HUMAN GAIT RECOGNITION USING DIFFERENCE BETWEEN FRAMES

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Keywords: Biometric, Frieze pattern, Gait recognition.

Abstract: In this paper, we address the problem of human identification using gait. Considering the recent work of Lee et al. (Lee et al., 2007) proposed for gait recognition. First we will introduce the algorithm proposed by Lee et al.. This method has two main steps: (1) extract key frames to define the gait cycle pattern, and (2) compute Shape Variation-based frieze patterns. These patterns are then used to classify and perform the gait identification. We modify the utilized features in this approach. We try to omit redundant features based on the effect of each feature on recognition rate and in next step, we improve performance of this approach by making some changes in way of feature extraction. Finally, we use the statistical characteristics of employed features instead of direct applying of remaining features. We test the proposed method on CASIA database. The experimental results are used to compare the proposed method with Lee et al. method.

1 INTRODUCTION

Nowadays, there is an ever growing need to determine or verify the identity of a person. Biometrics are one of most important tools for this purpose. Biometrics is a branch for identifying or verifying the identity of a person based on physiological or behavioral characteristics. Physiological characteristics include fingerprints and facial image. The behavioral characteristics are actions carried out by a person in a characteristic way and include signature, voice or gait, though these are naturally dependent on physical characteristics.

One of behavioral biometrics is gait. Gait as a biometric has been attracted by many researchers in recent years. It is non-invasively and can be performed from distance. All human have the same basic walking pattern, but their gaits are influenced by many factors like their musculo-skeletal structure, limb lengths, body mass and shape and several other factors (Murray et al, 1964)(Johansson, 1973). These make gait unique for each person.

Generally, gait recognition approaches can be categorized in two main groups: model-based approaches and model-free or appearance-based approaches.

Model-based methods simulate human body using a model. In model-based approaches, a general model is considered for human body and this model is fitted to body of each person. Then using this model, desired features are extracted. Model-based approaches are fairly robust to some covariates like view angle and occlusion, but they need large amount of computations. Joint trajectories (Wang et al., 2004), stride parameters (BenAbdelkader, 2002) and so on, can be categorized in this group.

Second category of methods, are model-free or appearance-based methods. In this category, different algorithms are used to capture human motion features, for example averaged silhouette (Liu and Sarkar, 2004), HMMs (Chen et al., 2006)(Sundaresun et al., 2003)(Kale et al., 2002)(Suk and Sink, 2006), PCA (Murase and Sakai, 1996), symmetry analysis (Hayfron-Acquah et al., 2003), etc.

Lee et al. (Lee, 2007) used difference between a key frame and the frames in a walking cycle for feature extraction. In this paper, first we will review their approach. Through the experiments we noticed that some employed features are redundant, so we omit redundant features in our proposed method. Then we will modify algorithm to improve its performance.

The rest of this paper is organized as follow. In

Karami M. and Ahmadyfard A. (2009).
HUMAN GAIT RECOGNITION USING DIFFERENCE BETWEEN FRAMES.
In *Proceedings of the Fourth International Conference on Computer Vision Theory and Applications*, pages 327-332
DOI: 10.5220/0001793003270332

section 2 we will review the algorithm proposed by Lee et al. (Lee, 2007). In section 3 we investigate the employed features in their algorithm and effect of these features on recognition rate. Section 4 includes the proposed modification in order to improve performance of Lee algorithm. Section 5 shows the experimental results and finally in Section 6 we draw the paper to conclusion.

2 PREVIOUS WORKS

Lee et al. (Lee, 2007) introduced a method for recognition of human based on gait. The algorithm mainly consists of two parts. First we need to extract key frames for each gait cycle. We define one gait cycle as the period starting from a double support stance frames with left foot forward to the next. To do this, we seek reliable detection of frames occurring at the same relative offset within each gait cycle (for example, double support stance frames with left foot forward). Secondly, difference frames based on subtracting these key frames from silhouettes at other times are calculated and the Shape Variation-Based frieze pattern (SVB frieze pattern) is computed based on these difference frames.

