A Novel Human Gait Recognition Method by Segmenting and Extracting the Region Variance Feature

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Abstract

Existing methods of gait recognition suffer from some shortcomings, which are discussed at the beginning of the full paper. In order to suppress these shortcomings as much as possible, we proposed a new automatic gait recognition approach based on the region variance feature. 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 three regions (head region, trunk region and legs region). Next, the variance features of these regions are extracted respectively. Together with the ratio of the silhouette's height and width, the gait signature vectors are constructed to identify different subjects. Finally, similarity measurement based on the gait cycles and NN and KNN classifiers are carried out to recognize the different subjects. Experimental results show that the proposed novel method is very effective and correct recognition rates are over 92% and 97% on UCSD and CMU database, respectively.

1. Introduction

Human gait recognition as a new biometric aimed to recognize person via the style of people walking, which contains physiological or behavioral characteristics of human. Compared with other biometrics, such as face, iris or fingerprint, it has the following three advantages: distant recognition, non-invasive and difficult to conceal. As a result, gait recognition is a potential solution for the applications of human identification, and it is a challenge in the area of computer vision.

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. Existing holistic-based gait recognition approaches can't achieve excellent identification due to the static shape information used only, while model-based ones are very complex to build an appropriate model. Aiming at these limits, we proposed a novel gait recognition method based on the region variance feature.

The paper is organized as follows. Section 2 describes the preprocessing procedure. Section 3 introduces how to extract the gait signature. Pattern classification and experimental results are presented in Section 4. Finally, the conclusion is drawn in Section 5.

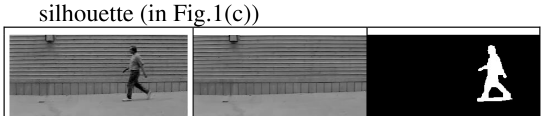
2. Preprocessing

2.1 Silhouette Extraction

In our experiments, the camera is assumed to be static and that body in the field of view is not occluded.

The silhouette extraction plays an important role in gait recognition. It is essential to extract the required human body by eliminating the irrelevant background from each frame. The details are described as follows.

- To obtain an approximate background from the image sequence of a walking people, a mean image is computed by averaging the gray-level at each pixel over the entire image sequence (in Fig.1 (b)).
- Background subtraction is used to detect moving objects in each frame.
- Erosion, dilation and component labeling are used to remove small amount of noise introduced to the binary image map and fill the small holes in the silhouette (in Fig.1(c))



(a) Original image | (b) Background | (c) Silhouette

Figure 1. The procedure of silhouette extraction

2.2 Image Template

In order to eliminate redundancies and speed up the processing, we need to normalize the segmented

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images into a scaled template. For each binary silhouette in the sequence, we firstly calculate the centroid, named as (x_c, y_c), and the height and width of segmented object. Then an appropriate length of side L is chosen, for example, $L = 64$. Finally, by centering on the centroid (x_c, y_c), we can fit the human silhouette into a fixed $L \times L$ image template.

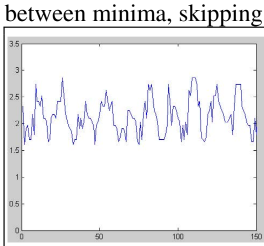
(a) Original image

(b) Scaled image template 64×64

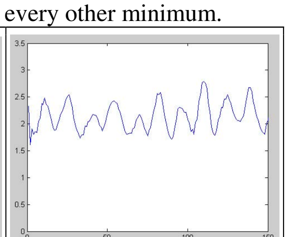
Figure 2.Scaled image template from segmented object.

2.3 Gait Periodicity

A salient feature of gait is its periodicity. By observing, the width of the silhouette was changing periodically with the time-lapse. The width of the silhouette will reach a maximum when the two legs are farthest apart (full stride stance) and drop to a minimum when the legs overlap (heels together stance). At the same time, the height of silhouette has slight change in the procedure. Consequently, we can get the estimation of gait cycle length through analyzing the width-height ratio curve of a gait sequence. Figure 3 shows an instance of a sequence's width-height ratio curve and the smoothed one by Gaussian filtering. Notice that two consecutive strides constitute a gait cycle. We compute the median of the distances between minima, skipping every other minimum.



