Gait Recognition using Gait Energy Image

Hayder Ali, Jamal Dargham, Chekima Ali, Ervin Gobin Moung

Computer Engineering Program, School of Engineering and Information Technology, University Malaysia Sabah, Kota Kinabalu - 88999, Sabah, Malaysia, mdhayderali@yahoo.com

Abstract

In this paper, Gait Energy Image (GEI) has constructed to apply Principal Component Analysis (PCA) with and without Radon Transform (RT). The Radon Transform is used to detect features within an image and PCA is used to reduce dimension of the images without much loss of information. The side view of slow walk; fast walk and carrying a ball walk have been selected from the CMU MoBo database for experimental purposes. The two techniques achieved equal error rates (EER) of 94.23%, 82.28%, and 90.38% for PCA only and 96.15%, 82.70% and 92.30% for PCA with RT for slow walk, fast walk and carrying a ball walk respectively.

Keywords: *Gait recognition, Gait energy, PCA, Radon transform.*

1. Introduction

Gait recognition system can be classified depending on the sensors used into three groups namely; motion vision based, wearable sensor based and floor sensor based. The motion vision can be divided into two groups namely; appearance based methods and model based methods. The appearance based method can be also subdivided in two types; state space methods and spatio-temporal methods. The classification of the recognition system is shown in figure 1 (Feng *et al.*, 2009; Moeslund *et al.*, 2006; post 2007; Gufurov *et al.*, 2005). Figure 2 shows motion vision based system flow chart.

Biometric gait recognition refers to verifying or identifying persons using their walking style. Human recognition based on gait is relatively recent compared to other biometric approaches such as fingerprint, iris, facial etc.

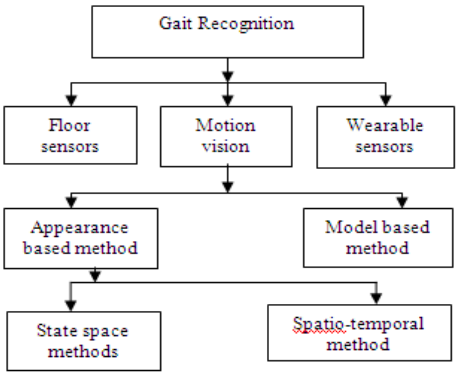

Figure 1: Classification of gait recognition system (Hayder et al., 2010)

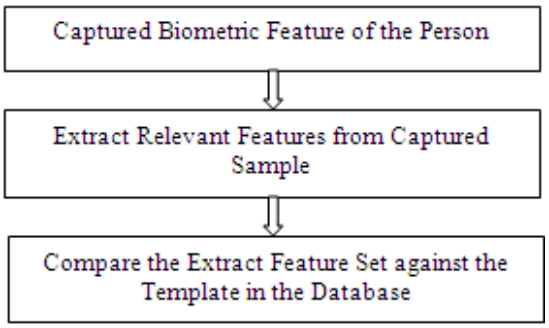

Figure 2: Motion vision based system flow chart (Hayder et al., 2010)

In the next section, the literature review will be discussed briefly. In section III system design is described while in section IV results are discussed. Conclusion and future directions are given in section V.

2. Literature Review

Lee *et al.*, (2009) proposed for efficient gait recognition with carrying backpack. They have been constructed gait energy image (GEI) to apply recursive principle component analysis technique. This method is aim to remove subject backpack without losing subject original shape and information. They applied to their method to normal walk, slow walk, and fast walk for experiment. They have used CASIA C dataset for conducting the test. They achieved better recognition rate after comparing others result.

Shingh and Biswas (2009) are approached gait energy image (GEI) method for human identification. They selected normal walk, wearing a coat or jacket or carrying a bag for recognition purposes. They informed that normal walk sequence is obtaining better recognition rate compared to carrying a bag or wearing a jacket or coat. They focused on subject body alignment with bottom and upper part of the body as feature. They also reported that gait recognition rate can be improved by applying GEI method. They selected large CASIA gait database for the experiment.