2.1 Key Frames

For computing SVB frieze pattern, we need to determine a key frame as a reference frame for each walking cycle. The key frame is defined as the starting frame of one walking cycle, which is one of the two double-support positions, (two feet on the ground) where left foot is front. Each walking cycle starts from the key frame and ends before the next key frame. First, all silhouette images are aligned by calculation centroid of silhouette.

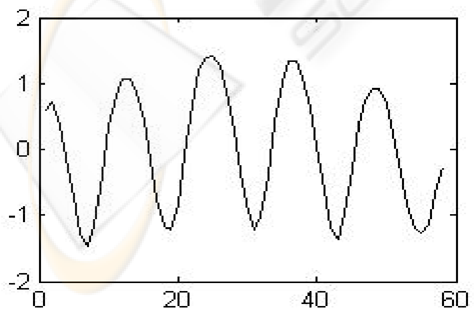

Figure 1: Normalized distance variation vector between feet.

To find the start point of each cycle, projection of the lower part of body for each silhouette perpendicular to the horizontal axis is computed and its width is obtained. Figure 2 is the plot of this width vector over time.

After the key frame is obtained, a series of difference frames are computed between key frame and successive frames in gait cycle.

$$D(x,y,t) = \left| I_{key}(x,y,t_{key}) - I(x+dx, y+dy, t) \right| \quad (1)$$

Here, (dx,dy) is the offset for minimum frame difference and I(x,y,t) is the frame at time t inside a given cycle. Figure 2 shows the process of computing difference frames based on a key frame.

2.2 Shape Variation-Based Frieze Pattern Extraction

SVB frieze patterns can be obtained by projecting pixel values of difference frames along horizontal or vertical axes.

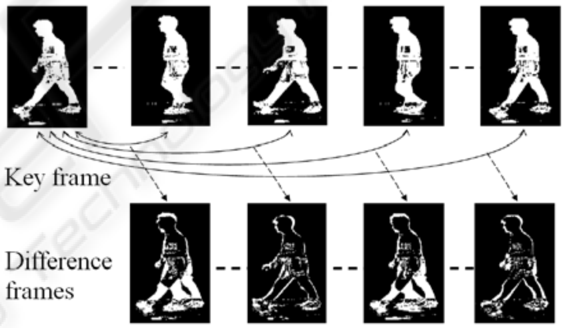

Figure 2: Key frame and difference of other frames from it (Lee et al, 2007).

By Projection of each difference frame, it is converted into 1D vector. The SVB frieze pattern is obtained by putting these vectors next together over time.

$$FP_h(y,t) = \sum_x D(x,y,t) \quad (2)$$

$$FP_v(x,t) = \sum_y D(x,y,t) \quad (3)$$

$D(x,y,t)$ is difference frame at time t. Summation in formula 2 is over x's (rows) of $D(x,y,t)$. In formula 3 Summation is over y's (columns) of $D(x,y,t)$.

Figure 3 shows a horizontal SVB frieze pattern and Figure 4 is a vertical SVB frieze pattern. Each column of a SVB frieze pattern at time t represents the difference frame at time t.

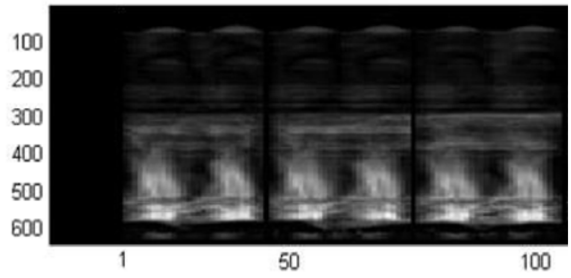

Figure 3: Typical horizontal SVB frieze pattern.

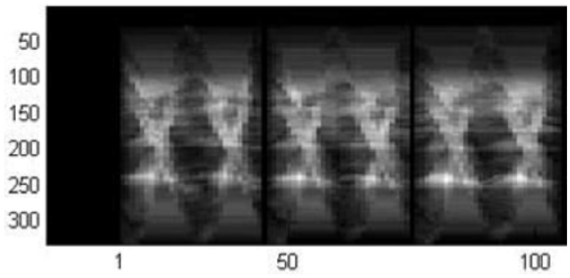

Figure 4: Typical vertical SVB frieze pattern.

