A novel approach of gait recognition based on motion analysis

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Abstract

Gait recognition is a newly coming biometric identification technology for human identification, surveillance, control area etc. In this paper, we propose an automatic gait recognition approach for analysing and classifying human gait by computer vision techniques. Our approach incorporates knowledge of the shape and dynamics of human gait into the feature extraction process. Different from the model-based approaches, this paper proposes a novel method to attain the limb angle information by analyzing the variation of silhouette width without needing the human body model. First, a background subtraction is used to separate objects from background. Gait cycle is obtained by analyzing the variety of the silhouette width and height. Then, we use Discrete Cosine analysis to analyze the shape and leg angle characteristic and represent the gait features. The multi-class SVM is used to distinguish the different gaits of human. The performance of our approach is tested using different gait databases. And our approach shows a better recognition rate.

Keywords: Biometrics, Gait recognition, Motion analysis, Discrete Cosine analysis, SVM

1. Introduction

Biometrics technologies verify a person's identity by analyzing human characteristics such as fingerprints, facial images, irises, gait, heat patterns, keystroke rhythms, and voice recordings. Gait as a biometric may be performed at a distance or at low resolution, while other biometric need higher resolution. Apart from this, it is difficult to disguise, and it requires no body-invading equipment to capture gait information. Medical studies [1] suggest that gait is unique if all gait movements are considered. In these cases, gait recognition is an attractive biometric and becoming increasingly important for surveillance, control area etc. More and more researchers have devoted to this area.

Early approaches to automated recognition by gait used marked-based technology, which needs expensive specialized hardware. Most recently approaches based on computer vision extract features for recognition from image sequences. Current approaches to gait recognition can be divided into two categories: Appearance-based ones [2-4] that deal directly with image statistics and Model-based ones [5-11] that first model the image data and then analyze the variation of its parameters. The appearance-based approaches are simple and fast. But the silhouette appearance information is only indirectly linked to gait dynamics.

In this paper, A newly approach combining the appearance-based approach with the model-based approach for analyzing and extracting human gait is presented. The gait period is estimated by analyzing the variation of silhouette width and height. The static features extracted from human shape include body height, body width, stride length, etc. Kinematic information of gait is represented by joint angles. Different from the model-based approaches, this paper proposes a novel method to attain the motion information without needing to model the human body. This method can extract the equivalent information with low cost of computation by analyzing the variation of silhouette width. We use Discrete Cosine analysis to analyze the shape and leg angle characteristic and represent the gait features. Our approach is tested on some gait databases and the recognition results show the validity of it.

2. Silhouette Extraction

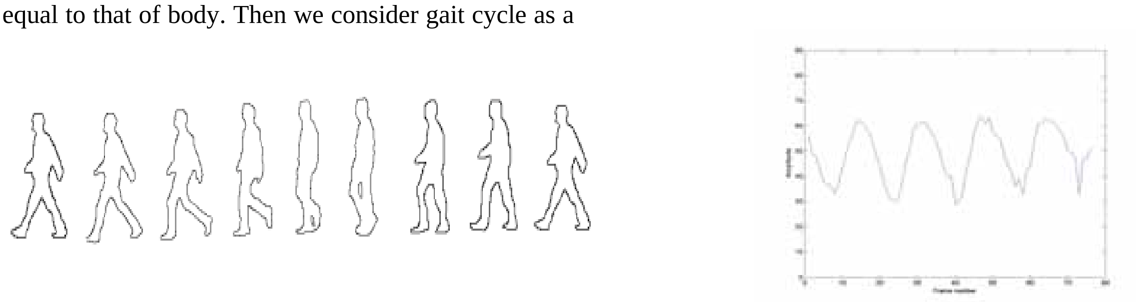
We use a background subtraction technique to segment the body's silhouette from the video sequence. A foreground image is obtained by thresholding and applying morphology[12]. Fig1 shows an example of silhouette extraction.