Ju and Bir (2006) proposed gait energy image (GEI) method for person recognition individually. They created statistical gait features from actual and artificial gait templates for the experiment. They selected USF HumanID gait database for gait recognition purposes. They also used others gait database to compare recognition rate with current method with selected gait database. The GEI method is obtained better recognition rate after comparing published gait result.

Okumura *et al*., (2010) described a large scale gait database that can use widely for vision based gait recognition. They focused on gait energy image method for recognition on gender or age groups. From the experiment, female subjects are achieving better recognition rate compared to male. For the age grouping, it's evaluated according to maturity of walking ability and also physical strength. They have got different fluctuation from different age groups. They also compared with several gait databases to evaluate their method performance.

Cheng *et al.*, (2006) proposed gait recognition based on PCA and LDA. PCA is mainly used for dimensional reduction technique and LDA is performed to optimize the pattern class. For the experiment, they used their own database and achieved better recognition rate from PCA compared to LDA.

3. Systems Design

3.1 Gait Energy Image (GEI)

Gait Energy Image (GEI) is the sum of images of the walking silhouette divided by the number of images. GEI is a useful representation with superior selective power and strength against segmental errors (Miciak 2010). The equation (1) present the pre-processed binary gait silhouette images $B_t(x,y)$ at time t in a sequence, GEI is computed by

$$G(x,y) = \frac{1}{N}\sum_{t-1}^{N} B_t(x,y) \quad (1)$$

Where N is the number of frames in the full gait cycle and x and y are a value in the image coordinates (Miciak 2010). The Figure 3 shows the constructed sample of GEI from a sequence of silhouettes.

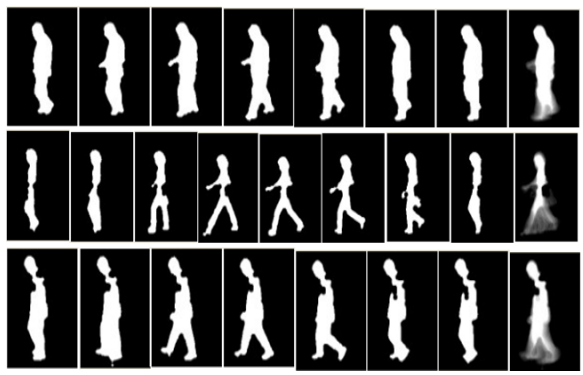

Figure 3: The constructed sample of GEI from a sequence of silhouettes

3.2 PCA Technique Only

PCA is used to simplify the data structure and still account for as much of the total variation in the original data as possible [15]. Several theoretical details parameters which are mean image, zero mean matrix, covariance matrix, eignvectors and eigenvalues, and sorting of eigenvalues. The Empirical mean is defined as

$$u[m] = \frac{1}{N}\sum_{n=1}^{N} X[m,n] \quad (2)$$

Where, the empirical mean is taken along each dimension m=1, 2, . . ., M. here mean vector **u** of dimension M x 1. To calculate the deviations from the mean, subtract the empirical mean vector **u** from each column of the data matrix X which is defined as $B = X - uh$, where mean subtracted data in the M x N matrix B and h is a 1xN row vector of all 1's. The covariance matrix is defined as:

$$C = E[B \otimes B] = E[B.B^*] = \frac{1}{N}\sum B.B^* \quad (3)$$

Where, B is the expected value, and $\otimes$ is the outer product. The computed matrix V of eigenvectors which is diagonalizable the covariance matrix C is defined as: $V^{-1}CV = D$, where D is the diagonal matrix of eigenvalues of C (Miciak 2010; Hayder *et al.*, 2010))

Figure 4 shows the block diagram for gait recognition using PCA method that used for this chapter. A 2-D gait images are concatenated to form 1-D image vectors. A zero mean 1-D

training images set are computed. PCA is then applied on the collection of 1-D zero-mean images set vector to produce a low-dimensional features vector.

