Multi-View Gait Based Human Identification System with Covariate Analysis

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Abstract: *This paper presents a multi-view gait based human identification system. The system is able to perform well under different walking trajectories and various covariate factors such as apparel, loan carrying and speed of walking. Our approach first applies perspective correction to adjust silhouettes from an oblique view to side-view plane. Joint positions of hip, knees and ankles are then detected based on human body proportion. Next, static and dynamic gait features are extracted and smoothed by the Gaussian filter to mitigate the effect of outliers. Feature normalization and selection are subsequently applied before the classification process. The performance of the proposed system was evaluated on SOTON Covariate Database and SOTON Oblique Database from University of Southampton. It achieved 92.1% correct classification rates for both databases.*

Keywords: *Gait recognition, biometrics, human identification, covariate factors and classification.*

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1. Introduction

Gait based human identification system is automated recognition of persons based on their behavioral characteristics [9]. Human gait is a complex yet distinctive locomotive pattern which comprises synchronized movements of body parts, joints and the interaction among them [3]. Thus, it can be considered as a distinctive component for biometric. In 1973, psychological research discovery from Johannson [13] has proven that human can recognize walking friends based on the light markers that are affixed to them. Ever since then, many research works have been carried out on gait analysis and it has been proven that gait can be used to recognize people. In addition, gait is an unobtrusive biometric, which can be captured from a distance and without requiring any intervention from the user.

Performance of gait recognition system can be affected by many covariate factors such as light illumination, duration, load carrying, speed of walking, apparel of subject and camera view-point. Therefore it makes gait recognition system as a challenging issue. Lately most research works focused on the view-invariant gait recognition system. As in realistic surveillance situation, subjects are expected to walk in various directions so as to reach the destination.

In this paper, we propose a gait based human identification system which consists of four stages: 1). view normalization to cope with the changes in camera viewing angle; 2). gait feature extraction to extract the required gait feature from normal and occluded silhouettes; 3). feature normalization and selection to determine the significant features; 4). four classification techniques to show the effectiveness of the extracted gait features in human identification.

The performance of the proposed system was assessed in terms of Correct Classification Rate (CCR) on two databases from the University of Southampton. The first database is SOTON Oblique Database (Oblique DB) [22], which consists of walking sequences that are captured in oblique view. Another database is SOTON Covariate Database (Small DB) [22], which consists of fifteen covariate factors such as apparel, load carrying and speed of walking, as these changes portray a realistic situation.

Despite many research works on gait databases from the University of Southampton, there is no study of gait classification on Oblique DB. 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, one with oblique view-point and another one with fifteen covariate factors.

The rest of this paper is organized as follows: Section 2 reviews the background on gait features extraction approaches and related works on multi-view normalization. In section 3, the proposed system is presented. In section 4, experimental setups and the corresponding results discussion. Finally, section 5 concludes the paper.

2. Related Works

Numerous research works have been carried out in gait based human identification. This section reviews the related approaches on gait features extraction and multi-view normalization.

2.1. Gait Features Extraction Approaches

Basically, gait features extraction approaches are separated into two major approaches, namely model-based approach and model-free approach. Model-based approach usually mimics the body structures as blobs or rectangles and matches them as model components [4, 6, 7]. It incorporates knowledge of the body outline and gait motion during the extraction process. The gait features are directly extracted by determining joint positions from the model components, rather than correlating with other measures (such as motions of other unrelated objects). Thus, the noise effects from the surrounding environment can be removed easily. However, it creates many parameters and end up with a complex model.

Conversely, model-free approach usually distinguishes the entire body by a concise representation such as silhouette or skeleton without considering the underlying structure [3, 19]. The advantages of this approach are fast processing, low computational cost and small data storage. However, the performance of this approach is intensely affected by the background noise or covariate factors such as the changes of the subject's apparel, load carrying and shooting camera view-point.

As gait includes the static body parameters and the dynamics of human walking stance, we present a model-free approach 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, which are normally disastrous for other model-free approaches.

2.2. Multi-View Normalization

There are three major approaches in multi-view normalization, namely view invariant gait feature, view synthesis and view transformation.

