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Multi-view Gait Based Biometric System

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Abstract. ***This paper presents a multi-view gait based biometric system that able to work well in various walking trajectories and covariate factors such as clothing, load carrying and speed of walking. Our approach first applies perspective correction to alter the silhouettes from oblique view to side-view plane. Next, joint locations of hip, knees and ankles are estimated based on a priori information of human body proportion. Dynamic and static gait features are then extracted by the proposed extraction technique. Gaussian filter is applied to smooth the features in order to reduce the influence of outliers. Feature normalization and selection are subsequently applied before the classification process. The experiments were carried out on SOTON Oblique Database and SOTON Covariate Database from University of Southampton. From the experimental results, the proposed system achieved 92.5% and 96.0% correct classification rates for both databases respectively.***

Keyword: ***gait recognition, biometrics, covariate factors***

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1. Introduction

Human gait is a unique locomotive pattern which comprises synchronized movements of body parts, joints and the interaction among them [1]. Therefore, it can be counted as a unique biometric identifier. In 1973, psychological research finding from Johannson [2] has demonstrated that human can identity walking subjects based on the light markers that are attached to their legs. From there onwards, it has inspired many researchers to work on gait analysis for human identification purpose.

Gait is an unobtrusive biometric, which can be captured from a distance and without require any intervention from the user. However, its performance can be affected by covariate factors, for example illumination of light, time, load carrying, speed, clothing and camera view-point. For this reason, it makes gait recognition system as a challenging issue. Recently, many research works concentrated on the multi-view gait analysis. As in realistic surveillance scenarios, subjects are supposed to walk in various directions during the journey.

In this paper, we presented a new multi-view model based gait biometric system with joint detection approach. The gait based biometric system able to compute joint angular trajectories precisely even in occluded silhouettes. It consists of four phases: (a) view normalization to handle the changes of camera capturing angle; (b) gait feature extraction to extract the required gait feature from subject silhouettes; (c) feature normalization and selection to find those positive significant gait features; (d) classification is carry out to demonstrate the performance of the propose system.

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Two databases from University of Southampton, SOTON Oblique Database (Oblique DB) [3] and SOTON Covariate Database (Small DB) [3] have been used for training and testing in this paper. Oblique DB consists of walking sequences that are captured in oblique-view (45^o). On the other hand, Small DB consists of walking sequences that are captured in side-view plane. Both databases were captured with fifteen covariate factors such as different clothing, load carrying and speed of walking, as we believe that these changes portray a realistic scenario of changing walking subjects and can act as a challenge in gait recognition. The performance evaluation was in terms of correct classification rate (CCR), true positive rate (TPR) and false positive rate (FPR)

The rest of this paper is organized as follows. Section 2 reviews the approaches on view-point normalization and gait features extraction. Section 3 describes our proposed system. Performance assessment and the corresponding experiment results are discussed in Section 4. Lastly, discussion and conclusions are drawn in Section 5.

2. Literature reviews

Various research works have been conducted in gait based biometric system. This section reviews the related literatures on view-point normalization techniques and gait features extraction approaches.

2.1 View-point normalization

There are three major techniques that resolve the issues on subject walking in multi trajectories, namely view invariant gait feature, view synthesis and view transformation.

In the first technique, researchers aim to extract invariant gait features that cope to the changes in walking trajectory and camera view-point. Jean et al. [6] implemented homograph transformations to normalized various walking trajectories to a single side-view plane. Bouchrika et al. applied [7] rectification method to normalize extracted gait features from various view-points. Kale et al. [8] utilized perspective projection and optical flow to synthesize images from arbitrary-view. Lee et al. [9] developed multi-linear generative model to decompose gait parameters with view-point factors. However, this technique can only be effective in limited viewing angles and easily disrupted by occlusion due to self-occlusion or clothing.

In the second technique, researchers calibrate multiple view-point cameras to reconstruct 3D gait information. Bodor et al. [10] applied image-based rendering technique and Shakhrovich et al. [11] built 3D visual hull model to reconstruct gait. They managed to generate precise synthetic images with detail gait information. However, this technique requires heavy computational resource and involves complex technical setup.

In the third technique, researchers magnify the mapping relationship between gait features across various view-points. Makihara et al. [12] obtained frequency domain of gait features from Fourier operation to developed view transformation model. Kusakunniran et al. [13] and Bashir et al. [14] optimized Gait Energy Image to extract gait features that comprise of motion frequency, temporal and spatial changes of a walking sequence. The propagation of noise during the reconstruction process, which degrades the recognition performance, is the drawback of this technique.

