# Recognition human by gait using PCA and DTW

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***Abstract***-With the increasing demand of visual surveillance systems, human recognition at a distance has gained extensive research interest. Gait is a potential behavioral feature to identify humans based on their motion. This paper describes a new scheme for extracting and selecting features from the gait of a human for recognition. The scheme combines two methods: principal component analysis (PCA) and dynamic time warping (DTW). PCA is applied to remove correlation between the features and also to reduce its dimensionality of the data features. These extracted feature vectors are used to recognizing the individuals. Dynamic time warping is used to recognize the individual. Firstly, the binary silhouette of a walking person is detected from each frame of the monocular image sequences. Then we divide the two dimensional silhouette of the walker into 7 parts in order to calculate the angle between front and back thigh. Finally, similarity measurement based on the gait cycles is calculed to recognize the different subjects. The result of experiments conducted on CASIA-A gait database show that the proposed gait recognition approach can obtain encouraging accurate recognition rate.

## I. Introduction

Biometrics are automated methods of recognizing a person based on a physiological or behavioral characteristic. Among the features measured are; face, fingerprints, hand geometry, handwriting, iris, gait, retinal, and voice. Biometric technologies are becoming the foundation of an extensive array of highly secure identification and personal verification solutions. As the level of security breaches and transaction fraud increases, the need for highly secure identification and personal verification technologies is becoming apparent.

Biometric-based solutions are able to provide for confidential financial transactions and personal data privacy. The need for biometrics can be found in federal, state and local governments, in the military, and in commercial applications. Enterprise-wide network security infrastructures, government IDs, secure electronic banking, investing and other financial transactions, retail sales, law enforcement, and health and social services are already benefiting from these technologies.

Gait recognition is a relatively new research direction in biometrics aiming to identify individuals by the way they walk. Using gait has many advantages over other biometrics, such as fingerprints, iris, and face recognition, most notably because it is noninvasive and available at low resolution. Human gait recognition works from the observation that an individual's walking style is unique and can be used for human identification. Using human gait as biometric is a relatively new area for Computer Vision researchers.

Gait recognition approaches can be broadly categorized into the model-based approach, where human body structure is explicitly modeled, and the model-free approach, where gait is treated as a sequence of holistic binary patterns (silhouettes).

- **Model-based approaches:** Model-based approaches employ models whose parameters are determined by processing of gait sequences (binary silhouettes). These methods are scale, view invariant and requires good quality video sequences. In these methods, parameters used as features are the height, the distance between head and pelvis, the maximum distance between pelvis and feet and the distance between feet. In [1], the silhouette of a walking person is divided in to some regions (generally seven regions). Subsequently, ellipses or rectangles are fit to each region and region feature vectors are determined. This includes averages of the centroid and the aspect ratio. Fig. 1 shows the examples for model-based approaches.

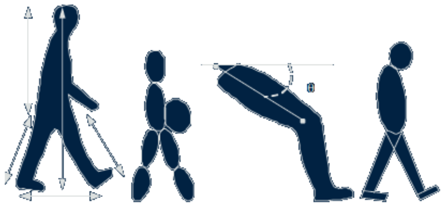

Figure 1. Model-based

- **Holistic approaches :** Holistic methods operate directly on binary silhouettes without assuming any specific model for the walking human. The contour of the silhouette is the most reasonable feature in this method. For high quality binary silhouettes, width of outer contour of the silhouette was proposed as a suitable feature. For low quality binary silhouettes, the binarized silhouette may be is used as a feature. Example of holistic approaches is shown in Fig. 2.

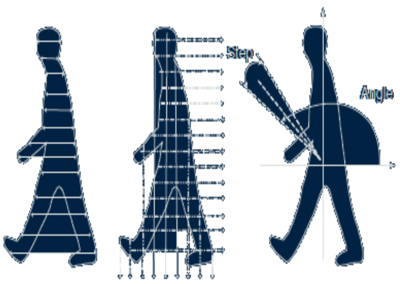


Figure 2. Model-holistic

In the last decades, a great number of referential and valuable approaches have been proposed in the literatures, which include the analysis of a subject's trajectory [1], principal components analysis (PCA) [2], velocity moments [3], discrete symmetry operator [4], continuous HMMs [5] and some of approaches based on the kinematics and dynamics model [6][7]. The main task of gait recognition is to extract the appropriate salient features that effectively describe the motional characteristics of the parts of body.