In the first approach, researchers intended to obtain gait features that are invariant to changes in walking trajectory and camera view-point. Jean *et al.* [12], applied homograph transformations to normalize trajectories to side-view plane. Bouchrika *et al.* [7], developed rectification method to normalize extracted gait features from various view-points. Kale *et al.* [14], used perspective projection and optical flow to synthesize images from arbitrary-view. Lee *et al.* [16], constructed multi-linear generative model to decompose gait parameters with view-point factors. Nevertheless these techniques can only be applied in limited viewing angles and the gait features extraction might be disrupted by apparel or self-occlusion.

In the second approach, researchers restructured gait by 3D information from calibrated multiple view-point cameras. Bodor *et al.* [5], employed image-based rendering technique to reconstruct gait. Shakhrovich *et al.* [21], constructed 3D visual hull model to render virtual views. Both techniques are able to generate precise synthetic images, but they involve heavy computational resource and complicated technical setup due to camera calibration.

In the third approach, researchers computed the mapping relationship between gait features and the subject across view-points by reconstructing the gait features into the same view. Makihara *et al.* [17], applied view transformation model to acquire frequency domain of gait features by using Fourier operation. Kusakunniran *et al.* [15] and Bashir *et al.* [2], utilized Gait Energy Image to extract gait features that comprise motion frequency, temporal and spatial changes of the walking subject. Nevertheless this approach propagates noise during the reconstruction process, which degrades the recognition performance.

We employed perspective correction for view invariant gait feature extraction, which is comparable to [12]. 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. In addition, our technique does not require the detection of half gait cycle. Besides that, our approach is free from view synthesizing and camera calibration processes, it is more straightforward and faster than the view synthesis and view transformation approaches.

3. Methodology

According to Murray [18], it is impractical to measure pelvic and thorax rotations and they were found to be inconsistent for a given individual in repeated tests. Thus, we consider gait features from the lower limbs only.

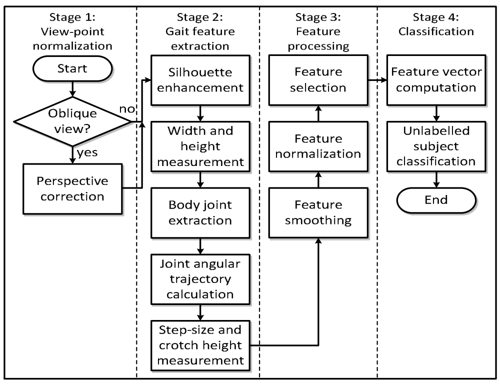


Figure 1. Flowchart of the proposed system.

The first stage in the proposed approach is view-point normalization in which perspective correction technique is employed. As our approach is free from view synthesizing and camera calibration processes, it is more straightforward, faster and simpler than the view synthesis and view transformation approaches.

Our method for gait feature extraction does not attempt to detect both legs. Thus, it can handle self-occluded silhouettes and those occluded by apparels or load carrying, which are normally disastrous for view invariant techniques. To mitigate the effect of outliers, all the extracted features are smoothened by the Gaussian filter before their average values are applied in the later processes. Finally, the smoothened features are normalized to eliminate any biasing towards a particular feature. The flowchart in Figure 1 illustrates the flow of the processes involved.

3.1. View-Point Normalization

To normalize the oblique walking sequence into the side-view plane, the perspective correction technique is employed. Figure 2 shows the result of superimposing all silhouettes in a walking sequence into a single image. In order to apply perspective correction, line A and B are drawn horizontally according to the highest and lowest point among the silhouettes.

As the normal gait cycle is periodic, a sinusoidal line is formed when the highest points of all silhouettes in a walking sequence are connected. The perspective correction technique consists of two stages: vertical and horizontal adjustments. For vertical adjustment, line C is drawn by connecting the first peak and the last peak of the sinusoidal line, as shown in Figure 2. 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.

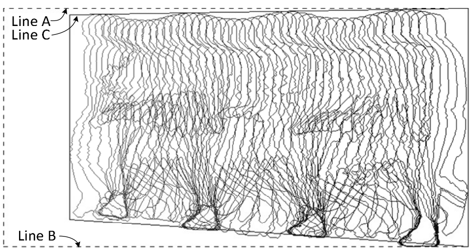


Figure 2. Superimposed silhouettes from one walking sequence.

