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Multiple Views Effective for Gait Recognition Based on Contours

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Abstract

Gait is one of well recognized biometrics that has been widely used for human identification. However, the current gait recognition might have difficulties due to viewing angle being changed. This is because the viewing angle under which the gait signature database was generated may not be the same as the viewing angle when the probe data are obtained. This paper present an effective multi-view gait recognition based on motion contour (MVGRMC) approach which tackles the problems mentioned above. Initially the background modeling is done from a video sequence. Subsequently, the moving foreground objects in the individual image frames are segmented using the background subtraction algorithm. Then, the morphological skeleton operator is used to track the moving silhouettes of a walking , Finally, when a video sequence is fed, the proposed system recognizes the gait features and thereby humans, based on self-similarity measure. The proposed system is evaluated using gait databases and the experimentation on outdoor video sequences demonstrates that the proposed algorithm achieves a pleasing recognition performance. The proposed algorithm can significantly improve the multiple view gait recognition performance when being compared to the similar methods. These results are illustrated with practical examples on popular gait databases.

Keywords: Gait Recognition; Biometric; silhouette; Motion analysis; Feature extraction

1. Introduction

Biometrics technologies verify a person's identity by analyzing human characteristics such as fingerprints, facial images, irises, gait, 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 field.

Early approaches to automated recognition by gait used marked-based technology, which needs expensive specialized hardware. Most recent 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 [2,3] that deal directly with image statistics and Model-based ones [4,5]that first model the image data and then analyze the variation of its parameters. The majority of current approaches are the appearance-based approaches which are simple and fast. But the silhouette appearance information is only indirectly linked to gait dynamics. Little and Boyd [6] used frequency and phase obtained from optical flow to identify walkers. Furthermore, Lee and Grimson [2] divided the silhouette into seven regions to extract both the gait average appearance feature vector and the gait spectral component feature vector for recognition. Wang et al. [7] converted 2D silhouette contour to 1D signal that composed of distances to shape centroid and classified the walkers after having reduced the dimensionality of the feature by Principal Component Analysis. Furthermore, Johnson and Bobick [8] presented a gait recognition technique based on static body parameters recovered during the walking action across two different side-views in depth with a single camera. Huang and Boulgouris [3] investigated the contribution of each view direction to the recognition performance using the CMU MoBo database.

Our study aims at establishing an automatic gait recognition method based upon silhouette analysis. Gait includes both the body appearance and the dynamics of human walking motion. Intuitively, recognizing people by gait depends greatly on how the silhouette shape of an individual changes over time in an image sequence. So, we consider gait motion to be composed of a sequence of static body poses and expect that some distinguishable signatures with respect to those static body poses can be extracted and used for recognition by considering temporal variations in those observations. Based on these considerations, we propose a new extraction scheme for gait feature. First, we obtain the gait features by scanning the outer contour of the binarized silhouette forgetting more information about body appearance and structure. This method can extract the equivalent information with low cost of computation by analyzing the variation of silhouette contour.

2. Human Extraction Silhouette

The gait images are firstly pre-processed before gait recognition. It includes two steps: human silhouette extraction and human contour stereo matching. The details are described as follows:

- The LMS (Least Median of Squares) method [9] is used for retrieving the background image from image sequences captured by a from stereo vision system firstly.
- The moving individual silhouette is detected through background subtraction.
- Mathematical Morphology Method is employed to fill in holes and remove noise in binary images.
- A binary connected component analysis is used to extract a single-connective moving object.
- A contour of moving object can be accomplished by Canny edge detection operator.
- Stereo match on contour is performed in order to get the disparity of the pairs of stereo image.

