Recognizing Human Gait in Video Sequences

Soumia Benbakreti*[1], Samir Benbakreti[2] and Mohammed Benyettou[1]
[1] LAMOSI: Laboratoire de modélisation et de d'optimisation des systèmes industriels, Computer Science Department,
University of Sciences and the technology
Mohammed Boudiaf,
Oran, Algeria
soumiabenbakreti@gmail.com
med_benyettou@yahoo.fr

[2] INTTIC: Institut National des Telecommunications et des TICs
Oran, Algeria
thn20@hotmail.fr

***Abstract*—The recognition of humans and their activities from video sequences is currently a very active area of research because of its applications in video surveillance, design of realistic entertainment systems, multimedia communications, and medical diagnosis. This paper presents an automatic gait recognition system that recognizes a person by the way he/she walks. The gait signature is obtained based on three values of angles: angle between front thigh and back thigh , the angle between the back foot and back thigh , the angle between the front foot and front thigh. Next, we applied the principal component analysis (PCA) to reduce the dimensionality of the data set. This paper uses the dynamic time warping to distinguish the different gaits of human. The performance of the proposed method is tested using CASIA database B.The proposed algorithm has a promising performance because the identification rate is 92,3% .**

Keywords- Gait, Angle,Biometrics, Accuracy, Video.

I. Introduction

Biometrics is the science of using human measurements to identify people. Unlike passwords, pin-codes, tokens etc. biometrics cannot be stolen or forgotten. The main advantage of biometric authentication is that it establishes explicit link to the identity because biometrics use human biological (fingerprint, hand geometry, iris,…) and behavioral characteristics (Voice, Signature, Gait, Odor,...).

Biometric resources, such as iris, fingerprint, palmprint, and shoeprint, have two disadvantages: 1) they do not work well in low resolution images, for example those taken at a distance; and 2) user cooperation is required to achieve good results.Gait, which concerns recognizing individuals by the way they walk, is a relatively new biometric without these disadvantages.

Gait analysis is a challenging research topic and recently that identification from gait has received attention and has become an active area of computer vision. For biometrics research, gait is usually referred to include both body shape and dynamics, i.e. any information that can be extracted from the video of a walking person to robustly identify the person under various condition variations.

The demand for automatic human identification system is strongly increasing and growing in many important applications, especially at a distance and it has recently gained great interest from the pattern recognition and computer vision researchers for it is widely used in many security-sensitive environments such as banks, parks and airports.

In recent years, various techniques have been proposed for human recognition by gait. These techniques can be divided as model-based and model-free approaches.
Model-based Gait Recognition concerns identification using an underlying mathematical construct(s) representing the discriminatory gait characteristics (be they static or dynamic), with a set of parameters and a set of logical and quantitative relationships between them.

Unlike model-based approaches, holistic solutions operate directly on the gait sequences without assuming any specific model for the walking human. This approaches aim to derive data from the human walking sequence that is similar for each subject but different for different people.

This approaches are insensitive to the quality of silhouettes and have the advantage of low computational costs comparing to model-based approaches. However, they are usually not robust to viewpoints and scale.

Little and Boyd [2] extracted frequency and phase features from moments of the motion image derived from optical flow to recognize different people by their gait. Huang *et al.* [4] presented a weighted multi-view fusion gait recognition algorithm by assigning different weights to different views to improve the recognition accuracy.

Baumberg and Hogg [3] describe the shape of the silhouette of walkers. Bobick and Davis [5] accumulate motion information into a motion energy image and a motion history image to recognize human activities. Using the human shapes and their temporal changes during walking, Murase and Sakai [6] proposed a template-

978-1-4673-1520-3/12/$31.00 ©2012 IEEE

matching method which uses the parametric eigen space representation, as applied in face recognition , to recognize different human gait. Bobick and Johnson [1] subdivide the binary silhouette of walking people into body parts and measure different relations among limbs.