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:

$$W_2 = \frac{H_2}{H_1} W_1 \tag{1}$$

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

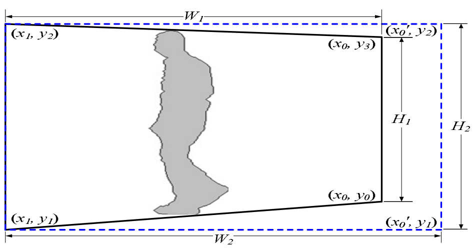


Figure 3. Dimensions of a human silhouette.

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

$$g(x, y) = f(x', y') = f(a(x, y), b(x, y)) \tag{2}$$

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:

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

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

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

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

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

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 4 shows the results of superimposing the silhouettes after the correction.

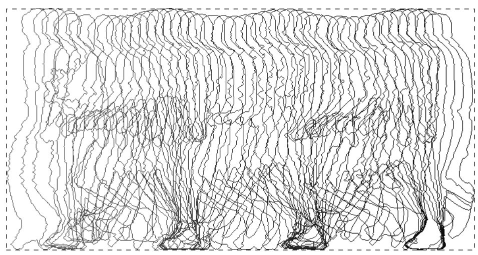


Figure 4. Superimposed silhouettes after perspective correction.

3.2. Gait Features Extraction

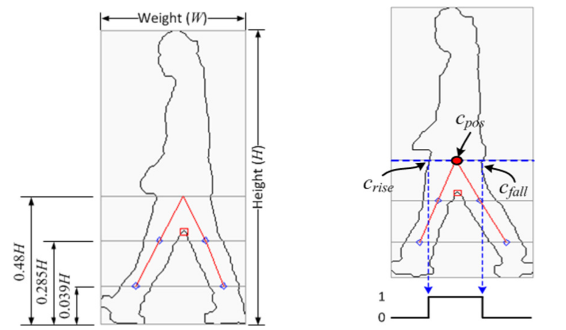
The general processes for gait feature extraction are described as follows:

- *Phase 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 7×7 diamond shape structuring element.
- *Phase 2:* measure the width (W) and height (H) of the subject obtained from the bounding box of the enhanced silhouette. Figure 5-a shows the two extracted gait features.

- *Phase 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 [8].
- *Phase 4:* determine the horizontal center position of the hip by calculating the midpoint between both edges using the following equation:

$$c_{pos} = c_{rise} + \frac{c_{fall} - c_{rise}}{2} \quad (7)$$

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.



a) The width and height of a human silhouette.

b) Image profile of horizontal line drawn through the hip.

Figure 5. Dimension of human silhouette and center of hip detection.

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:

$$k_{fPos} = k_{fRise} + \frac{k_{fFall} - k_{fRise}}{2} \quad (8)$$

$$k_{bPos} = k_{bRise} + \frac{k_{bFall} - k_{bRise}}{2} \quad (9)$$

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 Figure 6-b. The horizontal center knee positions are 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.

$$k_{fPos1} = k_{rise} + \frac{c_{pos} - k_{rise}}{2} \quad (10)$$

$$k_{bPos1} = c_{pos} + \frac{k_{fall} - c_{pos}}{2} \quad (11)$$

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 Figure 6-c. The horizontal center ankle positions can then be determined by using the following equations:

$$A_{fPos} = A_{fRise} + \frac{A_{fFall} - A_{fRise}}{2} \quad (12)$$

$$A_{bPos} = A_{bRise} + \frac{A_{bFall} - A_{bRise}}{2} \quad (13)$$

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 Figure 6-d. The horizontal center ankle positions can then be determined by finding the midpoint between both edges using the following equations:

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

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

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}.