As a result, 3D coordinates of the contour are finally recovered by using the disparity, the known calibration parameters and the known 2D coordinates of the contour, which yield the 3D silhouette. An instance of human contour extracted is shown on Figure 1

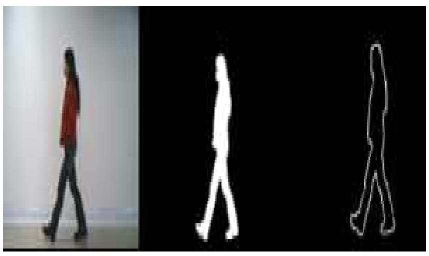


Figure 1. Instance of human silhouette extraction

The continuous change of the silhouette of a moving individual along with time denotes that it is a complex spatio-temporal signal. For analyzing the rule of the change of moving silhouette and reducing the complexity of algorithm, we represent the moving 3D contour with a 1D silhouette signal named the stereo silhouette vector (SSV). The transformation of stereo silhouette vector reflects the changes of moving silhouette along with time. The extraction process of stereo silhouette vector is shown on Figure 2.

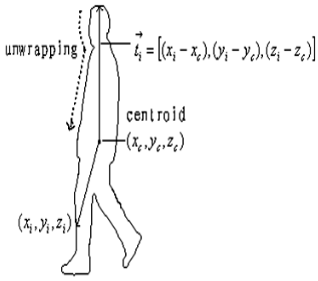


Figure 2. Illustration of stereo silhouette vector

Let (x_i, y_i, z_i) represent a pixel on the 3D silhouette, i=1,2,…,N, N is the total number of pixels. Then, the centroid

(x_c, y_c, z_c) of 3D silhouette can be computed by $x_c = \frac{1}{N}\sum_{i=1}^{N} x_i$, $z_c = \frac{1}{N}\sum_{i=1}^{N} z_i$

and $y_c = \sum_{i=1}^{N} y_i$ Thus, the stereo silhouette vector can be depicted as

$$\vec{t_i} = [(x_i - x_c),(y_i - y_c),(z_i - z_c)], i = 1,2, \dots, N$$

We unwrapped the extracted 3D silhouette from top to bottom to calculate all of the stereo silhouette vector. Finally, the 3D silhouette can be described by

$$F = \{\vec{t_i}\}, i = 1,2, \dots, N$$

For decreasing the calculation, we only utilized the L2-norm of stereo silhouette vector as a crude stereo gait feature. It is described by the below expression

$$\|\vec{t_i}\| = \sqrt{(x_i - x_c)^2 + (y_i - y_c)^2 + (z_i - z_c)^2},\ i = 1,2, \dots, N$$

Finally, we normalized the 1D silhouette signal by employing both maximum-norm and equal interval sampling so that the effect of scale and length on correct recognition rate can be partly eliminated. Figure 3 demonstrates a sample of normalized stereo gait feature.

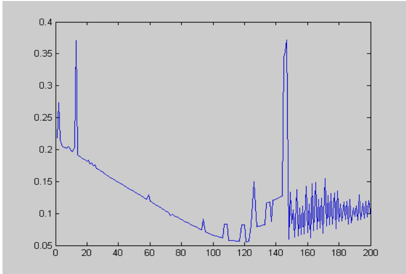


Figure 3Illustration the normalized L2-norm

3. Gait Feature Representations and Extraction

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, both shape and dynamic feature have been extracted. We normalized the same start for each sequence. Murrary [1] suggested that human gait is a form of periodic motion. [4] has given some relative definition of gait cycle. Our previous work 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. Figure 4 shows the periodic gait signals

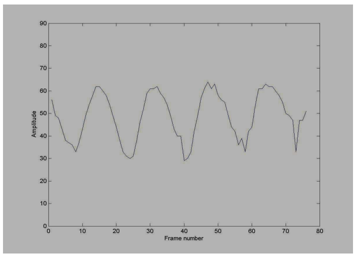


Figure 4 The periodic gait signals

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 , 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 Figure 5, 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. 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.