BenAbdelkader et al. [7] compute self-similarity plots from silhouettes and apply subspace methods to recognize individuals therefrom. Other authors base their work on a statistical theory of shape developed by Kendal [8], Veeraraghavan et al. [9] and Wang et al. [10] apply Procrustean distances to compare and classify human silhouettes.

In this paper, we introduce a new approach for gait recognition using the model-based. The proposed method is shown in Figure1.

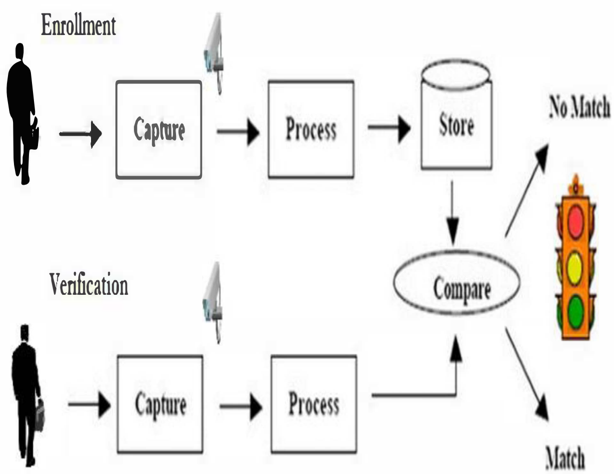

Fig 1. General block diagram of a gait recognition

The rest of the paper is organized as follows: Section 2 describes feature extraction. Section 3 presents the pattern classification. Experimental results are reported in Section 4 and conclusions are drawn in Section 5.

II. FEATURE EXTRACTION

A. Silhouette extraction

Background subtraction is a process of visual computation which extracts foreground objects from a particular scène. The objective of background subtraction algorithms is to identify interesting areas of a scene for subsequent analysis. “Interesting” usually has a straightforward definition: objects in the scene that move. In our work, this object is a person. The principal idea of this algorithm is to detect moving objects in an image. This is achieved by evaluating the difference between the pixel features of the current scene image and those of a reference background image. In our work, this object is a silhouette of person [11]. Figure 2 shows an example of background subtraction. Then we apply the two principal morphological operations: *dilation* and *erosion*. Dilation allows objects to expand, thus potentially filling in small holes and connecting disjoint objects. Erosion shrinks objects by etching away (eroding) their boundaries.

Fig 2. Background subtraction

We extract the binary silhouettes from the gait sequences. The reason we work on silhouette images is because silhouette images are invariant to changes in clothing color/texture and also lighting condition. Once a silhouette is generated:

- A bounding box is placed around the silhouette in order to divided the silhouette into seven parts (head, front of torso, back of torso, front thigh, back thigh, front foot , back foot) conformity with anatomical literature, which is shown in figure 3.
  Then we calculate : 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) , and we compute, the angle between the back foot and back thigh(α_1), the angle between the front foot and front thigh(α_2), and the angle between front thigh and back thigh (α_3) which is shown in figure 4.
- We represent the three angles in the form of curve in order to facilitate the clustering, which is shown in figure 5.