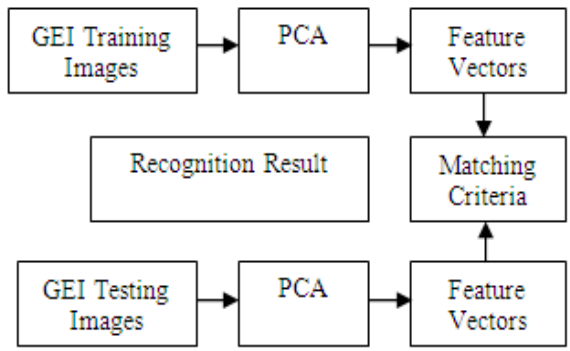

Figure 4: Block diagram for gait recognition using PCA (Hayder et al., 2010)

3.3 Principal component analysis and RT technique

The Radon Transform is one of powerful techniques used to identify features within an image. Let L(m, n) be an image function, the Radon Transform is defined as:

$$F(\rho,\theta)=\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}(x,y)\partial(\rho-x\cos\theta-y\sin\theta)dxdy \qquad (4)$$

Where x is defined as integral along a line through the mage θ is the angle and ρ is the distance of the line from the origin of the coordinate system as shown in figure 5.

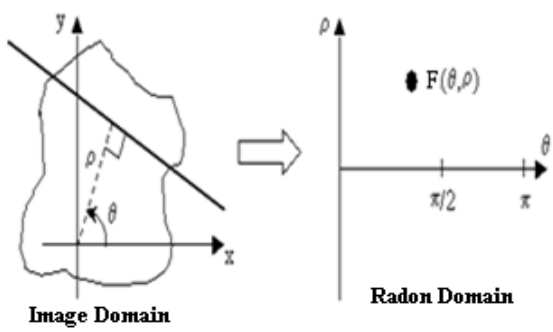

Figure 5: Image domain and radon domain (Hayder et al., 2010)

Figure 6 shows the block diagram of Radon Transform with PCA. Radon transform will be applied on the image to compute its 2D projection image along angles varying from 0^0 to 180^0. The result of the projection is the sum of the intensities of the pixels in each direction. All the projections of the image are concatenated to form 1D Radon Transform's vector. The 1D Radon Transform's vector for all training images are computed. PCA is then applied on the collection of 1D Radon Transform's vector to produce a low dimensional feature vector.

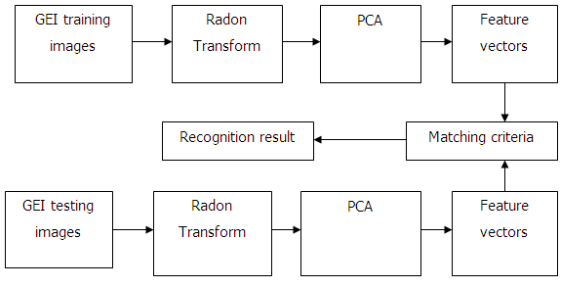

Figure 6: Block diagram for gait recognition using PCA with RT (Hayder et al., 2010)

3.4 Training and Testing Database

The CMU MoBo gait database has been selected for the experiment as it is freely available by requesting from Dr. Ralph (2001). In this database, 25 subjects are trained on the tread mill. Around the tread mill, the six cameras have set to capture the images in six different viewing angles. The provided database has four kinds of walking pattern which are slow, fast, incline and carrying a ball walk. Each subject walking pattern has six kind of view in different angles. Each view captured 340 frames that can be calculated minimum 14 gait cycles and each cycle has generally 18 to 20 frames. One cycle frames are combined and prepared a GEI frame. So one subject got minimum 14 GEI images. For the training and testing, 10 GEI frames selected for training and 4 GEI frames selected for testing to perform the experiment for one subject. Total number of GEI training and testing frames are 13*10=130 and 13*4=52 frames respectively. For the unknown subject, one cycle has been selected to make GEI unknown frames. The figure 7 shows set of training and testing GEI database.