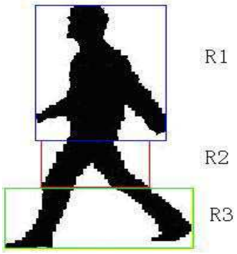


Figure 5 Three contiguous sub-bounding boxes

4. Dynamic feature 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 represented human body model by a 2D stick figure configuration. [5] Modeled the human legs as two pendula joined. *L. Wang* 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.

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

$$x_k = x_{kl} + (x_{kl} - x_{kr})/2;$$

$$y_k = y_{kl} = y_{kr},\ k = k1, k2$$

Where $k1$ and $k2$ denote the two knee positions. For the front knee, x_{kl} denotes the horizontal position of the first pixel of the left border of R2, x_{kr} represents the second pixel on one leg. For the rear knee, x_{kr} denotes the horizontal position of the right border of R2. The width of R2 is the distance between $k1$ and $k2$. 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 and, respectively. a_1 and a_2 At low cost, all positions of joints are located. Figure 6 (a) shows the positions of the angles. There are five joint we attained in previous section. As follows:

$$(x_p,y_p),(x_{k1},y_{k1}),(x_{k2},y_{k2}),(x_p,y_p),(x_{a1},y_{a1})\ and\ (x_{a2},y_{a2})$$

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 neighboring lines. Figure 6 (b) shows the joint angles we defined at each frame of an image sequence. All the angles are measured relative to the horizontal axis. We denote the angles as, $\theta_t$and θ_{k1}, 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: $\theta_k = \pi + \vartheta_l - \theta_t$ 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.

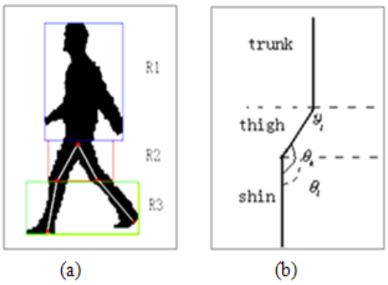


Figure 6: (a) The positions of the angles and (b) the angles of lower limb

This paper adopts the similar method as that one in [7] to determine the period of each gait sequence. The basic procedure is illustrated in Figure 7. It is a complicated procedure for the case of frontal view video sequence.

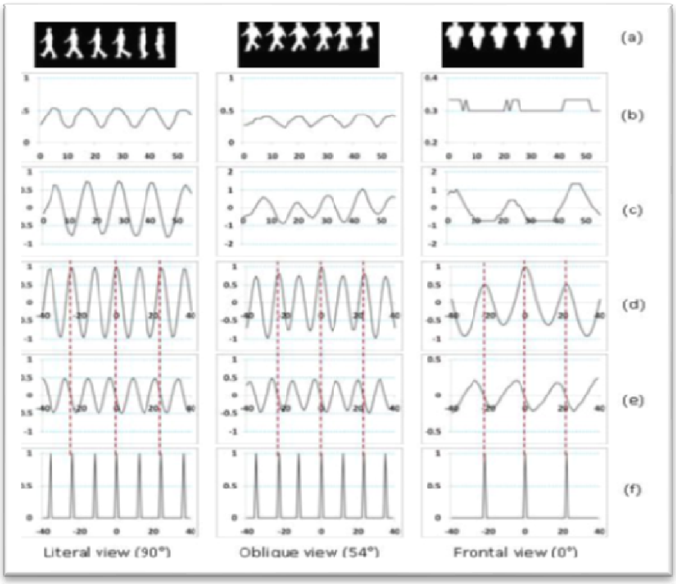


Figure 7. Gait period estimation. (a) Sample silhouette sequences of walking people. (b) Aspect ratio of silhouette bounding box. (c) Normalization of aspect ration followed by mean filtering. (d) Autocorrelation of aspect ration under various offset. (e) First order derivative based on (d). (f) Peak positions indicating the periods.