The rest of the paper is organized as follows: Section 2 describes the preprocessing procedure. Section 3 introduces how to extract the gait signature and presents the pattern classification. Experimental results are reported in Section 4 and conclusions are drawn in Section 5.

## II. PREPROCESSING

In our method, three vieuw angles are chose, including 0° (front vieuw), 90° (fronto parallel vieuw), and 180° (back vieuw). After several test, the fronto parallel vieuw presentation contains more information for gender classification.

The silhouette is usually extracted by finding the difference between the background and current image [8,9] or grouping optic flow to find the coherent motion[10,11].There are inevitably spurious pixels, holes inside moving subject and other anomalies in the detected sections. Mathematical morphological operations, such as erosion and dilation, are widely used to remove spurious pixels and fill small holes inside the extracted silhouettes. To eliminate the size difference caused by the varying distance between the subject and camera, the silhouettes are usually height scaled and centered. Even if the original images were of good visual perception, some inaccuracy may not be repaired by mathematical morphological operations. Silhouette incompleteness caused by body portion lost has a greater effect on recognition than other errors, such as shadows and spurious pixels.

When the heads or feet are missing, height scaling will cause serious shape distortion. Fig. 3 shows some sample images of the background images, original images, raw silhouettes and preprocessed silhouettes.

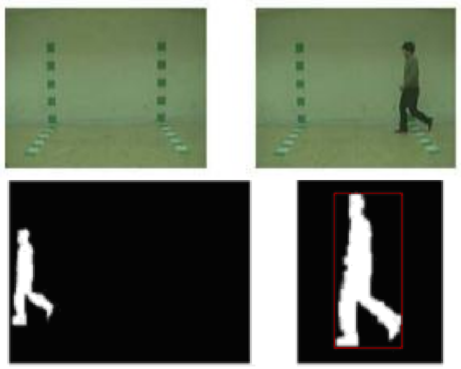

Figure 3. Sample images of human silhouettes and their preprocessed silhouettes.

## III. GAIT SIGNATURE EXTRACTION

### A. *Silhouette decomposition*

Gait signature extraction is the key task in human gait recognition. It must be reasonably robust to the varying conditions and should yield good discrimination across individuals. Intuitively, the silhouette appears to be a good feature to utilize since it captures the motion of most of the body parts and also encodes structural as well as transitional information [3]. Particularly, it is independent of the clothing, illumination and textures etc.

It is well known that the parts of body move differently when walking. For example, some people's head may have slight movement while others do not have the same behaviors. And some people's torso is almost still while another's one oscillate severely. At the same time, the oscillation of legs is different too [12,13].

All these salient features of the body's parts constitute the subject's unique gait signature for person identification.

According to Fig. 5, we get the human parts proportions, and then for each silhouettes of a gait video sequence we divide it into 7 regions in conformity with anatomical literature, which is shown in Fig. 4. These 7 parts roughly correspond to: head region, front of torso, back of torso, front thigh, back thigh, front foot, and back foot.

For each of the parts, we fit an ellipse to the foreground in this region, and we draw the major axis and we calculate his length. Finally we compute the angle between front thigh and back thigh.