We just exactly follow our previous papers database [6] that arranged to make GEI frames for this paper. The total numbers of GEI testing frames which will compare GEI training frames for recognition purposes. The GEI testing frames will be used to test the recall capability of the gait recognition system. Another 12 subjects called GEI unknown frame which has 1 cycle for three walking styles to prepare for rejection capability of the system. The techniques of RT with PCA and PCA only are applied for recognition purposes in this paper.

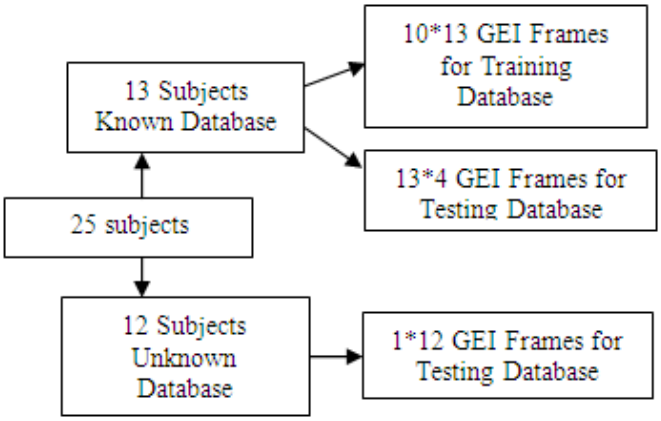

Figure 7: Design of testing and training dataset (Hayder et al., 2010)

3.5 Matching Criteria

The Euclidean distance is used for measuring purposes. If the Euclidean distance between frame A and frame B in the training database is smaller than a fixed threshold value T, then frames A and B are proved to be the same subject. The threshold T is the largest Euclidean distance between any two images in the training database, divided by a threshold tuning value (Tcpara) as given in equation (5). The threshold is defined as

$$T = \frac{[\max\langle \| \Omega j - \Omega k \| \rangle]}{Tcpara} \tag{5}$$

Where, Tcpara is a tuning value; j, k = 1, 2, 3. . . , N. N is the total number of training images and Ω reduces dimensional images (Hayder *et al.*, 2011). The sample of the Euclidean distance to verify matching frame to frame and it has shown in figure 9 for one subject. From the figure 9, it can be seen that each frame displayed different magnitude on one complete cycle. So it is easy to select gait cycle by applying Euclidean distance method and even it can be obtained to get gait cycle by manually.

In the algorithm, two performances have been measured which are namely recall and reject. For recall, if a test image is correctly identified to an image of the same person from the training database it is called Correct Classification. If the test image is incorrectly matched with another subject images it is called False Acceptance. If an image is rejected by the system which from the training database then it is False Rejection. For reject, if any test frame from the unknown test cannot identify by program then it Correct Classification. If the test image can detect by program then it False Acceptance.

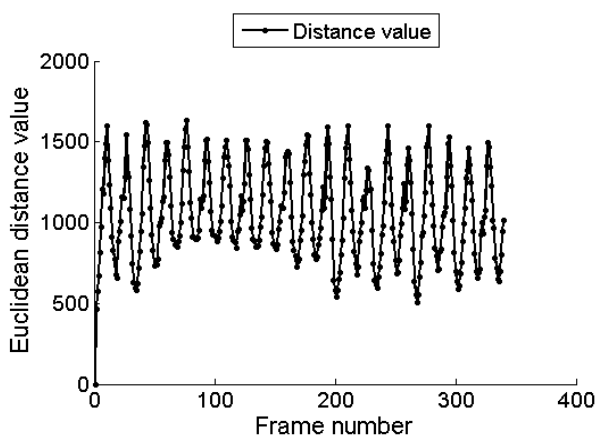

Figure 9: Sample of gait cycle using Euclidean distance

3.6 Threshold tuning parameter

The value of the threshold tuning parameter can be used to tune the performance of the system to have either high correct recall with high false acceptance rate for application such as boarder monitoring or high correct rejection rate for unknown persons for application such as access control. For this work, the threshold tuning parameter was set so that the system has equal correct recall rate and correct rejection rate. The TCPARA (threshold) value mentioned that was chosen for each system is shown figure 10, to figure 15 and each walking system has different TCPARA value.