Figure 7(a) shows three samples of silhouette sequences obtained under the side view, oblique view and front view respectively. Along the time of image sequences, the aspect ratio of each silhouette bounding box is recorded (Figure 7(b)). In order to more precisely estimate the gait period, the curves in Figure 7(b) are further processed by deleting the mean value and normalized by its standard deviation. Then, the results are processed by mean filtering (Figure 7(c)). Autocorrelation based on the results in Figure 7(c) are calculated. The correlation between the curve in Figure 7(c) and the curve by shifting itself in some degree is calculated. The offset range t in this paper is $-40 \leq t \leq 40$ as shown in Figure 7(d). From Figure (b) and (c), it can be seen that the change of bounding box aspect ration is a kind of periodic signal.

Thus, when calculating autocorrelation in Figure 7(d), there will be a peak if the offset equals to a gait period or its integer multiple. To more clearly identify the period transition position, first order derivative (Figure 7(e)) is calculated based on the results of Figure 7(d). The period transition position is defined at the zero crossing point along the positive-to-negative direction. According to [7], because of the bilateral symmetry of human gait under any viewing angle except frontal view, the autocorrelation signals sometime contain minor peaks located half way between each pair of consecutive major peaks. So the final period transition positions are shown and aligned using dash lines on Figure 7(f)

5. Gait Analysis and Classifier

In this section, we analyze different features to exploit redundancy in the gait data for reduction. The time series we attain in previous section including, $W_{R1}(t)$, $W_{R2}(t)$,$W_{R3}(t)$, $W(t)$,$\theta_t(t)$, $\theta_{k1}(t)$ and $\theta_{k2}(t)$ are all 1D vectors. The time series are considered to be periodic. $x(m), m = 0,1, \ldots\ldots, M-1$. Denotes a sequence of periodical signal in one gait cycle. We adopt Discrete Cosine analysis to describe the periodical sequences. Discrete Cosine analysis is performed on $x(m)$ 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 $x(m)$ needs to be symmetrical before being transformed. To insure $x(m)$ is symmetrical, we extend $x(m)$ to be the new series , $y(n)$, n=0,1,…N-1, $y(n)$ is even function.

The number of $y(n)$ is twice of $x(m)$, but it does not affect the features we need. And the number of descriptors of after discrete cosine analysis is equal to that of Fourier descriptors of $x(m)$ 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 $y(n)$ can be represented by the discrete cosine series:

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

And these DC coefficients can be calculated by DCT. Frequency spectrum is

$F = \{f_0, f_1, \ldots, f_{N-1}\}$ where f_i is frequency spectrum at frequency i

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

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

The extracted discrete cosine frequency spectrum of $W_{R3}(t)$ is shown as Figure 8.

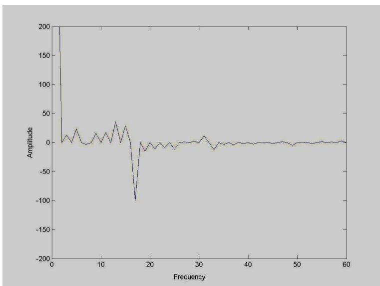


Figure 8 The magnitude spectrum discarded the high frequency of $W_{R3}(t)$

Then we apply the gait appearance features and kinetic features to identify the human. We trained and tested support vector machines on our gait features. This is a multi-class support vector machine [10]. The kernel function of our classifier is Gaussian kernel,

$$K(x_1, x_2) = \exp\left(\frac{|x - x_i|^2}{2\sigma^2}\right)$$

The algorithm of classify is $L(x) = argmax\{f_x(x)\}, k = 1, \ldots, n$ as

$$f_k(x) = \sum_{j=1}^{k} y_{jk} a_{kj} K(x, x_j) + b_k$$

where x is the gait features data, $f_k(x)$ is the k function for classifying. Figure 9 show original gait sequence and silhouette extraction with the coefficients of DCT.