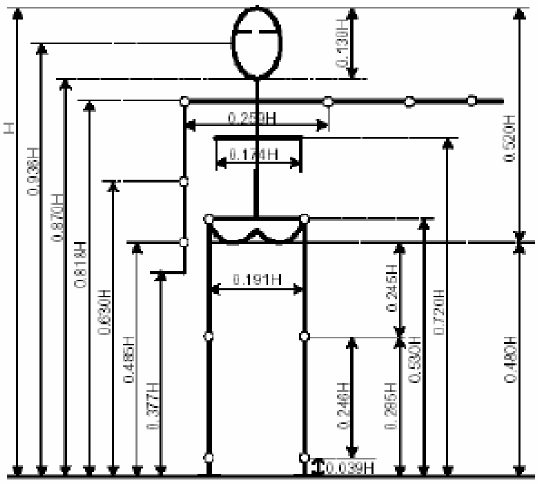


Figure 4. Human parts proportions

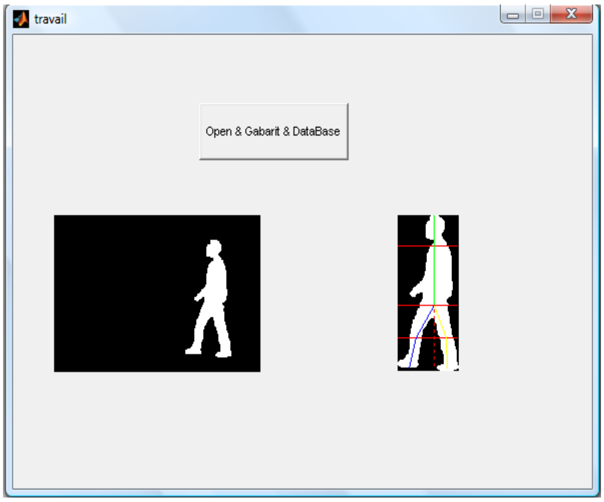


Figure 5. Human parts segmentation

Now, we have five dimensional features, respectively; the distance between the head and pelvis (A1), length of front thigh (A2), length of back thigh (A3), length of front foot (A4), length of back foot (A5).

In our approach we calculate the angle between front thigh and back thigh (alpha), by following formula:

$$\text{alpha} = \arccos\left(\langle A2.A3\rangle / \|A2\|.\|A3\|\right) \qquad (1)$$

Such as < . , .> is a dot product of two vectors and ||.|| is a euclidian norm.

These features, however, contain the information of gait of only one frame, not whole gait sequence. To represent the information of gait sequence, we apply the decomposition of silhouette for every frame in the sequence. At a result, we have array of data for each person. Thie dimension of this array is equal to the number of the frame in the sequence (n). Finally, we have n angle for each person.

Now, we use PCA to reduce dimensionality of database [15]. We obtain 0.9804261 for a Cumulative Proportion of 2 principals components.

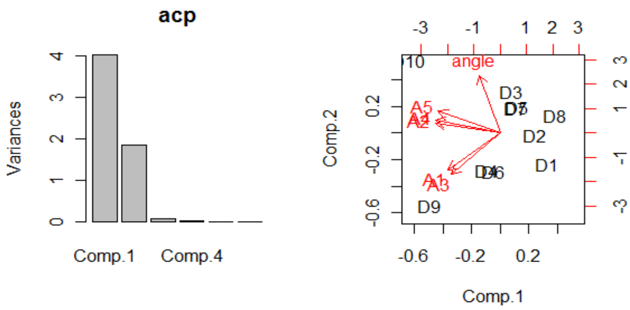


Figure 6. PCA

We conclude that we can reduce data angle with another feature; but angle must be present in the rest of treatment.

*B. Dynamic time warping*

Dynamic time warping is an algorithm for measuring similarity between two sequences which may vary in time or speed. For instance, similarities in walking patterns would be detected, even if in one video the person was walking slowly and if in another he or she were walking more quickly, or even if there were accelerations and decelerations during the course of one observation, DTW has been applied to video, audio, [14].

Given two sequences X = (x1; x2;....; xn) and Y =(y1; y2;....;ym), the distance DTW(X,Y ) is similar to the edit distance. To calculate the DTW distance D(X,Y ), we can first construct an n-by-m matrix, as shown in fig. 7. Then, we find a path in the matrix which starts from cell (1; 1) to cell (n;m) so that the average cumulative cost along the path is minimized. If the path passes cell (i; j), then the cell (i; j) contributes cost(xi; yj) to the cumulative cost. The cost function cost(xi; yj) can be defined flexibly depending on application, for instance, cost(xi; yj) = (xi – yj)2. This path can be determined using dynamic programming, because the following recursive equation holds:

$$D(i,j)=cost(x_i,y_j)+\min\{D(i-1,j), D(i-1,j-1), D(i,j-1)\} \qquad (2)$$

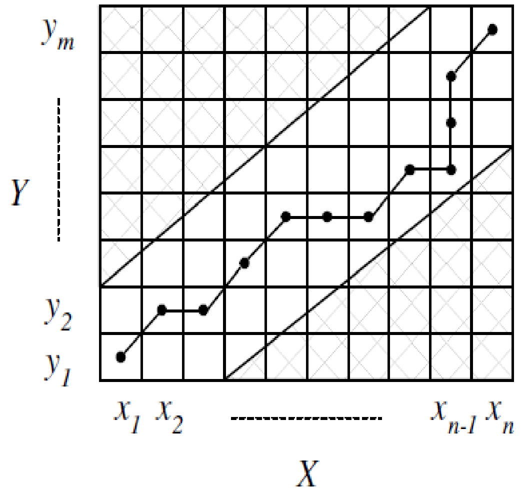


Figure 7. Illustration of Dynamic Time Warping

## IV. EXPERIMENTAL RESULTS

### A. *Experimental Data*

The CASIA Gait Database [15] was used for evaluating the performance of the proposed approach. It was created on Dec. 10, 2001, including 20 persons. Each person has 4 sequences. The original image size of the database is 320x240. The database thus includes a total of 80 (20×4) sequences. The length of each collected sequence varies with the pace of walker, but the average is about 20 frames.

### B. *Results*

We performed the experiments with probe sequences in Dataset A of CASIA, where subjects motions are parallel to image plane. We use Dynamic time warping (DTW) to calculate the distance between a test sequence and a reference sequence (Fig. 8).

Using DTW all distances between test and reference frames are computed and the total distance is defined as the accumulated distance along the minimum-distance path (termed the optimal warping path).

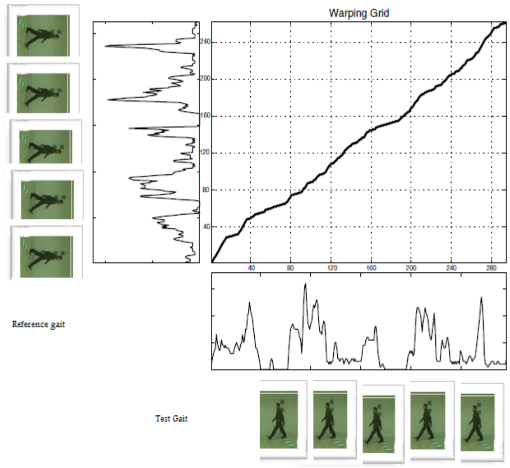


Figure 8. Gait recognition using DTW

*Having computed* the distances between a test subject and all subjects in a reference database, the recognition decision is taken as

$$Identity(i)=\arg\min_j D_{ij} \qquad (3)$$

where Dij denotes the cumulative distance between the i th test subject and the jth reference subject. This means that the identity of the test subject is assumed to be the identity of the reference subject with which the test subject has the minimum distance.

Once a similarity (probability) measure, also known as opinion and score, is obtained, the decision implies the computation of a decison threshold. If the similarity is smaller than a threshold, the decision is ACCEPT, otherwise it is REJECT.

Contrarity, if the matching block produces a distance (dissimilarity) measure, the person is accepted if the score is greater than the threshold, and otherwise it is rejected.

For the learning, 10 persons are used to determine the rejection threshold: for each person, the 2 first sequences are used as the gait of reference (enrollment) and the others (2 sequences) plus all the sequences of other persons (10 persons) are used to evaluate the FAR and FRR. The mean FAR and FRR could be determined for the 10 signers and the threshold is defined when we obtain the EER.

For the test phase, the threshold defined previously is kept and we operate the test with the 11th person (that was not used during learning) as a new person to authenticate: we use its 2 first sequences as references (enrollment) and then we use the remaining sequences of this person and all the others of the database to evaluate the FAR and FRR. The entire procedure (learning and testing) is repeated such as every person is used once in the test phase.

The Fig 9. and Fig 10. shown the result of DTW between 2 person how have the same gait and 2 person how have different gait.

