Human Gait Recognition using Silhouette Vector and Principal Component Analysis

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ABSTRACT

Lot of research in the field of human recognition is being carried out. Gait recognition is a relatively new approach which is gaining momentum in biometrics. We have demonstrated a simple approach as a solution to this problem. We have taken a feature which was proposed earlier i.e. the Silhouette Vector. This is the distance of boundary points from the centroid of the silhouette as it rotates 360 degrees. Additional to the silhouette vector, we divided the silhouette image into three equal parts vertically (Rectangular Features) and computed some statistical properties of these parts. These properties were also added to the silhouette vector and given to the PCA training system. Training was performed using silhouette vectors and rectangular vectors for each subject. For testing the system, nearest neighbor method was used which is one of the simplest algorithms used for classification problems. The test subject is assigned to the class which is the minimum Euclidean distance from it. Inclusion of the additional features has improved the system performance greatly. Cumulative match score was used to analyze the system performance.

General Terms:

Biometrics, Gait Recognition

Keywords:

Gait Cycle, Silhouette Vector, Rectangular Vector, PCA

1. INTRODUCTION

Gait analysis is a study which has been gaining momentum in the past few years for a number of reasons. The most common application is biometrics i.e. identification of a person [1] - [4], [9], [12], [15], [17], [19] - [22], [24]. Biometrics is intended to address this issue by making use of the physiological traits such as face, iris and fingerprint recognition or behavioral characteristics such as gait, key stroke etc. of the people. Gait can be defined as coordinated cyclic combination of movements that results in human locomotion[37]. This second generation biometrics has several advantages like from a distance, non touching and even works with lower quality video. Gait biometrics does not require subject willingness as it can be captured from a distance but the first generation biometrics technology requires subject willingness to get identified. Gait analysis is also used for medical purposes like to develop an intelligent black box that can take the physiological signals and interpret them to give accurate information on the position and movement of the knee as done in[16], detection and evaluation of lameness[18]. Other than humans, gait analysis has also been used on animals like horses[18]. It has also used for the determination of ethnicity of an individual, as a soft biometrics[26]. Hence, the usefulness of gait analysis has been increasing in the past few years. A wide number of techniques have been used in these works. Methods available in literatures are classified as model free method, model based method and fusion of model free and model based methods. The model free method characterizes body movement by the statistics of the space - temporal patterns generated in the image sequence by the locomotive person. Model - based method constructs human model to extract some features describing gait dynamics, such as stride dimensions and the kinematics of joint angles [31]. An initial approach was done by Jonhansson [14] by using moving light display (MLD) on subject's joints. The aim was to study the visual information from some typical motion patterns in the human body. Some of the work done using model free methods are [15], where eigenspace transformation (EST) and canonical space transformation (CST) were used and temporal changes of the detected silhouettes are then represented as a sequence of complex vector configurations are analyzed using the Procrustes shape analysis method to obtain mean shape as gait signature. This combined with supervised pattern classification techniques based on the full Procrustes distance measure are adopted for recognition [17]. Another method in which each human silhouette in a gait sequence is transformed into a low dimensional feature vector consisting of average pixel distances from the center of the silhouette is used in [19]. In another work [1] stereo silhouette vector (SSV) is extracted from $3D$ contour and transformed to a $1D$ silhouette signal as the stereo gait feature (SGF). K - L transform is applied for reducing the dimensionality of feature and the complexity of computing. Finally, KNN and NN are applied to gait classification and recognition. Computational intelligence has also been used as in [24]. One of the interesting approach is used in [8] where the authors tried to make the gait recognition system independent of view angle by using angle normalization technique.In [10] dynamic static silhouette template are used for recognition. Factored interval particle filtering is used in [23], where as KPCA is used in [25]. Radon transform is used for geometric gait analysis along with the height and stride length information is extracted for detection of soft biometrics [27] where a sensor based approach is given in [29]. Some model-based methods have been used in [9], [20], [32] - [34]. Some approaches which are the fusion of model free and model based methods are [6], [21], [35] are used. Methods such as neural networks [16], PCA [1], [15], [22], wavelet descriptors [4], [5], [11] have all been used in gait recognition. We propose a method which falls into the statistical - based model free methods. We took the readily obtained silhouettes from the CASIA A database and preprocessed them. We extracted the gait cycle using the width of the silhouettes and then found the silhouette vectors (SV) for the single best gait cycle. Additional to the silhouette vector, we divided the silhouette image into three equal parts vertically, rectangular features (RV) and computed some statistical properties of these parts. After collecting features of all the subjects, the system is trained using Principal Component Analysis. To test the system, the SV, RV of a new subject are extracted and classified by finding the nearest neighbor. The cumulative match score is used to evaluate the results. The rest of the paper is organized as follows. Section II describes the features used for the training section and the procedure for extracting the features. Section III briefs the Principal Component Analysis and how it is applied to our problem is explained. Section IV explains the experimental setup and the results. Conclusion and future work are discussed in Section V.