2.2 Gait features extraction

Gait features extraction is divided into two major approaches, namely model-based approach and model-free approach. Model-based approach mimics the body structures as blobs or rectangles and matches them as model components [4, 5]. It integrates knowledge of the body shape and gait dynamics during the extraction process. The gait features can be directly extracted by determining joint positions, rather than correlating with other motions of unrelated objects. Therefore, the noise effects from the surrounding environment can be removed easily. However, many parameters are created from this approach and ending up with a complex model.

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On the other hand, model-free approach normally distinguishes the entire body by a concise representation such as silhouette or skeleton without taking the essential structure into consideration [1]. This approach is fast in processing and only requires small computational resource. On the contrary, its performance is intensely affected by the background noise and covariate factors such as the changes of the subject's clothing, load carrying and camera view-point.

As gait includes the static body parameters and the dynamics of human walking stance, we present a model-based joint detection approach. It is able to extract static features (height, width, step- size and crotch height) and dynamic features (joint angular trajectories). Our method does not attempt to detect each of the lower limbs. Thus, it can handle occluded silhouette either from self-occluded or those occluded by apparels, such as subject apparel (long blouses or baggy trousers) or load carrying. We utilized perspective correction for view-point normalization, which is comparable to Jean et al. [6]. However, we do not extract the spatiotemporal trajectories of body parts for gait modeling. This would mitigate the problems with missing head or foot in the silhouettes as faced by Jean et al [6]. In addition, our approach is more straightforward and faster comparing with view synthesis and view transformation approaches.

Despite a lot of research works on gait databases from University of Southampton, there is no study of gait classification on Oblique DB [3]. Thus, this research work aims to prove that the proposed approach is able to provide high correct classification rate in Oblique DB and Small DB with fifteen covariate factors.

3. Methodology

According to Murray et al. [15], ankle rotation, pelvic tipping and spatial displacements were shown to possess individual consistency in repeated tests. Therefore, this paper only considers those gait features from the lower limbs for the recognition system. Figure 1 illustrates the flow of the processes that involved.

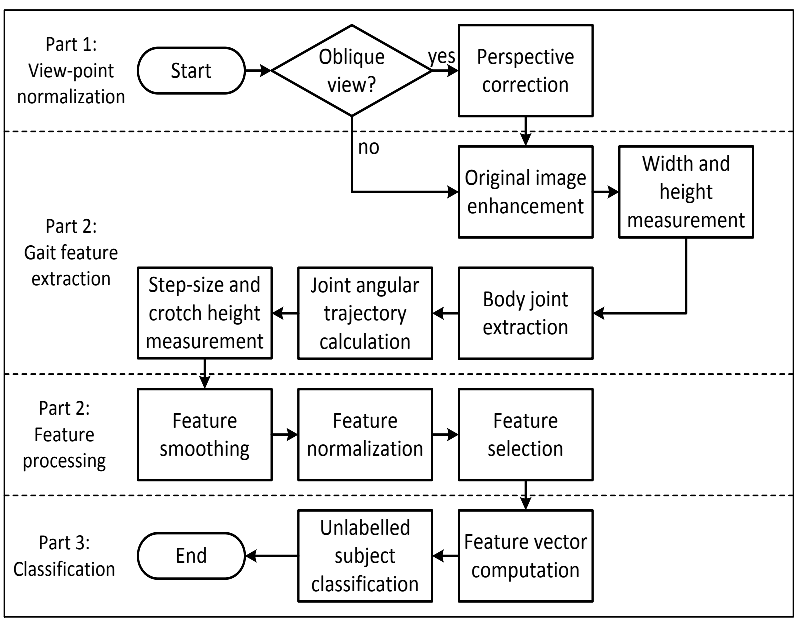

Figure 1. Flowchart of the proposed system

3.1 View-point normalization

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To normalize the oblique walking sequence into the side-view plane, the perspective correction technique is employed. First, all silhouettes in a walking sequence are superimposed into a single image, as shown in Figure 2. Then, line A and B are drawn according to the highest and lowest point among the silhouettes. Finally, line C is drawn by connecting the first peak and the last peak of the sinusoidal line.