(a) Original one



(b) Smoothed curve

Figure 3.The W-H-ratio curve of a gait sequence

3. Gait Signature Extraction

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. All these salient features of the body's parts constitute the subject's unique gait signature for person identification. Since it is not enough to extract holistic information only, we divide the two dimensional silhouette of the walker into three regions, namely, head region, trunk region and legs region, and extract specific features in these regions, respectively. The sequence of the features from one region over the whole image sequence characterizes the salient motion of the corresponding region. In this way, we not only avoid the issue to build the complicated model but also overcome the shortcomings of the holistic approaches.

The variance is one of several indices of variability that statisticians use to depict the dispersion among the measures in a given population. During walking, the region variance varies with the motion of the corresponding part of body so that we can choose it as gait signature for recognition. In the paper, we regard the top 20% of the silhouette as the head region and the bottom 40% as the leg region. The rest of the silhouette, i.e., the middle 40% part is considered as the torso region. The variance of the specific region is computed as:

$$\sigma_K{}^2 = \frac{1}{M^2} \sum_{(x,y) \in W_K} [X_K(x,y) - \overline{X}_K]^2 \qquad (1)$$

where $K = 0,1,2,...,M^2$ represent the pixel number in one region and $\overline{X}_K$ is the mean in the region K.

The other two important cues in gait recognition are the width and height of the body, which represent a person's figure well. However, the two features often vary with the camera's focus. As a result, it's not advisable to use them as gait features directly. In this paper, we proposed to use the ratio of the silhouette's height and width (H-W ratio), which is comparatively stable. For each frame in one sequence, the variances of three body regions and the H-W ratio will constitute a gait feature vector for training and recognition.

4. Experimental Results

4.1 Experimental Data

The video sequences are taken from the following databases, which is used to examine the effect of the size of database, outdoor/indoor and fast /slow walk.

1. UCSD database: It was taken in the outdoor scene. The distance between the camera and subjects is comparatively far. There are 6 subjects and 7 sequences for each subject and 2-3 gait cycles in

each sequence. The original images of 320×160 are normalized into 64×64 image templates for our experiments.

2. CMU database: It was taken on an indoor treadmill. The distance between the camera and subjects is comparatively small. It has 25 subjects walking at a fast pace and slow pace respectively. There are about 7-8 gait cycles in each sequence. The original images of 640×480 are fitted into 64×64 image template for our experiments.

4.2 Training Phase

Given a gallery with C sequences, a four-dimensional gait feature vector of (V_h, V_t, V_l, r) is extracted from each frame in the sequence by using the procedure described in Section 3. Herein, V_h, V_t and V_l represent the variance of head, torso trunk and leg region, respectively, and r represents the H-W ratio of body. Then the gait feature vector of the j^{th} frame from the i^{th} sequence is denoted by $X_{i,j} = (V_{ij}^h, V_{ij}^t, V_{ij}^l, r_{ij})$, where N_i is the number of frames in the sequence, and $1 \le i \le C$, $1 \le j \le N_i$.

4.3 Recognition Phase

Let $X_g = \{X_{g,1}, X_{g,2}, \cdots, X_{g,N_g}\}$ be a sequence in the gallery, and $X_p = \{X_{p,1}, X_{p,2}, \cdots, X_{p,N_p}\}$ be the arbitrary one in the probe, where N_g and N_p are the frame numbers of the two sequences, respectively. Due to the gait's periodicity, we adopted a spatio-temporal similarity measurement based on the gait cycles, which is similar to the method in [8].

Suppose the period length of the gait is N in a sequence. We can partition the whole sequence into $\lfloor N_p / N \rfloor$ subsequences. The k^{th} subsequence is denoted by $X_p(k) = \{X_{p,k+1}, X_{p,k+2}, \cdots, X_{p,k+N}\}$. Then for a subsequence in the probe and another one in the gallery, the distance between them can be calculated as

$$dis_{(X_p(k), X_g)}(l) = \sum_{j=1}^{N} \left\| X_{p,k+j} - X_{g,l+j} \right\| \qquad (2)$$

where l is the starting frame in the gallery sequence, from which we compare the two subsequences. The similarity of two whole sequences is defined as

$$Sim(X_p, X_g) = 1 - \frac{1}{K} \sum_{k=1}^{K} \min_l (dis_{(X_p(k), X_g)}(l)) \qquad (3)$$

The classification process is carried out by NN (nearest neighbor classifier) and KNN (K-nearest neighbor classifier) classification methods.