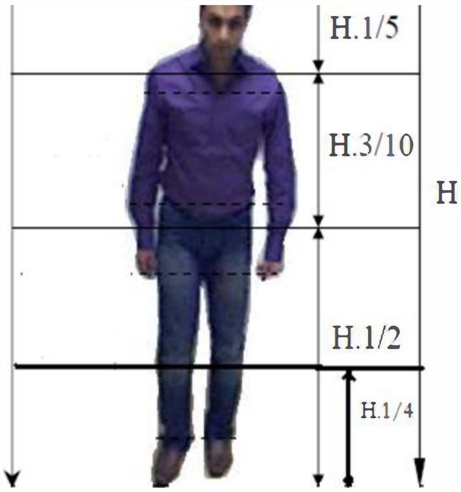

Fig 3. Anatomical decomposition

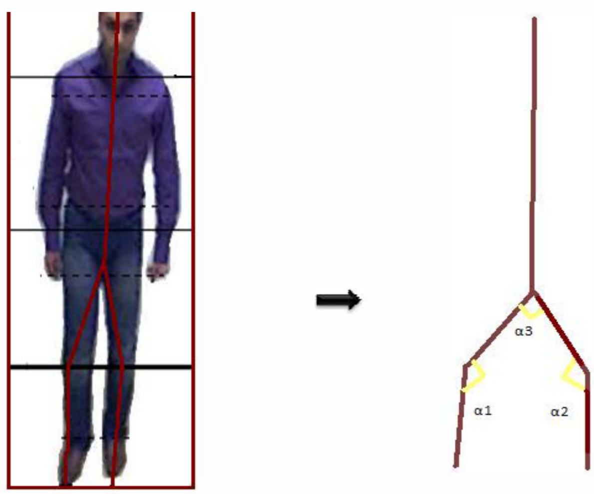

Fig 4. Calcul of angle

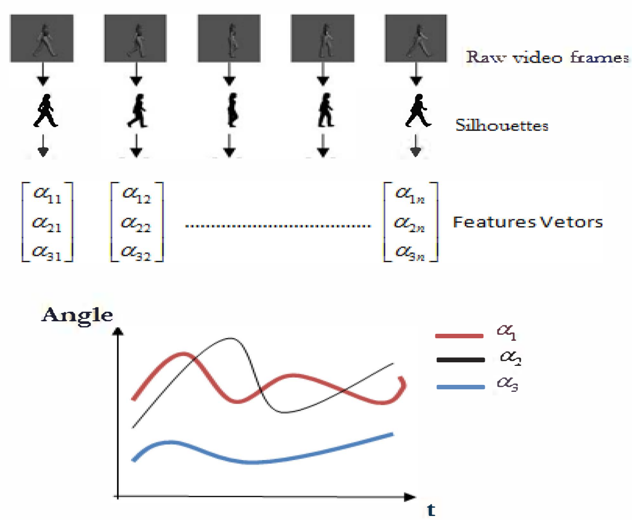

Fig 5. Curve of angle

III. GAIT RECOGNITION

A. Principal component analysis:

Principal component analysis is a multivariate method used for data reduction purposes. The basic idea is to represent a set of variables by a smaller number of variables called principal components. These are chosen in such a way that they are uncorrelated.

Principal component analysis is used where the columns of array X correspond to the observations on different variables. The transformation is to a set of orthogonal variables such that the first principal component accounts for the largest possible amount of the total dispersion, measured by λ1, the second principal component accounts for the largest possible amount of the remaining dispersion λ2, and so forth. The total dispersion is given by the sum of all eigenvalues, which is equal to the sum of squares of the original variables.

In our approach, to determine the correlations between the characteristics of human, we apply Principal Component Analysis (PCA). The first two principal components account for 96% of the total sum of squares of the original variables. The plot of the first two principal components from our data is given in Figure 6. The coordinates of each point are given by the correlation between the corresponding data (distance and angle) index and the principal components (the orthogonal axis).

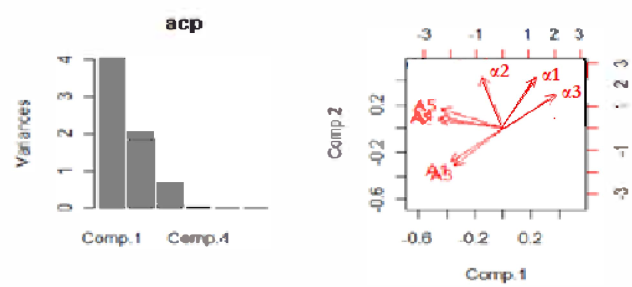

Fig. 6 PCA

B. Clustering with DTW:

Dynamic Time Warping (DTW) distance measure [13] is a well-known shaped-based similarity measurement. It uses a dynamic programming technique to find the optimal warping path between two time series sequences. Suppose we have two sequences, a sequence $X_{1....n} = <x_1; x_2;....; x_i;....x_n>$ and a sequence $X_{1....m} = <y_1; y_2;....; y_j;....y_m>$. The distance is calculated by following the equations.