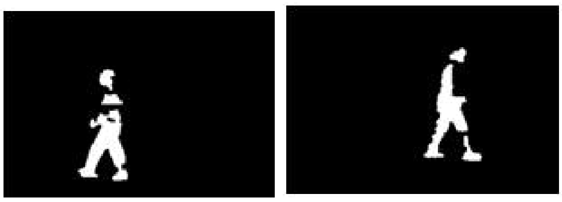

Fig. 1. Silhouette of inferior quality

2. SILHOUETTE VECTOR EXTRACTION

This section explains the feature extraction part of the system. It has five parts. The first is the preprocessing, second is about quality factor, third is the gait cycle extraction, fourth is the SV extraction and finally fifth is about rectangular features (RV).

2.1 Preprocessing

In order for our algorithm to work well, we need a well defined silhouette. However some of the silhouettes from the CASIA A database have many breaks and holes as shown in Figure 1. Hence the need arises for preprocessing. The main operation used for the preprocessing stage is morphological closing. It bridges the gaps and closes the holes in the silhouette. After labeling the connected components these morphological operations are performed. Some statistical properties like centroid, bounding box are measured. All these operations are performed on 20 subjects walking at an angle 0.

2.2 Quality Factor (Q)

After performing these preprocessing morphological operations we found that some of the image frames changed drastically due to noise, breaks and holes present in it. We have to do compromise with the quality of image frame to eliminate the complete noise from it. There are 75 frames for the first subject "fyc" and likewise there are 20 subjects. It will be very complicated task to select such frames those having low noise or ideally noise free. To overcome this problem we defined a quality factor Q. We set the standard quality Q at 10, and every time when a closing operation is required, the value of Q reduced by one unit. Hence each frame is associated with a numerical value i.e. quality factor. This is used to calculate the quality of the cycle and the cycle with the highest quality value is used for feature extraction.

2.3 Gait Cycle Extraction

After plotting the width of the bounding box of each silhouettes in the image against the frame numbers, we found that there is a periodic variation as shown in Figure 3. In Figure 2, one complete gait cycle is shown. The variation in the widths of the images can be easily observed. This is shown in Figure 3 which has a number of cycles. We can manually choose any cycle among the all if the Q has not been defined. As we have Q now we can automate this step by selecting cycle with maximum Q.

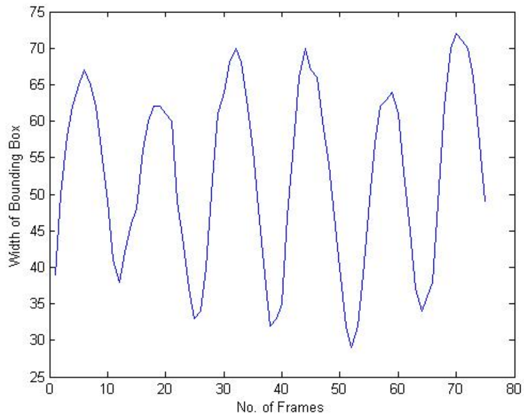

Fig. 3. Variation in width with no. of frames

2.4 Silhouette Vector Extraction

The first feature used is the Silhouette Vector(SV). For extraction of SV, we referred [1] & [2], which performs a stereo silhouette vector (SSV) extraction which is applied to a $3D$ contour. We are not using $3D$, but extracting SV from our $2D$ images. To obtain the SV, we need to extract the boundary of the silhouette. A simple edge detector is used for extracting boundary. Then the centroid of the silhouette is found and the distance of selected boundary points to the centroid is calculated as shown in Figure 4. The SV for all silhouettes need to be of uniform length and hence we consider angle of rotation. If we want 180 points on the SV, we keep rotating the image every 2 degrees and we take the distance from the centroid to the boundary point.