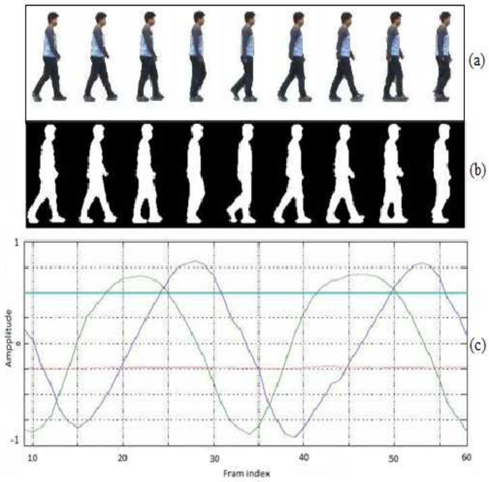


Figure 9: shows silhouette gait sequence and DCT sequence. (a) Original gait sequence frames 11, 16, 21, 26, 31, 36, 41, 46 and 51. (b) Silhouette extraction frames 11, 16, 21, 26, 31, 36, 41, 46 and 51 (c) corresponding DCT sequence.

6. Experiments

6.1 Databases

The existing gait databases are summarized in Table I. First, we briefly review the walking condition variations in the databases. The USF dataset [16] is one of the most widely used gait datasets and is composed of a gallery and 12 probe sequences under different walking conditions that include factors such as views, shoes, surfaces, baggage, and time. As the number of factors is the largest of all the existing databases, and despite the number of variations for each factor being limited to 2, the USF database is suitable for evaluating the inter-factor, instead of intra-factor, impact ongait recognition performance. The CMU MoBo Database [17] contains image sequences of persons walking on a treadmill captured by six cameras. As the treadmill can control the walking speed and slope, the database includes gait images with speed and slope variations as well as view variations. As a result, this database is often used for performance evaluation for speed-invariant or viewinvariant gait recognition [18].

The CASIA dataset [19] contains the largest azimuth view variations and hence, it is used for analysis and modeling of view impact on gait recognition [20]. The OU-ISIR Gait Database [21] contains gait images with the largest speed variations (7 speeds: 1 km/h interval from 2 km/h to 7 km/h) and clothing variations (32 combinations at most), and therefore, it is used for evaluating speed-invariant [22] and clothing-invariant [23] gait recognition. Next, we review the number and variation of subjects. As shown in Table I, relatively large-scale gait databases with more than a hundred subjects are limited to the following three: USF dataset, Soton database [24], and CASIA dataset . Although these three databases provide a statistically reliable performance to some extent, the number of subjects are still not sufficient compared with other biometrics such as fingerprints and faces. In addition, populations of genders and ages are biased in these databases; e.g., there are no children in the USF dataset, while in the CASIA dataset most of the subjects are in their twenties and thirties and the ratio of males to females is 3 to 1. Such biases are undesirable in performance evaluation of gait-based gender and age estimation and performance comparison of gait recognition between genders and age groups.

Table I Existing gait databases

Database	# Subjects	Walking conditions
USF database [16]	122	2 views, 2 shoes, 2 surfaces, baggage (w/ and w/o), time
CMU Mobo database [17]	25	6 views, 2 speeds, 2 slopes, baggage (ball)
Soton (Southampton) database [24]	115	Multiple views
CASIA database [19]	124	11 views, clothing (w/ and w/o coat), baggage (w/ and w/o)
MIT database [25]	24	Multiple views
Georgia Tech database [16]	20	Multiple views, time, distance
The OU-ISIR gait database [21]	68	32 clothes combination (at most
	34	7 speeds

Table 2 results by different recognition algorithms on CMU MoBo

	CMU [11]	UMD [12]	MIT [2]	SVB [13]	Frieze [14]	SSP [15]	MVGRMC
Slow vs. Slow	100%	100%	100%	100%	100%	100%	100%
Fast vs. Fast	-	100%	-	100%	100%	100%	100%
Ball vs. Ball	-	100%	-	100%	100%	-	100%
Slow vs. Fast	73%	77%	70%	82%	100%	54%	88%
Fast vs. Slow	-	86%	-	80%	84%	39%	89%
Slow vs. Ball	90%	48%	50%	77%	81%	-	97%
Ball vs. Slow	-	40%	-	89%	50%	-	94%
Fast vs. Ball	-	44%	-	61%	50%	-	80%
Ball vs. Fast	-	49%	-	79%	50%	-	81%