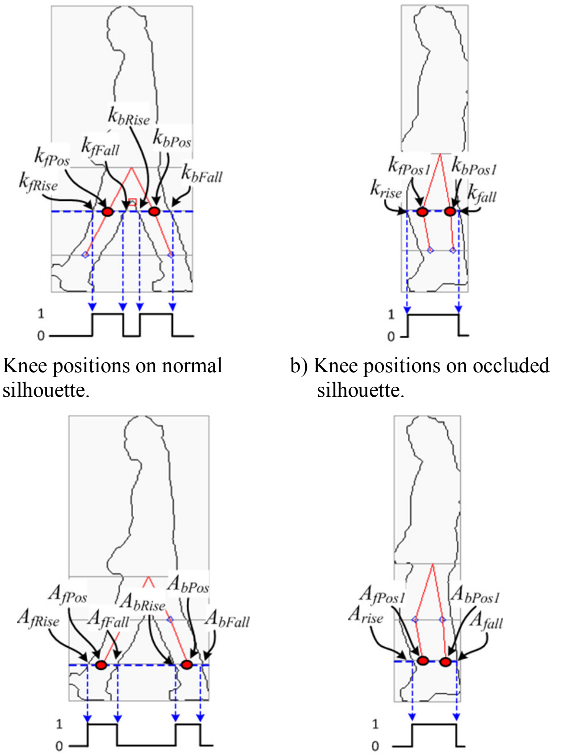
- *Phase 5:* determine the joint angular trajectory from two joints as illustrated in Figure 7-a. The joint angular trajectory (θ) is determined by the following equations:

$$\phi_1 = \tan^{-1}\left(\frac{p2_x - p1_x}{p2_y - p1_y}\right) \quad (16)$$

$$\phi_2 = \tan^{-1}\left(\frac{p3_x - p1_x}{p3_y - p1_y}\right) \quad (17)$$

$$\theta = \phi_1 + \phi_2 \quad (18)$$

where $p1_x$, $p2_x$, $p3_x$ and $p1_y$, $p2_y$, $p3_y$ are the x-coordinates and y-coordinates of joint $p1$, $p2$ and $p3$, respectively.



a) Knee positions on normal silhouette.

b) Knee positions on occluded silhouette.

c) Ankle positions on normal silhouette.

d) Ankle positions on occluded silhouette.

Figure 6. Detection of joijnt positions.

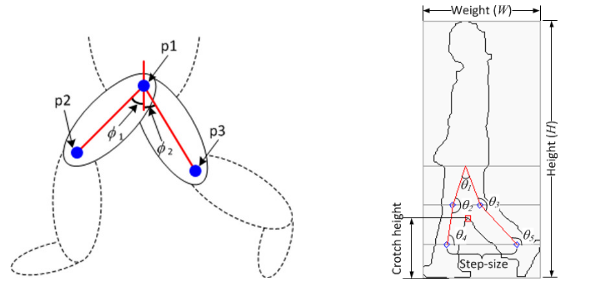
In total, five joint angular trajectories have been extracted. These angular trajectories are hip angular trajectory (θ_1), front knee angular trajectory (θ_2), back knee angular trajectory (θ_3), front ankle angular trajectory (θ_4) and back ankle angular trajectory (θ_5).

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 silhouette.

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 are used in classification. It normalizes the individual extracted feature 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 [1] is employed to normalize each feature to the range between 0 and 1.



a) Joint angular trajectory computation.

b) Nine extracted gait features.

Figure 7. Calculation of joint angular trajectory and extracted gait features.

3.4. Features Selection

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 below:

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

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.

In the proposed approach, Ranker [11], is used to rank features by their individual evaluations, which helps to identify those extracted features that 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 in our approach.

3.5. Classification Techniques

To evaluate the performance of our approach, four classification techniques were applied to find correct classification rate and to verify the consistency of the results. Multi-class Support Vector Machine (SVM), Fuzzy k-Nearest Neighbor (Fuzzy k-NN) with euclidean distance metrics, Linear Discriminant Analysis (LDA) and Back-Propagation Artificial Neural Network (BPANN) were employed.

For SVM, experiments were carried out to examine the effects on kernel functions-Linear (Ln), Polynomial (Poly) and Radial Basis Function (RBF).

The kernel's parameters such as *d* (degree), *g* (gamma), *r* (coefficient) and regularization parameter *C* were trained. For Fuzzy k-NN, numerous numbers of neighbors, *k* has been tested. For BPANN, various numbers of hidden layers have been trained as well.