The correction technique consists of two stages: vertical and horizontal adjustments. For vertical adjustment, each silhouette is then vertically stretched from line C towards line A. In addition, each silhouette is also vertically stretched from the bottom towards line B.

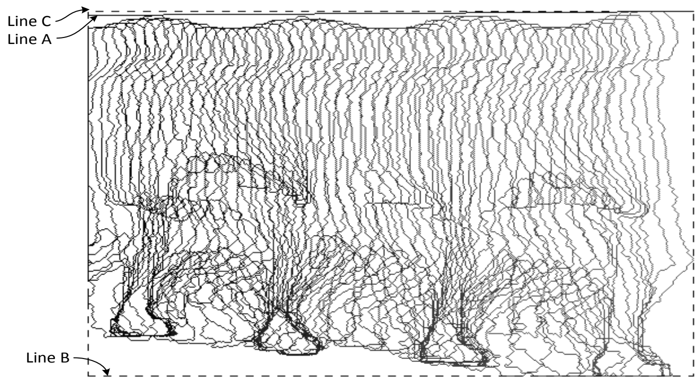

Figure 2. Superimposed silhouettes from one walking sequence.

To preserve the aspect ratio of the silhouettes, horizontal adjustment is applied by horizontally stretching each silhouette with the same proportion, using the following expression:

$$W_2 = \frac{H_2}{H_1} W_1 \qquad (1)$$

where H_1, H_2, W_1 and W_2 are as shown in Figure 3.

To facilitate both vertical and horizontal stretching, polynomial warping is used to perform a geometrical transformation with the resulting image defined by:

$$g(x, y) = f(x', y') = f(a(x, y), b(x, y)) \qquad (2)$$

where $g(x, y)$ represents the pixel in the output image at coordinate (x, y) and $f(x', y')$ is the pixel at (x', y') in the input image that is used to derive $g(x, y)$, $a(x, y)$ and $b(x, y)$ are polynomials in x and y, whose coefficients are given by P and Q, and specify the following spatial transformations:

$$x' = a\left(x, y\right) = \sum_{i=0}^{1} \sum_{j=0}^{1} P_{i,j} x^j y^i \qquad (3)$$

$$y' = b\left(x, y\right) = \sum_{i=0}^{1} \sum_{j=0}^{1} Q_{i,j} x^j y^i \qquad (4)$$

The coefficients P and Q are determined by using least square estimation based on the following polynomial functions:

$$x_{in} = \sum_{i,j} P_{i,j} x_{out}^j y_{out}^i \qquad (5)$$

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$$y_{in} = \sum_{i,j} Q_{i,j} x_{out}^{j} y_{out}^{i} \tag{6}$$

where $i = \{0, 1\}$, $j = \{0, 1\}$, $x_{in} = \{x_0, x_1, x_1, x_0\}$, $x_{out} = \{x_0', x_1, x_1, x_0'\}$, $y_{in} = \{y_0, y_1, y_2, y_3\}$ and $y_{out} = \{y_1, y_1, y_2, y_2\}$, as shown in Figure 3.

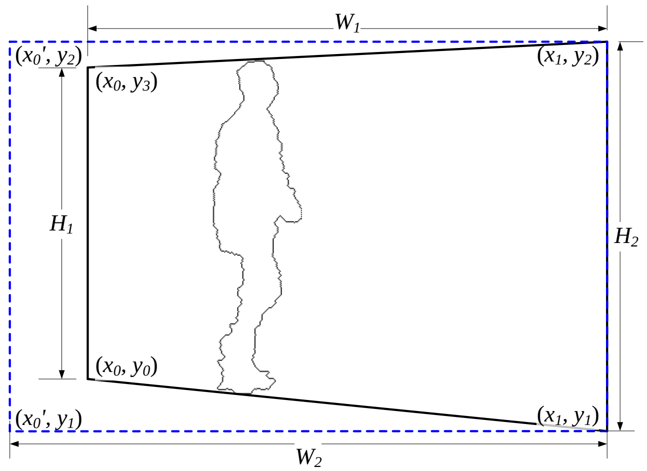

Figure 3. Dimensions of a human silhouette

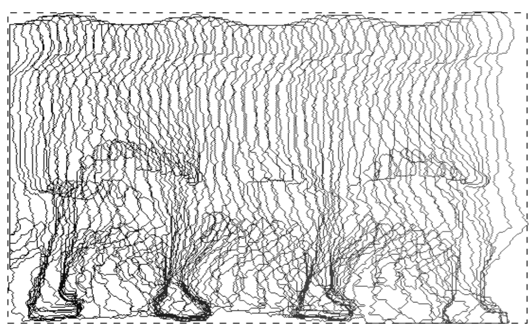

Figure 4. Superimposed silhouettes after perspective correction

3.2 Joint detection approach

The general steps for joint detection approach are described as follows:

- **Step 1:** apply morphological opening to remove shadows which are chronically present near the feet and morphological closing to remove gaps in the silhouettes due to inefficient segmentation. Otherwise, both shadows and gaps will obstruct the feature extraction as it interferes with the essential body point identification. Both morphological operations are using a 7x7 diamond shape structuring element
- **Step 2:** measure the width (W) and height (H) of the subject are obtained from the bounding box of the enhanced silhouette. Fig. 5(a) shows the two extracted gait features.
- **Step 3:** estimate the vertical position of body joints, hip, knee and ankle as 0.48H, 0.285H and 0.039H with respect to the body height H by referring to a priori information of the human body proportion [16].

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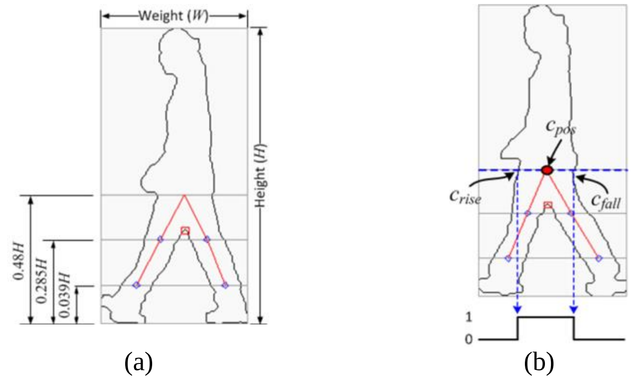

Figure 5. The width and height of a human silhouette; (b) Image profile of horizontal line drawn through the hip

- **Step 4:** determine the horizontal center position of the hip by calculating the midpoint between both edges using the following equation:

$$c_{pos} = c_{rise} + \frac{c_{fall} - c_{rise}}{2} \tag{7}$$

where c_{rise} is the horizontal position of the rising edge, c_{fall} is the horizontal position of the falling edge and c_{pos} is the horizontal center position of the hip.

To determine the center horizontal positions of both knees, a horizontal line is drawn at knee height across the silhouette. For a normal silhouette without self-occluded or occluded by apparels, there should be four edges on the image profile along this horizontal line, as indicated by two dots beside each knee in Figure 6(a). The horizontal center knee positions can be discovered by finding the midpoint between two adjacent edges on each leg using the following equations:

$$k_{fPos} = k_{fRise} + \frac{k_{fFall} - k_{fRise}}{2} \tag{8}$$

$$k_{bPos} = k_{bRise} + \frac{k_{bFall} - k_{bRise}}{2} \tag{9}$$

where k_{fPos} and k_{bPos} are the horizontal center positions of the front and back knee for normal silhouette, k_{fRise} and k_{bRise} are the horizontal positions of the rising edge on the front and back knee, k_{fFall} and k_{bFall} are the horizontal positions of the falling edge on both knees.

For occluded silhouette, there will be only two edges on the image profile, as highlighted in Fig. 6(b). The horizontal center knee positions can be determined by computing the midpoint between each edge with respect to the horizontal center position of the hip, which is shown in Figure 6(b).

$$k_{fPos1} = k_{rise} + \frac{c_{pos} - k_{rise}}{2} \tag{10}$$

$$k_{bPos1} = c_{pos} + \frac{k_{fall} - c_{pos}}{2} \tag{11}$$

where k_{fPos1} and k_{bPos1} are the horizontal center positions of the front and back knee for occluded silhouette, c_{pos} is the horizontal center position of the hip, k_{rise} is the horizontal position of the rising edge and k_{fall} is the horizontal position of the falling edge on the corresponding image profile.

To determine the horizontal center position of the ankles, a similar technique is employed. If a horizontal line is drawn at ankle height on a normal silhouette, there should be four edges on the image profile along the horizontal line, as highlighted in Fig. 6(c). The horizontal center ankle positions can then be determined by using the following equations:

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$$A_{fPos} = A_{fRise} + \frac{A_{fFall} - A_{fRise}}{2} \tag{12}$$

$$A_{bPos} = A_{bRise} + \frac{A_{bFall} - A_{bRise}}{2} \tag{13}$$

where A_{fPos} and A_{bPos} are the horizontal center positions of the front and back ankle for normal silhouette, A_{fRise} and A_{bRise} are the rising edge on the front and back ankle, and A_{fFall} and A_{bFall} are the falling edge on the front and back ankle.