(a)Original image (b) the extracted object

Fig1 An example of silhouette extraction

3. Gait Cycle Detection

Murrary [1] suggested that human gait is a form of periodic motion. [5] has given some relative definition of gait cycle. Our previous work[13] has found that the width and height of person body fluctuate as walking. The fluctuating of silhouette is equal to that of body. Then we consider gait cycle as a function of the silhouette width and height over time. Here, we define the bounding box for each observed body. The height and width of box alter along with the fluctuating of silhouette. Gait cycle is the time between the successive peak values of the width (height). Gait cycle is one of features for the latter recognition. Fig2 shows the periodic gait signals.



(a) Gait Sequences of subject 1 (b) Width signal of subject 1

Fig2 The periodic gait signals

4. Gait Feature

To classify the different person by their gait easily, we need some effective features. Good features should maximize interclass variance and minimize within -class variance. Here, the both shape and dynamic feature have been extracted. We normalized the same start for each sequence.

4.1. Width analysis

The variance of width is the important information for gait analysis based on silhouette. The width contains structural as well as dynamical information of gait. Different from [2], the width parameters in our approach are not merely the bounding box width. Through observing the gait of the same and different persons, we found that most changes occur during the swing of arms and the oscillation of legs. We subdivide the binary silhouette into three horizontal segments. As shown in Fig.3, the silhouette is divided into three contiguous horizontal segments according the anatomical literature And we denote the three horizontal segments as R1, R2 and R3, respectively.

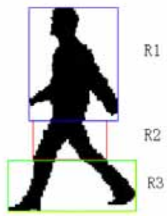


Fig .3 Three contiguous horizontal segments in sub-bounding boxes

W_{R1} , W_{R2} and W_{R3} are the width of above segments. Every segment has one sub-bounding box. Corresponding to the three sub-bounding boxes, the time series of the width in a period are denoted $W_{R1}(t)$, $W_{R2}(t)$ and $W_{R3}(t)$, respectively. $W(t)=\max(W_{R1}(t),W_{R2}(t)W_{R3}(t))$ denotes the width of the entire person's bounding box.

From analyzing the three sub-bounding boxes, we attain some apparent features including stride length, height and gait cycle. Stride length is estimated by tracking the person, estimating their distance walked over a period of time and then counting the number of steps. Height variance is analyzing in section2.

4.2. Joint Angle Analysis

The Kinematic information of gait is usually represented by the joint angles of limbs. The angles of body are useful and important information for improving the recognition rate. To extract the angle information, there are many methods in previous works. [8] represented human body model by a 2D stick figure configuration. [10] modeled the human legs as two pendula joined. [14] extracted angles from a model composed of 14 rigid body parts. Different from these methods, we attain the joint angle by analyzing the width of sub-bounding box not modeling the whole body. It is known that the swing of the limbs and other details of the body are retained in the width vector. And we attain the useful features with low cost of computation.

The joint angles are extracted in the sub-bounding box. The upper limbs have the severe self-occlusion, the joint angles are very difficult to track and measure. Therefore, we choose three joint angles of lower limbs as the gait features. The silhouette is divided into three contiguous horizontal segments based on the anatomical literature. To extract the joint angles, we should firstly locate the positions of joints. And here, we discuss the joints of lower part of body.

The first joint is pelvis. The position of this joint is calculated based on the W4 approach. The pelvis location within R2 is determined from the mean x-value and the mean y-value of the silhouette pixels in the pelvis region. The positions of knees and ankles are determined by the know properties of body segments and the direction of thigh and shin. The rough position of the front knee is estimated by the minimum distance from the left boundary of R2. The vertical of position of the rear knee is equal to or higher that the vertical position of the front knee. We locate the position of the rear knee in R2 and the position of the front knee around the border of R2. The position of knee is calculated by

$$x_k = x_{k_l} + (x_{k_l} - x_{k_r})/2;$$

$$y_k = y_{k_l} = y_{k_r}, \qquad k = k1, k2,$$

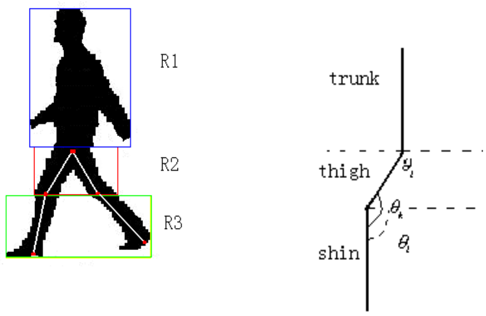
where $k1$ and $k2$ denote the two knee positions. For the front knee, x_{k_l} denotes the horizontal position of the first pixel of the left border of R2, x_{k_r} represents the second pixel on one leg. For the rear knee, x_{k_r} denotes the horizontal position of the right border of R2. The width of R2 is the distance between x_{k1_l} and x_{k2_r}. The knee position is the crossing between thigh and shin. Using the same method, the positions of ankles are calculated and we denote left ankle location and right ankle location as $a1$ and $a2$, respectively.