The length of the silhouette vector varies as the vector moves round the silhouette. The Figure 5 shows the variation in length of SV for every 10 degrees that it rotates. Hence the length of the SV is 36 points $(360/10)$. For calculation of SV, let's consider the co-ordinates of the centroid as (X_i, Y_i). The co - ordinates of the centroid can be calculated as follows,

$$X_c = \frac{1}{N}\sum_{i=1}^{N} X_i, Y_c = \frac{1}{N}\sum_{i=1}^{N} Y_i, i = 1, 2, ...N \quad (1)$$

Fig. 2. Extracted complete gait cycle

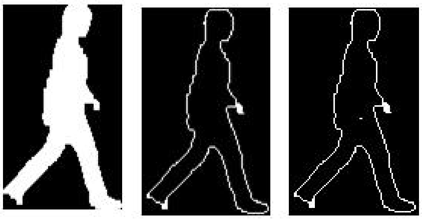

Fig. 4. Silhouette with centroid

Here i represent every silhouette pixel. N is the number of SV points. The co - ordinate of the point on the boundary as(X_b, Y_b). The SV can be depicted as,

$$S_i = [(X_b - X_c, Y_b - Y_c)], i = 1, 2, ...N \tag{2}$$

The length of the SV vector can be calculated as,

$$t_i = \{S_i\}, i = 1, 2, ...N \tag{3}$$

In Figure 5, we can observe the variation in the SV as it rotates clockwise. It starts with a high value since the distance is from the top of the head to the centroid and it keeps reducing. The two peaks in the middle are due to the legs. It increases again as it reaches back to the top of the head.

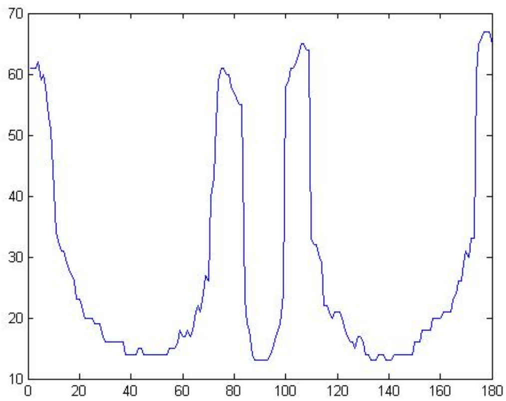

Fig. 5. Variation of silhouette vector for rotating angle 10 degree

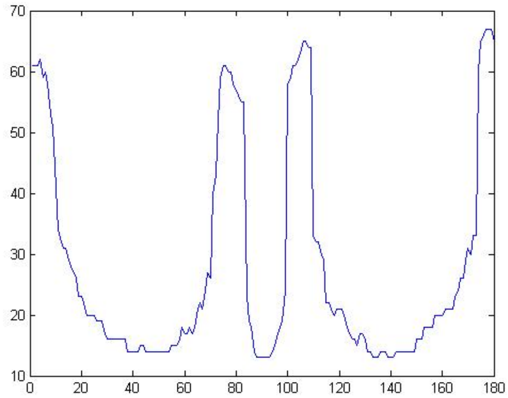

Fig. 6. Variation of silhouette vector for rotating angle 2 degree

2.5 Rectangular Feature (Vector) Extraction

Apart from the SV, it has been observed that identification of a person can be carried out by observing the properties of swing in the arms and legs which varies from person to person. For this purpose, the silhouette is divided into 3 equal parts vertically as shown in Figure 7 and the variation in the width of the bounding boxes for each is measured.

Fig. 7. Division of silhouette to measure arm and leg swing

Thus 9 more features are added to the SV that is the maximum, minimum and standard deviation of the three widths of each subject for a particular gait cycle.