For occluded silhouette, there are only two edges on the image profile, as highlighted in Fig. 6(d). The horizontal center ankle positions can then be determined by finding the midpoint between both edges using the following equations:

$$A_{fPos1} = A_{rise} + 0.25\left(A_{fall} - A_{rise}\right) \tag{14}$$

$$A_{bPos1} = A_{rise} + 0.75\left(A_{fall} - A_{rise}\right) \tag{15}$$

where A_{fPos1} and A_{bPos1} are the horizontal center positions of the front and back ankle for occluded silhouette, A_{rise} and A_{fall} are the horizontal positions of the rising and falling edge on the image profile, 0.25 and 0.75 are chosen to compute the first quarter and third quarter points between these edges as C_{pos} does not reflect the middle point between A_{rise} and A_{fall}.

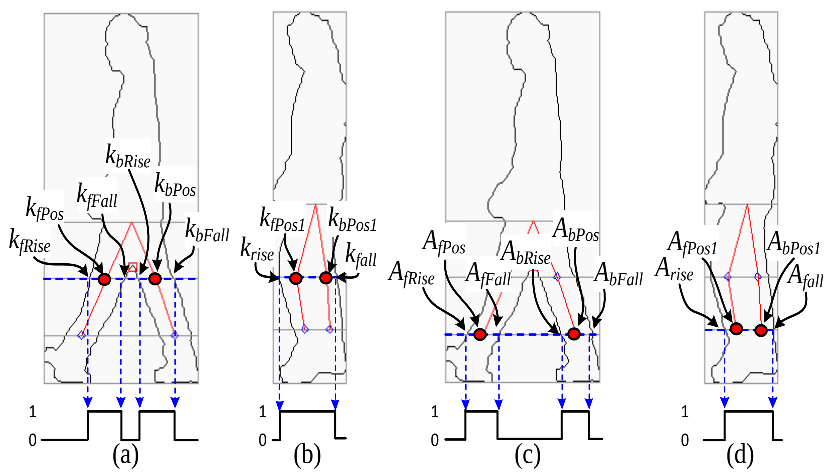

Figure 6. (a) Knee positions on normal silhouette; (b) Knee positions on occluded silhouette; (c) Ankle positions on normal silhouette; (d) Ankle positions on occluded silhouette.

- **Step 5:** determine the joint angular trajectory from two joints as illustrated in Figure 7(a). The joint angular trajectory is computed using the following equation:

$$\theta = \tan^{-1}\left(\frac{p2_x - p1_x}{p2_y - p1_y}\right) \tag{16}$$

where $p1_x$ and $p2_x$ are the x-coordinates of joint p1 and p2, respectively, and $p1_y$ and $p2_y$ are the y-coordinates of joint p1 and p2, respectively.

In total, five joint angular trajectories have been extracted. These angular trajectories are hip angular trajectory (θ_1), front knee angular trajectory (θ_2), back knee angular trajectory (θ_3), front ankle angular trajectory (θ_4) and back ankle angular trajectory (θ_5).

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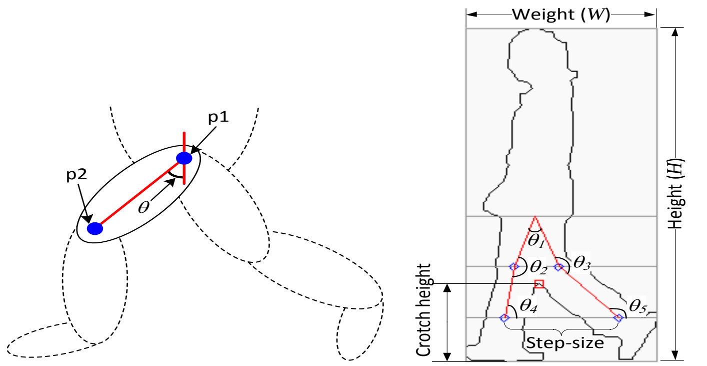
The Euclidean distance between both ankles is determined to obtain the subject's step-size (*S*). Crotch height (*CH*), the Euclidean distance between the subject's crotch and the floor is measured. If the crotch height is lower than the knee height, it is reduced to zero, as the crotch is considered occluded. Figure 7(b) shows nine gait features extracted from a human silhouette.