4.4 Results and Performance Analysis

We evaluated the performance of our method using the leave-one-out cross-validation rule to compute an unbiased estimation of the true classification rate [9]. There are 42 sequences in UCSD database, within which we leave one example out as the probe, and the rest as the gallery. The probe sequence is classified according to its similarity with the respect to the stored gallery sequences. This process is repeated for 42 times, and the recognition rate is obtained as the ratio of the number of correctly classified test examples out of the total 42. In the CMU database, there are 8 gait cycles in Fast Walk sequences and 7 cycles in Slow Walk sequences. We can also regard each gait cycle as a sequence, and then we executed the leave-one-out process in the same way for the 8 or 7 gait cycles. For the convenience of the later discussion, these experiments are numbered as A-C.

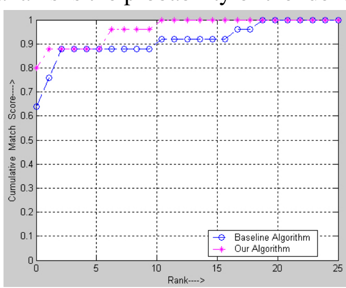
Furthermore, in order to evaluate the effects of speed of our method, we completed two other experiments on the CMU database with all the gait cycles: train on fast- walk and test on slow-walk and train on slow-walk and test on fast-walk. These two experiments are numbered as D and E, respectively. The correct classification rates (CCR) are summarized in Table 1. In [10], a Human ID Gait Challenge frame and a referential gait recognition baseline algorithm are proposed. With the same experimental circumstance and databases, we carried out the above experiments by using the baseline algorithm. The experimental

Table 1. CCR of different algorithm and their comparison

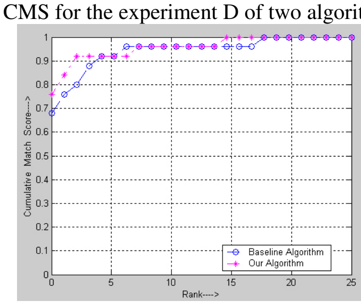
Database	Experiment	Speed of walking	Classifier	Our algorithm（%）	Baseline algorithm [10]（%）
UCSD Database	A: Leave-one-out	Normal walk	NN	95.24	90.48
			KNN($k=3$)	92.86	88.10
CMU Database	B: Leave-one-out	Fast walk	NN	98.50	96.50
			KNN($k=3$)	98.50	93.00
	C: Leave-one-out	Slow walk	NN	98.86	97.71
			KNN($k=3$)	97.71	95.43
	D: Train: fast, Test: slow	Fast & Slow	NN	80	64
			KNN($k=3$)	80	64
	E: Train: slow, Test: fast	Slow & Fast	NN	76	68
			KNN($k=3$)	76	68

results and their comparison are show in Table 1.

Moreover, we can use the measure of Cumulative Match Score (CMS) to evaluate the performance of gait recognition, where the CMS curve proposed in the face recognition community indicates the probability of the correct match included in the top n matches. By plotting the CMS curves of experiments D and E in Fig.4, we further compare the recognition performance of our algorithm with that of the baseline algorithm. Note that the horizontal axis of the graph is rank and the vertical axis is the probability of the identification.



(a) CMS for the experiment D of two algorithms.



(b) CMS for the experiment E of two algorithm.

Figure 4. Recognition performance based on CMS.

From Table 1, it is clear to find out that the recognition performance of the proposed novel method is much better than that of the baseline algorithm. By using our method, the recognition rates are over 92% and 97% on UCSD database and CMU database. The CCR of the experiments across speed test on the CMU database has also increased 16% and 8% for experiment D and E. The result is very encouraging.

On the whole, the walking speed and the distance between camera and subjects have some effect to the performance of identification. It is well known that the smaller the distance is, the clearer the image is and the more information can be utilized, which resulted in the better performance, that's why the results of B and C is obviously better than A. The experiments across speed test for CMU database have also been completed. In the case of D and E, the drop in performance are caused by the fact that for some subjects, there is a considerable change in body dynamics and stride length when the walking speed varied. However, the CCR obtained by our proposed method is over 76% and much better than that of the baseline algorithm, i.e., 64%. And the CMS in Fig.4 also demonstrates the effectiveness of our method.

5. Conclusions

In this paper, we proposed a novel gait recognition method based on the region variance feature. By segmenting and extracting the variances of head, torso and legs region, together with the H-W ratio, we construct a gait feature vector for each frame in one sequence for recognition. Then the gait-cycles-based similarity and two different classifiers are used to fulfill the person identification. The experiments results on real sequences of both indoor and outdoor scenes have obtained the CCR as 92% and 97% for UCSD and CMU databases, respectively. These results indicate that our new method is quite effective.

6. Acknowledgment

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