4. Result and discussion

Figure 16 shows experimental performance using PCA with Radon Transform and PCA only for three walking styles. Figure 16 demonstrates the EER and fixed threshold values for both techniques for three walking styles. The recall correct classification is equal to reject correct classification called EER. For this work, the EER achieved 94.23%, 82.28%, and 90.38% for PCA only method and 96.15%, 82.28%, 92.30% for PCA with RT method for the three walking styles respectively. If we set TCPARA value 1 then the best correct classification rate attained above 95% for two methods for all three walking styles while reject correct classification rate 0%. From Figure 10 to Figure 15, the recall correct classification rate is decreasing as Tcpara increase. While the rejection correct classification rate is increasing as Tcpara value increase. Also, each walking style FAR and FRR might be calculated from both systems according to the recognition rate. However, the FAR for both recall and rejection is decrease as Tcpara value increases. So, different walking style has different threshold value for the system.

We observed three walking styles that slow walking style represented better EER compared to slow and carrying a ball walking styles. The carrying a ball walk achieved EER comparatively better than past walk style. The fast walk attained low EER rate than slow walk and carrying a ball walk style. For slow and carrying a ball walk, PCA with RT performed slightly better results than PCA only technique. The fast walk style results are identical using both techniques. In conclusion, slow walk presented better results on the GEI based system. The figure 17 displayed output of the matching frame "Test[9]-Train[29]" which correct matching frame in range of same subject's training and testing frames. The selecting testing frame for the subject matches with training frame from same subject.

We have compared our system with other methods reported in published papers as shown table 1. Seyyed et al. [16] proposed based on RT and PCA which provides high recognition rate (97%) based on own gait database. Bo and Yumei [17] approached PCA and LDA techniques and achieved recognition rate of 87% based on mixed gait database. Murat [18] applied PCA and eigen based PCA techniques for the experiment. He also implemented fusion tactic and obtained final recognition rate of 100% based on existing gait databases. Ju and bir [19] prepared real and synthetic GEI template and PCA used to extract the features. They used USF HumanID gait database and achieved 96% of recognition rate.

Table 1: Comparison of several methods based gait recognition on different gait database

Method	**Database**	**Recognition rate**
RT + PCA (sayyed at el., 2010)	Own	97%
PCA (ye and wen 2006)	Mixed	87%
PCA (GEI) (Ekinchi 2006)	CMU MoBo, NLPR	100%
PCA (GEI) (Han and Bahnu 2004)	USF HumanID	96%
Proposed method	**Database**	**EER**
PCA (GEI)	**CMU MoBo**	**94%**
PCA + RT (GEI)	**CMU MoBo**	**96%**