2.3 Symmetry Map of Frieze Pattern

One gait cycle consists of two half cycles. These two half cycles have almost the same pattern. But these two half cycle are not exactly similar. In fact there is some differences between them. These differences can be used as a feature for recognition. In Lee algorithm, these differences between two half cycles has been obtained from SVB frieze patterns by computing the difference between two half motion cycles of SVB frieze patterns as symmetry map (*SM*).

2.4 Classification

Four cues from each gait sequence: horizontal & vertical SVB frieze pattern and horizontal and vertical symmetry map. To obtain distance between i'th gallery to j'th probe following distance are computed:

$$\Phi_{FP_h} = \left| FP_h^i - FP_h^j \right| \tag{4}$$

$$\Phi_{FP_v} = \left| FP_v^i - FP_v^j \right| \tag{5}$$

$$\Phi_{SM_h} = \left| SM_h^i - SM_h^j \right| \tag{6}$$

$$\Phi_{SMv} = \left| SM_v^i - SM_v^j \right| \tag{7}$$

A single cost function is computed by summing up all four distance values.

3 EFFECT OF EACH FEATURE ON RECOGNITION RATE

In order to study the effect of each feature on recognition rate, we implemented the algorithm for individual features once at a time. We also evaluated the algorithm when *SMh* and *SMv* or *FPv* and *FPv* are employed as a pair. Finally recognition rate is computed when all four features are used all together.

We tested the algorithm on CASIA database. Obtained results in table 1 show that *SMv* and *SMh* have least success in making distinction between individuals. Best results achieved when *FPh* and *FPv* are used together. When all four features are utilized for identification, recognition rate is less than while only *FPh* with *FPv* are used as a pair. This indicates that *SMv* and *SMh* not only do not increase recognition rate but also degrade it. Therefore, we suggested using only *FPh* and *FPv* for our algorithm.

Table 1: Ability of each feature in recognizing individuals.

	nm-05		nm-06	
	Rank 1	Rank 5	Rank 1	Rank 5
FPh	62.2%	76.3%	61%	80.5%
FPv	68%	85.7%	72.9%	82.2%
SMh	46.2%	59.6%	46.6%	53.4%
SMv	44.5%	58%	42.3%	60.2%
FPh + FPv	68.9%	85.7%	71.2%	83.9%
SMh + SMv	47%	61.3%	50%	57.6%
All four features	64.7%	84%	67.8%	81.3%

4 PROPOSED CHANGES TO IMPROVE PERFORMANCE

In this section we introduce the modification suggested to improve Lee et al. method (Lee, 2007). First we use difference between successive frames rather than key frame based method, used in original paper. The experimental results show that this modification improves the recognition performance. In next step, we try out statistical characteristics of frieze patterns instead of direct use of them for calculation of cost function.

4.1 Difference Frames

In Lee et al. algorithm difference between a key frame with frames in a walking cycle is used to compute SVB frieze pattern. We can calculate difference between successive frames instead of difference between a key frame and other frames in a walking cycle. Figure 5 shows successive difference frames.

Figure 5: Successive difference between frames.

Difference between frames can be a representative for motion in a way and using this, we can capture dynamic features of walking. For this purpose, we obtain a starting frame for each gait cycle as previous. Then, differences between consecutive frames are achieved. By means of these new difference frames, *FPh* and *FPv* are computed.

Table 2 indicates achieved results. By implying this change to algorithm, performance fairly improves.

4.2 Statistical Characteristics of Frieze Pattern

Direct use of *FPh* and *FPv* in order to computation of distance between features of two individuals has some disadvantages. It increases sensitivity to noise. Moreover, the length of features must be the same to make comparison possible. So we need to align them, and this also adds extra noise to system. We can extract some characteristics of these features, and use these characteristics for calculation of distance function, instead of direct use of features.