At low cost, all positions of joints are located. Figure 4 (a) shows the positions of the angles.

There are five joint we attained in previous section. As follows:

(x_p, y_p), (x_{k1}, y_{k1}), (x_{k2}, y_{k2}), (x_{a1}, y_{a1}) and (x_{a2}, y_{a2}). The thigh lines are generated by connecting the pelvis position (x_p, y_p) to the knee positions. The shin lines are generated by connecting positions between knees and ankles. Joint angles are generated between the neighbouring lines. Figure 4 (b) shows the joint angles we defined at each frame i of an image sequence. All the angles are measured relative to the horizontal axis. We denote the angles as θ_t, θ_{k1} and θ_{k2}. $\theta_T(t)$, $\theta_{K1}(t)$ and $\theta_{K2}(t)$ are angles series in one gait cycle.

The thigh angles θ_t and the knee angles θ_k have the relationship: $\theta_k = \pi + \theta_l - \theta_t$



(a) positions of the angles (b) joint angles of lower limb

Figure 4 The positions of the angles and the angles of lower limb

The angle information extracted by analyzing the variation of silhouette width is equal to that extracted from dynamic model with a low cost of computation.

4.3. Gait features analyzing

In this section, we analyze different features to exploit redundancy in the gait data for reduction.

The time series we attain in section 3 including $\mathrm{W}_{\mathrm{R1}}(t)$, $\mathrm{W}_{\mathrm{R2}}(t)$, $\mathrm{W}_{\mathrm{R3}}(t)$, $\mathrm{W}(t)$, $\theta_{\mathrm{T}}(t)$, $\theta_{\mathrm{K1}}(t)$ and $\theta_{\mathrm{K2}}(t)$ are all 1D vectors. The time series are considered to be periodic. $\mathrm{x(m)}, m = 0,1,...,M-1$ denotes a sequence of periodical signal in one gait cycle. In this paper, we adopt Discrete Cosine analysis to describe the periodical sequences. Discrete Cosine analysis is performed on $\mathrm{x(m)}$ using the Discrete Cosine Transform. And DCT is very appropriate to analyzing our signals than other transforms. It should be noted that the data needs to be normalized and $\mathrm{x(m)}$ needs to be symmetrical before being transformed. To insure $\mathrm{x(m)}$ is symmetrical, we extend $\mathrm{x(m)}$ to be the new series $\mathrm{y(n)}$, $n = 0,1,...N-1$.. $\mathrm{y(n)}$ is even function.

The number of $\mathrm{y(n)}$ is twice of $\mathrm{x(m)}$, but it does not affect the features we need. And the number of descriptors of $\mathrm{y(n)}$ after discrete cosine analysis is equal to that of Fourier descriptors of $\mathrm{x(m)}$. The DCT is closely to K-L transform, which compression ratio is high.

Here, discrete cosine analysis is propitious to our signals. The time series $\mathrm{y(n)}$ can be represented by the discrete cosine series:

$$\mathrm{y(n)} = \frac{1}{\sqrt{N}} f_0 + \sqrt{\frac{2}{N}} \sum_{k=0}^{N-1} f_k \cos\frac{(2n+1)k\pi}{2N},$$

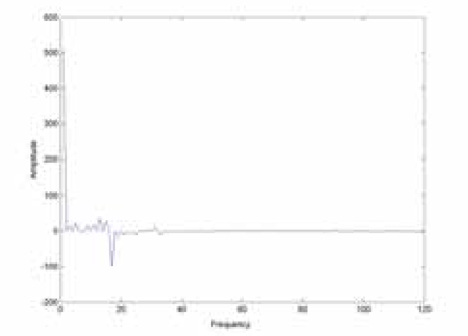
$$n = 0,1,...N-1$$

And these DC coefficients can be calculated by DCT. Frequency spectrum is $F = \{ f_0, f_1, f_2, ... f_i, ..., f_{N-1} \}$, where f_i is $\mathrm{y(n)}$ frequency spectrum at frequency i .