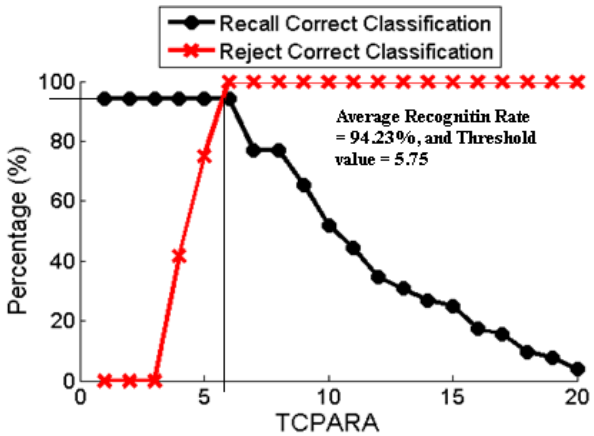

Figure 10: Recognition result using PCA with RT for slow walk

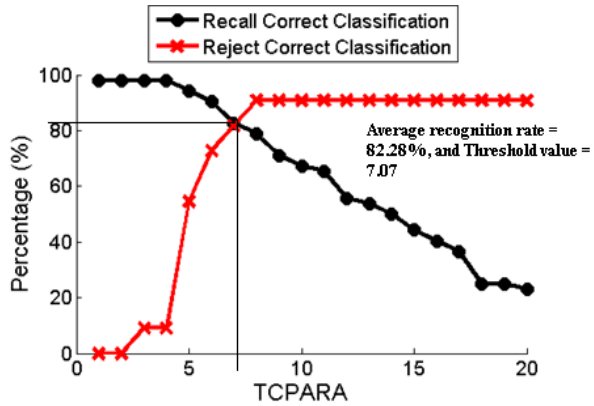

Figure 11: Recognition result using PCA with RT for fast walk

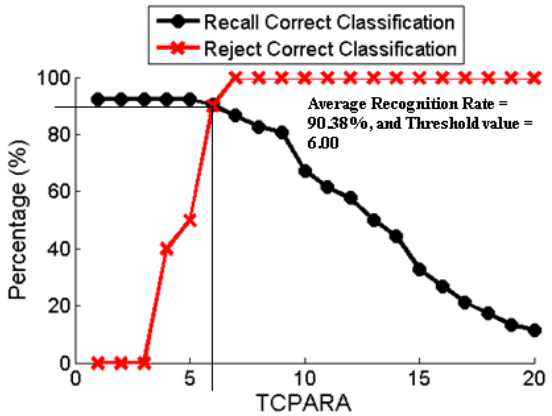

Figure 12: Recognition result using PCA with RT for carrying a ball walk

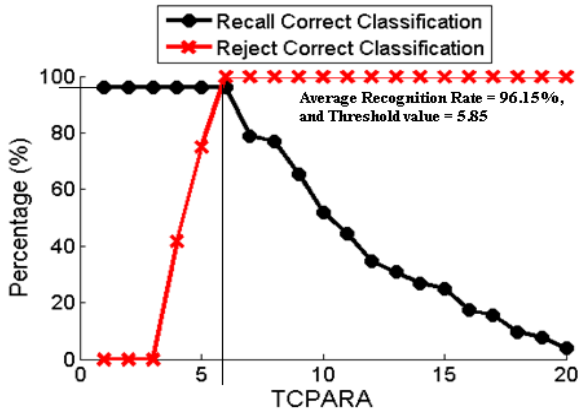

Figure 13: Recognition result using PCA with RT for slow walk

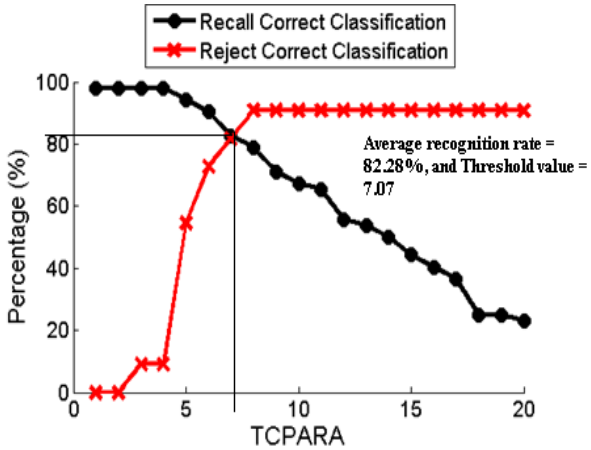

Figure 14: Recognition result using PCA with RT for fast walk

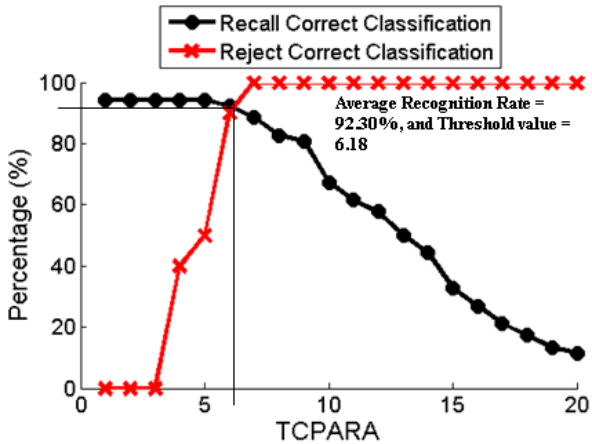

Figure 15: Recognition result using PCA with RT for carrying a ball walk

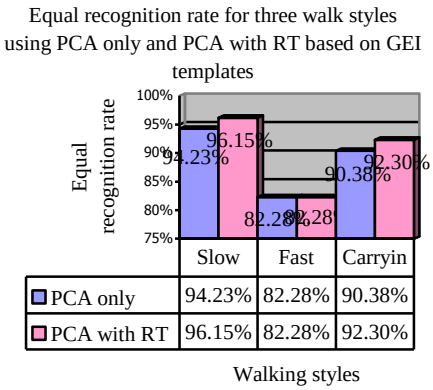

Figure 16: Equal recognition rate for three walking styles using PCA only and PCA with RT based on GEI templates