3. PRINCIPAL COMPONENT ANALYSIS

The goal of Principal Component Analysis (PCA) is to reduce the dimensionality of the data while retaining as much as possible of the variation present in the original dataset. It is a way of identifying patterns in data and expressing the data in such a way as to highlight their similarities and differences. The PCA system consists of two parts i. e. the training and the testing. The training procedure is to find the variance in the datasets as the ultimate goal is to represent the data by the dimensions which are least redundant i. e. the maximum variance. Then the eigenvectors of the covariance matrix are found which points in the direction of the highest variation of the initial data set. Finding the directions of maximum and minimum variance turns out to be the same as looking for the orthogonal least squares best fit line and plane of the data. The sums of squares for that line and plane can be written in terms of the covariance matrix. The eigenvector with the highest eigenvalue is the principal component of the data set. One can decide to ignore the components of lesser significance. There is possibility to lose some information but if the eigenvalues are small, you don't lose much. The original dataset is represented in terms of the eigenvectors by multiplying it with the eigenvectors. It will give us the original data solely in terms of the vectors we choose. This concludes the training part of the PCA system.

For testing, the variance of the test vector is found and it is projected on the eigenspace. A simple nearest neighbor method was used which is one of the simplest algorithms used for classification problems. The test subject is assigned to the class which is the minimum Euclidean distance from it.

4. EXPERIMENTS AND RESULTS

It is shown by [36] that maximum information regarding gait can be extracted when the subject is walking at an angle 0 i. e. side view. For our experiments, we used the CASIA Gait database. We used the dataset A which consists of 20 persons. Each person has 12 image sequences, 4 sequences for each of the three directions, i. e. parallel or 0 degrees, 45 degrees and 90 degrees to the image plane. We used the sequences which are parallel to the image plane i. e. side view. Sequence 1 and 3 are of gait sequences of people walking from the left to the right while sequence 2 and 4 are ones from right to left. Hence we trained using sequence 1 and tested on remaining three sequences i. e. 2, 3 & 4. Similarly, we trained using all sequences one at a time and tested on remaining sequences. Each feature vector consists of the silhouette vector and 9 more features which we are calling as rectangular features' representing properties of the bounding rectangle. The length of the silhouette vector depends upon on the step size used in rotation. When the silhouette vector is rotated by an angle of 2 degree we got 3240 silhouette vectors and 9 rectangular vectors, total 3249 feature points. When the silhouette vector rotated by an angle 10 degree the number of silhouette vectors we got are 648 and rectangular features 9, total features 657.

We initially used only the silhouette vector for recognition but found that the results are quite poor as shown in Figure 8. With the addition of the new features the results improved greatly. This is because it takes into consideration the properties of the stride as well as swing in arms which differs from person to person. It is interesting to note that with the increase in length of the silhouette vector, the performance of the system decreased. This can be seen in Figure 11 & Figure 12 with the help of CMS plot obtained by taking 180 points for silhouette vector. Comparing Figure 9 & Figure 10 with Figure 11 & Figure 12, we can see that more number of test subject obtained using lesser silhouette vector points are correctly recognized i. e. have rank 1 as compared to those obtained using greater number of silhouette vector points. This is quite contrary to what we might intuitively believe i. e. the results should improve with increasing number of points in the silhouette vectors. The reason for this may be having too many points on the feature vector brings lots of redundancy. Some of the unimportant features may be considered as important by the PCA system and give rise to

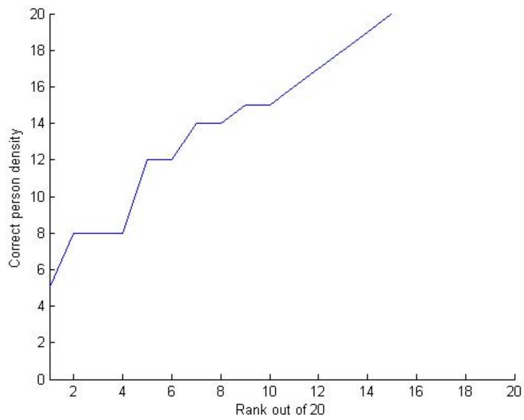

Fig. 8. CMS without RV & SV of length 36 trained on seq. 1 & tested on seq. 3

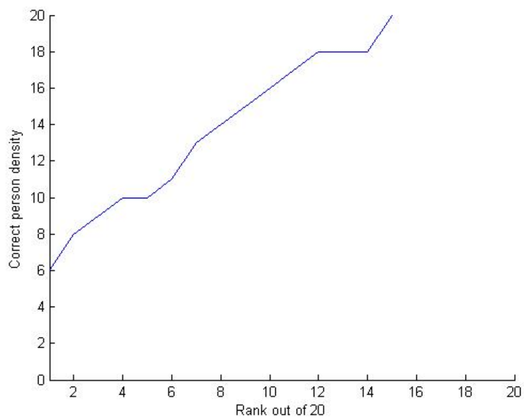

Fig. 9. CMS with RV & SV of length 36 trained on seq. 1 & tested on seq. 2

wrong results. A silhouette vector consisting of 180 points is shown in Figure 6.