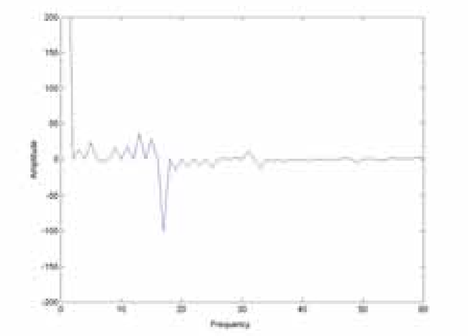
$$f_0 = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} \mathrm{y(n)} \quad ,$$

$$f_i = \sqrt{\frac{2}{N}} \sum_{n=0}^{N-1} y(n) \cos\frac{(2n+1)k\pi}{2N}, \quad k = 1,...N-1$$

The extracted discrete cosine frequency spectrum of $\mathrm{W}_{\mathrm{R3}}(t)$ is shown as Figure 5. We select the resulting magnitude spectrum of Discrete Cosine frequency as the gait feature because the phase spectrum includes less information. The analysis results still contain a lot of descriptors. But we can see that lots of frequency parts are centralized at the low frequency position. Most of the visually significant information about $\mathrm{y(n)}$ is concentrated in just a few coefficients of the DCT. The general features which have the highest inter-class variance are found in the low frequency. Then we discard the high frequency, and use the low-order descriptors to be the gait features. Using these gait features not only hold the primary information, but reduce the dimensions of data as well.



(a) magnitude spectrum



(b) magnitude spectrum discarded the high frequency

Figure 5 The discrete cosine frequency spectrum of $\mathrm{W}_{\mathrm{R3}}(t)$

5. Experimental Results

We apply the gait appearance features and kinetic features to identify the human and classify walking direction. We trained and tested support vector machines on our gait features. This SVM is a multi-class support vector machine[12]. The kernel function of our classifier is Gaussian kernel,

$$K(x, x_i) = \exp(-\frac{|x - x_i|^2}{2\sigma^2}) .$$

The algorithm of classify is $L(x) = \arg\max_k \{ f_k(x) \}, k = 1,...,n$

as $f_k(x)=\sum_{j=1}^{k} y_{k_j} a_{k_j} K(x,x_j)+b_k$,where x is the gait features data, $f_k(x)$ is the k th function for classifying.

We use leave-one-out cross validation technique. First, we evaluate our approach for the data set of Little and Boyd. The data set consist of 42 image sequences and 6 different subjects. Then, we train and test on the CMU MoBo data set**.** The data set contain 6 simultaneous motion sequences of 25 subjects walking on a treadmill. Image resolution is 640×480. Each subject is recorded performing four different types of walking: slow walk, fast walk, inclined walk and slow walk holding a ball. We test our method on the slow walk. We also evaluate the method on NLPR gait database. It includes 80 sequences from 20 subjects and four sequences per subject. The original resolution is $352\times$ 240.The recognition rates are listed in table 1.

TABLE 1 RECOGNITION RESULTS OF MULTI-CLASS SUPPORT VECTOR MACHINES

Database	CCR(%)
Little and Boyd	100%
CMU(slow walk)	92.2%
NLPR	92.6%

Table 1 shows excellent performance of our approach.

6. Conclusion

We presented an automated markerless approach for human identification from low resolution video fusing static and dynamic parameters of walking gait. The characteristic behaviors of two types of gait features, one based on appearance of gait and one based on kinematics information. The width is chose as the basic gait feature. We extract the angles features without needing to model the human body. And we analyze the motion signatures by Discrete Cosine analysis. The SVM is employed to classify the gait features. Experimental results demonstrate the feasibility of our approach. In future, we will pay more attention to the feature space for describing and recognizing the human gait on the larger database of subjects.

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