$$D(X,Y) = d(x_n, y_m) + \min \begin{cases} D(X_{1...n-1}, Y_{1...m-1}) \\ D(X_{1...n}, Y_{1...m-1}) \\ D(X_{1...n-1}, Y_{1...m}) \end{cases} \quad (1)$$

where D(Ø,Ø) = 0, D(Xi...n, Ø) = D(Ø, Yj... m) = ∞, and Ø is an empty sequence. Any distance metrics can be used for $d(x_i; y_j)$, including L1-norm, $d(x_i; y_j)$ = |xi-yj|, and L2-norm, $d(x_i; y_j)$ = $(xi\text{-}yj)^2$. For simplicity, we use L1-norm to describe our proposed method, but L2-norm isused in experimental evaluation to achieve better accuracy.

Table 1 contains pseudo-code of the DTW algorithm.

Input: $\mathbf{X} = (x_1, \ldots, x_M)$ and $\mathbf{Y} = (y_1, \ldots, y_N)$, distance function $d(\cdot,\cdot)$
Output: DTW matrix D
Algorithm:
1. $D(1,1) = d(x_1, y_1);$
2. for $m = 1 : M$
3. $\quad D(m,1) = D(m-1,1) + d(x_m, y_1);$
4. for $n = 1 : N$
5. $\quad D(1,n) = D(1,n-1) + d(x_1, y_n);$
6. for $m = 2 : M$
7. $\quad$ for $n = 2 : N$
8. $$D(m,n) = min\begin{Bmatrix} D(i,j-1) \\ D(i-1,j) \\ D(i-1,j-1) \end{Bmatrix} + d(x_m, y_n);$$

Table 1: Pseudo code for the DTW algorithm.

Once all necessary values of D have been calculated, the warping path can be determined by backtracking the minimum cost path starting from (M;N). We are just interested in the accumulated cost along the warping path, which is stored in D(M;N). As it is, this matching cost would be lower for shorter sequences, so we o_set this bias by dividing the total matching cost by the length K of the warping path, yielding

$$D(X,Y) = D(M,N) / K \qquad (2)$$

Then an acceptance or rejection decision is made by comparing the DTW distance averaged over the reference template set with a threshold , i.e., if

$$\frac{1}{NBR}\sum_{i=1}^{NBR} D_i\,(test\,, reference\,) < \lambda \qquad (3)$$

satisfies, we accept this keyword candidate. Here *NBR* and λ denote the number of the reference templates and threshold, respectively.

C. Experimental Results :

In this paper, we use CASIA gait database: Database B [14]. It's a large multiview gait database, which is created in January 2005. There are 124 subjects, and the gait data was captured from 11 views (cf. Figure 7).

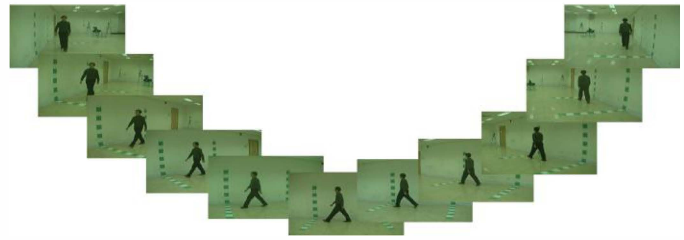

Fig 7. Different view of walking

Six gait sequences were captured for each person under each viewing angle. Therefore, 11x124x8 or 10912 gait sequences are used. The database is divided into 2 groups. The first group contains 54 subjects for feature extraction process. The second group contains 70 subjects for evaluating performance of our approach.