(a) (b)

Figure 7. (a) Joint angular trajectory computation; (b) Nine extracted gait features.

3.3. Features smoothing and normalization

As the presence of outliers and noise in the extracted features would hinder the classification process, Gaussian filter with sigma values (σ) equal to 1.5 is applied to remove them.

Feature normalization is an important process before the features can be used in classification. It normalizes the individual components of the extracted features in various dimensions, so that features can be independent and standardized. Otherwise, distance measures such as Euclidean distance would indirectly allocate more weight to features with larger range than those with smaller range. Therefore, problem of biasing towards a particular feature can be avoided. In our approach, linear scaling technique [17] is employed to normalize each feature to the range between 0 and 1.

3.4. Features vector computation

To construct the feature vector, maximum hip angular trajectory (θ_1^{max}) was determined during a walking sequence. When θ_1^{max} was identified, the corresponding *S*, *W*, *H*, θ_2, θ_3, θ_4, θ_5 and *CH* were also determined. To better describe the human gait, 24 features were used to construct the feature vector as shown:

$$F = \{\theta_1^{\max}, S, W, H, \theta_2, \theta_3, \theta_4, \theta_5, CH, A^W, A^H, A^{CH}, A^{\theta_1}, A^{\theta_2}, A^{\theta_3}, A^{\theta_4}, A^{\theta_5}, A^S,$$
$$R^{AH}, R^{ACH}, R^{AS}, R^{CH}, R^H, R^S\}$$

where A^W, A^H, A^{CH}, $A^{\theta 1}$, $A^{\theta 2}$, $A^{\theta 3}$, $A^{\theta 4}$, $A^{\theta 5}$ and A^S are the average of the local maxima detected for width, height, crotch height, hip angular trajectory, front knee angular trajectory, back knee angular trajectory, front ankle angular trajectory, back ankle angular trajectory and step-size, respectively; R^{AH}, R^{ACH}, R^{AS}, R^{CH}, R^H and R^S are the ratio of A^H, A^{CH}, A^S, *CH*, *H* and *S* to *W*, respectively.

As the performance of recognition system is determined by the effectiveness of the selected features, which can maximize inter-class variance. In this context, the redundant and inappropriate features which degrade the classification rate would be found and removed. In the proposed approach, Ranker [18] is used to rank features by their individual evaluations, which helps to identify those extracted features that

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contribute positively in the recognition process. Based on the scores obtained, all twenty four features have exhibited positive contribution. Thus, all of them are used for the propose system.

3.5 Classification technique

To evaluate the performance of the propose system in gait recognition, multi-class Support Vector Machine (SVM) with Radial Basis Function kernel (RBF) was applied. This is because RBF has proven to perform better than other SVM's kernels [19].The SVM experiments were implemented by the supporting of LIBSVM package [20]. During the training stage, experiments were carried out to examine the effects on kernel's parameters such as *g* (gamma) and regularization parameter *C.* The performance evaluation was in terms of correct classification rate (CCR), true positive rate (TPR) and false positive rate (FPR).

4. Experiment and results discussion

The Oblique DB [3] and Small DB [3] databases consist of eleven subjects walking in two directions (left to right and vice versa) on an indoor track, under controlled environment with a green chroma-key backdrop. Each subject was wearing six different types of footwear (flip flops, bare feet, socks, boots, own shoes and trainers), three different type of clothing (normal or with rain coat, trenchcoat) and carrying three types of load (hand bag, barrel bag and rucksack). They were also recorded walking at three different speeds (slow, normal and fast). The Oblique DB was captured oblique (45°) from the side-view plane, while the Small DB was captured by a side-view (90°) camera.

The video was captured by progressive scan CANON camcorder at 25 frames per second. Background subtraction with threshold optimization technique that proposed by Otsu [21] has been applied to segment out the subject from the background. The generated silhouette images have the resolution of 720 (width) x 576 (height) pixels. All 3036 walking sequences under Oblique DB and 3178 walking sequences under Small DB are used during the training and testing stages.