6.2 Evaluation measures

Recognition performance is evaluated by two measures: (1) Cumulative Match Characteristic (CMC) curve and (2) Receiver Operating Characteristic (ROC) curve. The CMC curve shows the relation between identification rates and a tolerant rank in a one-to-N matching scenario. For example, a rank *k* identification rate means the ratio of a probe to all other probes, where a correct gallery corresponding to the given probe occurs within a rank *k* score. The

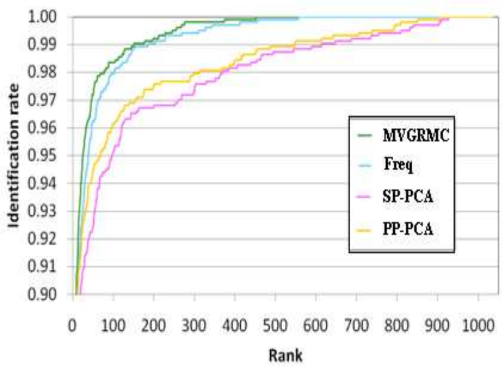
ROC curve denotes a tradeoff curve between a False Rejection Rate (FRR) and False Acceptance Rate (FAR) when the acceptance threshold is changed by a receiver in a one-tone matching scenario. In a one-to-one matching scenario, a z-normalized distance among galleries is adopted to improve the performance in this paper. Note that the CMC curve is dependent on the gallery size, whereas the ROC curve is essentially independent of the gallery size.

6.3 Comparison of gait recognition approaches

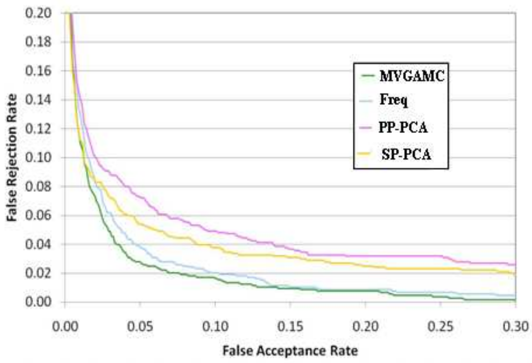
In this section, the recognition performance of each of the four approaches, PP-PCA, SP-PCA, MVGRMC, and FREQ, is compared using the whole set in the largest gait database as a preliminary experiment. The CMC and ROC curves are depicted in Figure. 10 (a) and 10 (b),. According to the results, MVGRMC achieves the best performance of all. PP-PCA, SPPCA, and FREQ are more sensitive to motion components than MVGRMC and therefore, their performance is possibly more severely affected by gait fluctuations between the gallery and probe.

7. Conclusions

This paper describes the construction of a database and a most up statistically reliable evaluation of performance of the motion recognition based on vision and have a less automated approach marker for human identification parameters from fusion of low resolution video Static and dynamic walking. The width was chosen as the function of basic gait. The characteristic features consist gait based on appearance of the progress and based on kinematics. We angles extract features without human body model and analyze motion signatures Discrete Cosine analysis. Used to analyze the shape and the dynamic characteristic and reduce running characteristics. In addition, this document uses the machines multi-class Support Vector to distinguish the different positions of humans. The performance of the proposed method is tested using different databases gait. Recognition results show Our approach provides an efficient way to extract, the model form of movement up sequence information, and to measure the difference between the models walking sequence that is robust to location gait cycle, the change in gross appearance, and time scaling. The proposed algorithm can significantly improve the throughput multiple view recognition when compared with similar methods.



(a)



(b)

Figure 10 (a) CMC curve of gait recognition approaches ; (b) ROC curve of gait recognition approaches.

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