5. CONCLUSION

We extracted basic features like area, centroid, gait cycle and silhouette vector. To make this system automatic in the sense of gait cycle selection quality factor Q is defined. After the analysis of the effect of rotating angle on the variation in number of silhouette vectors on the system performance, we came across a special case with silhouette vectors in which increasing the number of vectors does not necessarily give a more accurate result. Thus by keeping the number of vectors small, we are saving time, computations as well as increasing accuracy.

In this research work we had set out to use just the silhouette vector for recognition. But on experimentation, it was observed that silhouette vector as a standalone feature does not give us a robust enough system. Inclusion of Rectangular Vectors in feature vector gave out much better results. However, there is still need of improvement. In preprocessing it has been observed that there are too many holes and breaks present even after morphological opera-

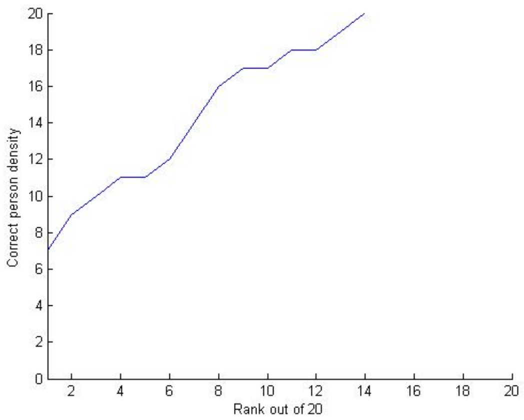

Fig. 10. CMS with RV & SV of length 36 trained on seq. 1 & tested on seq. 3

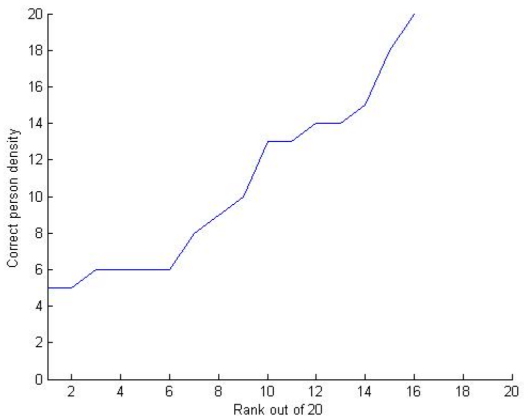

Fig. 11. CMS with RV & SV of length 180 trained on seq. 1 & tested on seq. 4

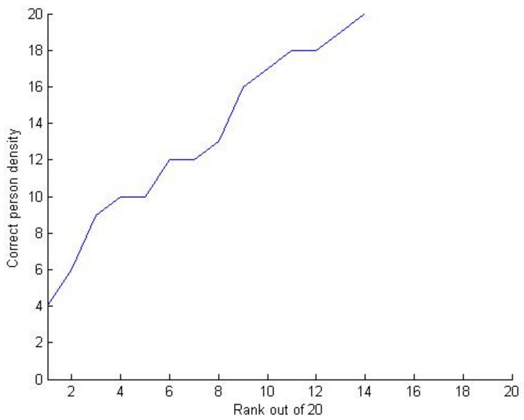

Fig. 12. CMS with RV & SV of length 180 trained on seq. 2 & tested on seq. 4

tions. For the extraction of gait cycle two successive peaks of width variation signal are consider. Instead of that it is required to check the significance of movement of other body parts in the gait cycle measurement. Finally the algorithm needs some modifications to recognize the subject which walks in opposite direction while testing. We got better results when trained and tested the system with the sequences in which the subject is walking in the same direction but the recognition rate decreases significantly when the subject is walking in opposite direction. PCA is one of the simplest classifier which is used in this system. In the future, we intend to carry out experiments replacing it with another classifiers and investigate some new features.

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