Ten folds cross validation for this paper, where the feature vectors generated from the gait database were randomly divided into ten disjoint subsets, nine subsets used for analysis training and one subset is used for validation. The cross-validation process was iterated for ten turns with features vectors of each disjointed subset channeled into classifiers as the validation test. The results obtained from the cross validation are then averaged to produce a single correct classification rate.

4.1. View-point normalization and covariate factors evaluation

In order to assess the performance of the proposed view-point normalized technique and features extraction technique on multiple covariate factors gait database, Experiment 1 (Ep. 1) consists of walking sequences with complete 15 covariate factors from Oblique DB [3] is carried out. In addition, another five experiments have been performed on the complete 11 subjects from Oblique DB: Experiment 2 (Ep. 2) consists of walking sequences at different speeds; Experiment 3 (Ep. 3) consists of walking sequences with a variety of shoes; Experiment 4 (Ep. 4) consists of walking sequences with various load carrying; Experiment 5 (Ep. 5) consists of walking sequences with various type of clothing; Experiment 6 (Ep. 6) consists of walking sequences from normal walking condition wearing own shoes and own cloth without carrying any object. The overall results are summarized in Table 1.

4.2. Covariate factors evaluation

In order to assess the performance of features extraction technique on side-view plane gait database. Six experiments have been performed on the complete 11 subjects from Small DB [3] : Experiment 7 (Ep. 7) consists of walking sequences from the entire 15 covariate factors. Experiment 8 (Ep. 8) consists of walking sequences at different speeds; Experiment 9 (Ep. 9) consists of walking sequences with a variety of shoes; Experiment 10 (Ep. 10) consists of walking sequences with various load carrying; Experiment

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11 (Ep. 11) consists of walking sequences with various type of clothing; Experiment 12 (Ep. 12) consists of walking sequences from normal walking condition. The overall results are summarized in Table 2.

Table 1. Experiment results of Oblique DB

	Ep. 1	Ep. 2	Ep. 3	Ep. 4	Ep. 5	Ep. 6
Covariate factor group	All	Speed	Shoes	Load carrying	Clothing	Normal condition
Number of walking sequences	3036	889	1100	1115	655	241
CCR (%)	92.49	94.48	91.27	93.00	91.15	93.78
TPR (%)	92.50	94.50	91.3	93.00	91.20	93.80
FPR (%)	0.80	0.70	0.90	0.70	0.90	0.60

Table 2. Experiment results of Small DB

	Ep. 7	Ep. 8	Ep. 9	Ep. 10	Ep. 11	Ep. 12
Covariate factor group	All	Speed	Shoes	Load carrying	Clothing	Normal condition
Number of walking sequences	3178	921	1164	1127	689	241
CCR (%)	95.97	97.29	97.94	93.61	96.52	98.34
TPR (%)	96.00	97.30	97.90	93.60	96.50	98.30
FPR (%)	0.40	0.30	0.20	0.70	0.40	0.20

Table 3 shows the comparison with other approaches using Small DB. The highest CCR (95.97%) obtained from Ep. 7 outperforms the results obtained by [14, 22] that have been tested on the same database. The poorer result in [14] may be due to the requirement to manually label model template to describe joints' motion. Conversely, our results are better than [22] as we do not involve the selection or estimation of gait cycle. Furthermore, we are the only group that have tested the complete database with 11 subjects, 15 covariate factors and 3178 walking sequences comparing with [14] (10 subjects, 11 covariate factors and 440 sequences) and [22] (10 subjects, 4 covariate factors and 180 sequences).

Table 3. Comparison with other approaches employing Small DB

	Bouchrika et. al. [14]	Pratheepan et. al. [22]	Our approach
CCR (%)	73.4	86.0	96.0
Number of subjects tested	Ten	Ten	Eleven
Number of covariate factors tested	Eleven	Four	Fifteen
Number of walking sequences tested	440	180	3178

5. Conclusion

The paper presented a new multi-view gait based biometric system by employing model based approach. The joint angular trajectories can be computed from the detection of the body joints precisely. The view-point normalization technique based on perspective correction method is found effectively in normalizing oblique-view walking sequences to side-view plane. The high CCRs and TPRs, low FPRs also show that it is robust and can achieve good performance either in gait databases with various covariate factors and multiple view angles.

The view-point normalization technique used in this system was only tested in limited view angle (45^o). Further experiment is required to test the robustness technique in other view angles. Besides that,

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the proposed system is only working in good and stable lighting environment. The poor lighting environment will create bad effect on the subject segmentation and features extraction process.

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