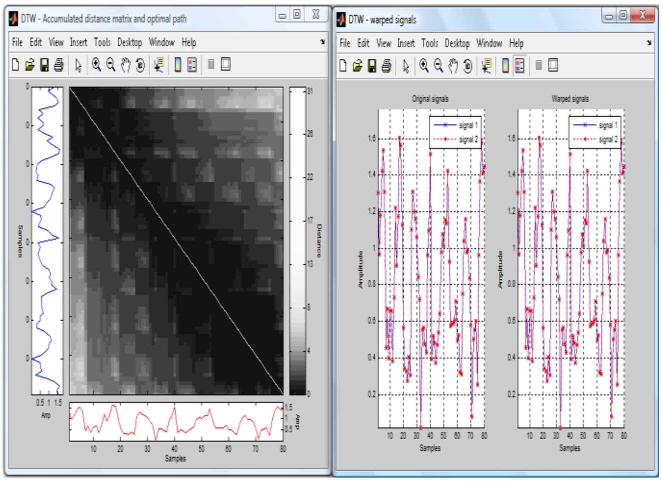

Figure 9. DTW between two identical people

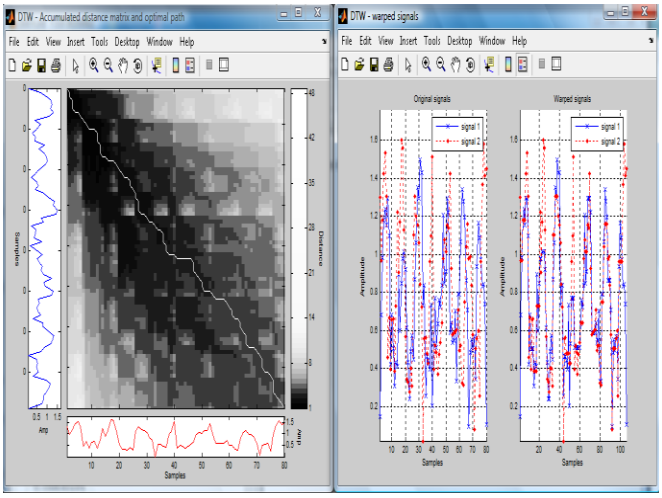

Figure 10. DTW between two different people

In our experience, we choose three several values from the threshold in order to evaluate the method. The Experimental Data and Results for Gait Recognition are shown in Table 1. If the value of the threshold is small, the precision increases.

TABLE I. THE RESULT

| Database CASIA | Number of probe sequences | Recognition accuracy (%) | | | |
|---|---|---|---|---|---|
| | | σ = 20 | σ = 10 | σ = 5 | **Average** |
| | | Dist ϵ [0, 200] | | | |
| | 80(4×20) **(DTW)** | 88 | 90 | 92 | **90** |
| | 80(4×20) **(PCA+DTW)** | 91 | 94 | 96 | **93.66** |

In the table 2 shows the accuracy of the algorithm proposed in this paper by comparing the classification results of the algorithms in littérature under the same database.

TABLE II. THE RESULT OF COMPARAISON

| | |
|---|---|
| Method of Ben Abdelkader et al. [16] | 72 % |
| Method of Collins et al. [17] | 71.25 % |
| Method of Phillips et al. [18] | 78.75 % |
| **Our approach** | **93.66%** |

## V. CONCLUSION

Human identification at a distance has recently gained more interest. Gait is a potential behavioral feature and many allied studies have demonstrated that it has a rich potential as a biometric for recognition. The development of computer vision techniques has also assured that vision based automatic gait analysis can be gradually achieved.

This paper has proposed a novel and effective method for gait-based human recognition by DTW and PCA.

The experimental results and analysis indicate that our method is effective in automated gait recognition. The key advantages include low computation cost and unnecessary learning by large data, both of which suggest it to be real-time and efficient for video surveillance. it requires clear-cut images, pre-processed images could be implemented for intact human silhouette before feature extraction and representation.

The system based on the DTW algorithm performed significantly better than the basic system.

The method is computationally efficient and runs in real-time.

Future work includes performance evaluation of other state-of-the-art gait recognition approaches, and gender and/or age group classification by gait using the very large scale gait database.

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