Calculation of statistical moments is one way to capture embedded information in given data. Mean and variance are most popular statistical moments. For this purpose, we calculate mean value of data in each row of *FPh* and *FPv*. By doing this, we convert each $m \times n$ matrix to a vector with size of $m \times 1$.

We apply this algorithm to *FPh* and *FPv*. Now, these mean vectors are used for obtaining distance functions rather than *FPh* and *FPv* themselves. We name these new features as *MFPh* and *MFPv*. By means of this change, we will have a great increase in recognition rate.

5 EXPERIMENTAL RESULTS

In this section, we demonstrate the result of experiment in which our algorithm is compared with the Lee et al. algorithm (Lee et al, 2007). In Lee et al. paper, MoBo database is used for evaluating the algorithm. We did not access to MoBo database instead we used CASIA database in this experiment. Nearest neighbour method is used for classification.

5.1 CASIA Database

CASIA gait database is collected by Institute of Automation, Chinese Academy of Sciences. This database is available on "http://www.sinobiometrics.com". CASIA database contains 124 subjects and for each subject there are 10 different capturing conditions ("nm-01" to "nm-06","bg-01","bg-02","cl-01" and "cl-02"). In subject nm-01 to nm-06, person is walking freely in different times but without changes in its appearance. In bg-01 and 2, subject is carrying a bag and in cl-01 and 2, clothing is changed. For each of above conditions subject is viewed from 11 different angles. We used only nm-01 to nm-06, while the viewing angle for walking subject is perpendicular to optical axis of camera. We used subsets nm-01 to 4 for training and nm-05 and nm-06 subsets for test.

5.2 Results

We have tabled the result of implementing original algorithm proposed by Lee et al. and our proposed changes in section 4 on CASIA database in tables 2 and 3, respectively.

Table 2 is result of algorithm after use of successive difference frames instead of key frame based difference frames. Fair improvement is observed by applying this change on main work. In this stage as a result of previous discussion about effect of each feature on recognition rate we ignored *SMh* and *SMv* and only *FPh* and *FPv* have been computed. First row shows recognition rate, when difference frames have been computed based on difference between a key frame and the frames in other times. Second row shows result of algorithm when successive difference frames have been used instead of key frame based differences.

Table 3 demonstrates achieved result using rows mean vectors (*MFPh* and *MFPv*) in comparison with direct application of *FPh* and *FPv*. Here, for computing the *FPh* and *FPv*, successive difference frames have been used. In order to use mean vectors, we first normalized each vector by subtracting

Table 2: Result of using successive difference between frames and computing *FPh* and *FPv*.

	nm-05		nm-06	
	Rank 1	Rank 5	Rank 1	Rank 5
Key frame differences	68.9%	85.7%	71.2%	83.9%
Successive differences	74.8%	84%	73.7%	84.7%

mean of each vector from it and then dividing it by its standard deviation. We obtain considerable increase in recognition rate when we use mean vectors.

Table 3: Result of using row mean of frieze patterns instead of frieze patterns themselves.

	nm-05		nm-06	
	Rank 1	Rank 5	Rank 1	Rank 1
FPh + FPv	74.8%	84%	73.7%	84.7%
MFPh+MFPv	90.7%	95%	87.3%	95.8%

6 CONCLUSIONS

In this paper, we introduced one way to recognize people based on their gait, proposed S. Lee et al. from the Penn state university. We tried to omit redundant used features in this algorithm. Then we applied differences between consecutive images to extract features instead of computation of difference between a key frame and other frames. Using these frames, vertical and horizontal frieze patterns are computed. In calculation of distance function, mean value of each row of frieze patterns in form of a vertical mean vector and a horizontal mean vector are used. We showed that applying mean vectors is more successful than direct use of frieze patterns.

We implemented our algorithm and previous work, on CASIA database. We indicated that our algorithm has better performance in comparison.

ACKNOWLEDGEMENTS

The authors thank Chinese Academy of Sciences. Portions of the research in this paper use the CASIA Gait Database collected by Institute of Automation, Chinese Academy of Sciences.

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