Figure 8, shows the scheme of the comparison for the first angle, we repeat this step for the other angle.

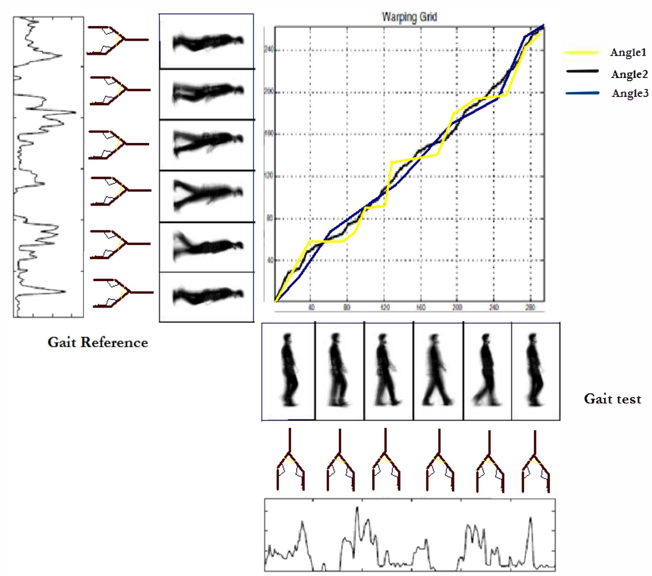

Fig 8. Comparison between different angle.

The decision nodes have the following format:

$$\begin{Bmatrix} \text{dtw}\left(\text{angle\_Reference1, angle\_test1}\right) < \text{Threshold1} \\ \text{dtw}\left(\text{angle\_Reference2, angle\_test 2}\right) < \text{Threshold2} \\ \text{dtw}\left(\text{angle\_Reference3, angle\_test 3}\right) < \text{Threshold3} \end{Bmatrix} \qquad (4)$$

In our contribution, we accept the person when the three conditions of the equation (4) are checked. In order to evaluate the performance of our system, we calculate the False Rejection Rate (FRR), False Acceptance Rate (FAR), and Accuracy (ACC).

- **False accept rate or false match rate (FAR or FMR)**: the probability that the system incorrectly matches the input pattern to a non-matching template in the database. It measures the percent of invalid inputs which are incorrectly accepted. In case of similarity scale, if the person is imposter in real, but the matching score is higher than the threshold, then he is treated as genuine that increase the FAR and hence performance also depends upon the selection of threshold value.

- **False reject rate or false non-match rate (FRR or FNMR)**: the probability that the system fails to detect a match between the input pattern and a matching template in the database. It measures the percent of valid inputs which are incorrectly rejected.

The Experimental Data and Results for Gait Recognition are shown in Figure 9 .

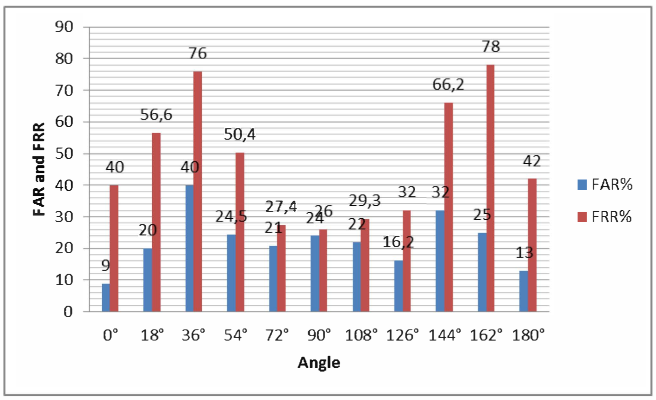

Fig 9. FAR & FRR

The proposed method achieves high performances for the 90°, up to 92,3% accuracy (Figure 10).

