhance non-verbal communication abilities of intelligent systems for HRI even with rather simple sensors, such as MEMS IMU sensors that allow collecting the data through wireless communication. Further work includes the creation of a comprehensive database of gait data on a wide range of people. Also, the optimization of both the exclusion order and the levels of the hierarchicals pace have to be improved when making use of the exclusion method. To enhance the response to classes in non-linear distribution we also plan to use Kernel PCA instead of PCA and then compare the Kernel based Feature Value Method with non-linear SVM in accuracy and computation speed [32].

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