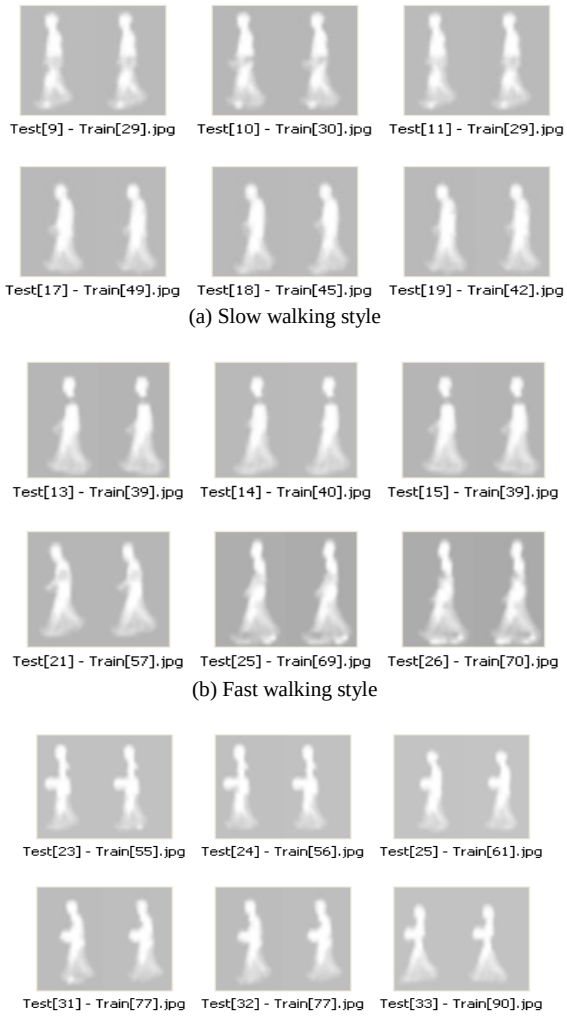

Figure 17: Sample of GEI output of the correct matching frames (a) slow walk, (b) fast walk, (c) carrying a ball walk

5. Conclusion

In this paper, a gait recognition style based on PCA with RT and only PCA techniques were proposed. We computed GEI template from gait sequences. The normal silhouettes frames data was applied for the experiment. The CMU MoBo gait database applied for testing. The results were compared with other published papers and reported that the proposed system gives efficient result. Some of researchers presented better recognition rate of walking style in different gait database conditions.

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