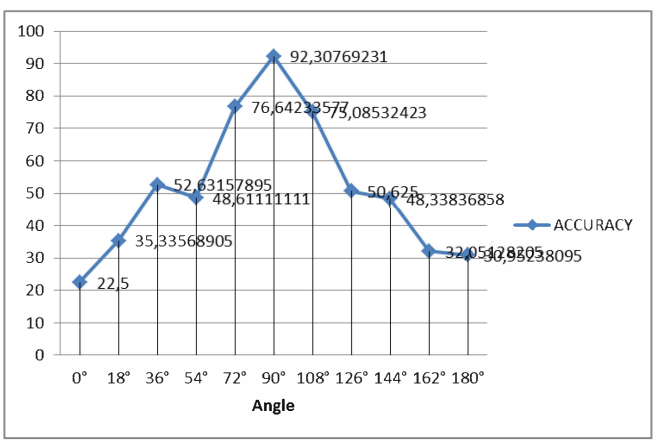

Fig 10. The result of accuracy

IV. Conclusion

We presented new approach to gait recognition problem using the model based. This method is sample because we use PCA in order to reduce the dimensionality of data.
This reduction is essential to make classification with DTW more efficient and save precious computing time to satisfy the requirement of real-time applications. We have evaluated the method on database CASIA.The proposed method has been verified with a large multiple view gait database. Experimental results have demonstrated the feasibility of the proposed method.

References

[1] A.Bobick and A. Johnson. Gait recognition using static, activity-specific parameters. In Proc. CVPR, volume I, pages 423.430, 2001.

[2] J.E Boyd and J.J. Little, “Silhouette based gait recognition”, in Encyclopedia of Biometrics, S.Z. Li(ed), Springer 2009.

[3] A. M. Baumberg and D. C. Hogg. Learning spatiotemporal models from training examples. Technical Report 95.9, University of Leeds School of Computer Studies, March 1995.

[4] S. Yu, T.Tan and K.Huang, et.al, "A Study on Gait-Based Gender Classification", *IEEE Trans. on Image Processing*, pp:1905-1910,V18(8),2009

[5] A. Bobick, and J. Davis, "The recognition of human movement using temporal templates," *IEEE Transaction on Pattern Analysis & Machine Intelligence*, **23**(3), March 2001.

[6] H. Murase and R. Sakai, BMoving object recognition in eigenspace representation: Gait analysis and lip reading,[Pattern Recognit. Lett., vol. 17, pp. 155–162, 1996.

[7] C. BenAbdelkader, R. Cutler, and L. Davis. Gait recognition using image self-similarity. EURASIP J. on Applied Signal Processing, 4:572.585, 2004.

[8] D. Kendall, Shape manifolds, procrustean metrics and complex projective spaces, Bulletin of the London Mathematical Society 16 (1) ,pp. 81–121, 1984.

[9] A. Veeraraghavan, A. Chowdhury, R. Chellappa, Role of shape and kinematics in human movement analysis, in: Proc. CVPR, vol. I, pp. 730–737, 2004

[10] L. Wang, T. N. Tan, W. M. Hu and H. Z. Ning, “Automatic Gait Recognition Based on Statistical Shape Analysis”, IEEE TIP, Vol. 12, No. 9, pp 1120-1131, Sep. 2003

[11] C. Ianasi, V. Gui, C. I. Toma, and D. Pescaru, “A fast algorithm for background tracking in video surveillance, using nonparametric kernel density estimation,” *Facta Universitatis Ser.: Elect. Energ.*, vol. 18, no. 1, pp. 127–144, Apr. 2005.

[12] www.cs.otago.ac.nz/cosc453/student_tutorials/principal_components.pdf

[13] D. Sankoff and J. B. Kruskal: *Time Warps, String Edits, and Macromolecules: The Theory and Practice of Sequence Comparison*. Addison-Wesley, Reading, MA, 1983.

[14] WWW.SINOBIOMETRICS.COM