4. Experimental Results and Discussion

The Oblique DB and Small DB databases consist of eleven subjects walking in two directions on an indoor track, under controlled environment with a green chroma-key backdrop. The former was captured oblique (45°) from the side-view plane, while the latter was captured by a side-view (90°) camera. Each subject was wearing a variety of footwear (flip flops, bare feet, socks, boots, own shoes and trainers), clothes (normal or with rain coat, trenchcoat) and carrying various objects (hand bag, barrel bag and rucksack). They were recorded walking at various speeds.

The video was captured by progressive scan CANON camcorder at 25 frames per second. The generated images have the resolution of 720 (width)x 576 (height) pixels. All the subjects' walking sequences under normal condition in Oblique DB are used to test the proposed view invariant gait feature technique. For covariate analysis, all walking sequences from Small DB with complete 15 covariate factors are used.

As cross validation process is important to evaluate the accuracy of the classification performance. Ten folds cross validation was employed 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 10 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. The experiment was carried out on four classification techniques with various optimization parameters that obtained during the training.

4.1. View Invariant Analysis

In order to assess the performance of the proposed view-point normalized technique, three experiments were carried out to measure the CCR from Oblique DB and Small DB: Experiment 1 (Exp. 1) consists of 241 walking sequences from Oblique DB on normal condition; Experiment 2 (Exp. 2) consists of 713 walking sequences from Oblique DB and Small DB on normal condition; Experiment 3 (Exp. 3) consists of 3419 walking sequences from Oblique DB on normal condition and Small DB on complete 15 covariate factors. We employed the oblique walking sequences and their normalized walking sequences to demonstrate the improvement that can be achieved. Figures 8, 9 and 10 show the overall results.

From Figure 8, the best CCR obtained is 92.1% (from LDA), which showed an improvement of 8.7% by using the proposed view-point normalized technique on the oblique walking sequences.

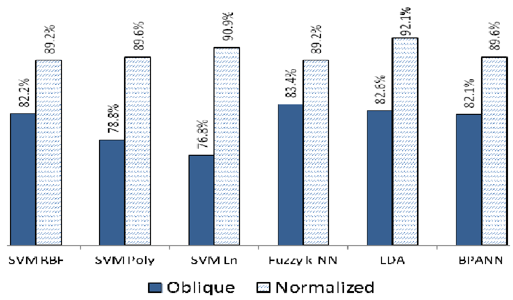


Figure 8. Correct classification rates for Exp. 1.

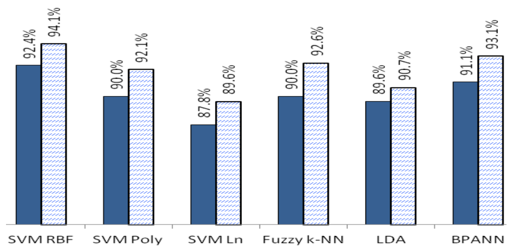


Figure 9. Correct classification rates for Exp. 2.

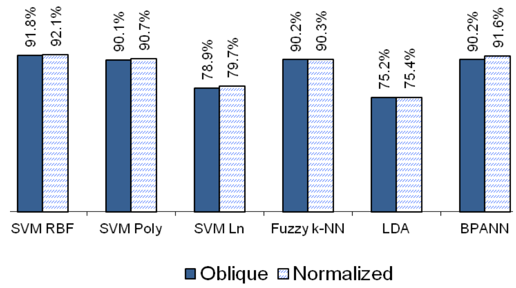


Figure 10. Correct classification rates for Exp. 3.

From Figure 9 and 10, there are only small improvements of 1.5% and 0.3% obtained comparing oblique walking with normalized walking sequences. This is due to the small number of oblique walking sequences, which is insignificant when compared to Small DB. Nevertheless, the high CCRs of 94.1% and 92.1% (from SVM RBF) have proved that human identification is effective.

From these three experiments, we observed that LDA outperformed other classifiers when the number of testing cases and the differences between class covariance matrices are small [10]. We noticed that the non-linear SVM (RBF or Poly kernel) outperforms linear SVM (Ln kernel). As our generated gait feature vectors are not linear, the kernel trick in the non-linear SVM allows the algorithm to fit the maximum-margin hyperplane in a transformed feature space [20].

4.2. Covariate Analysis

In order to evaluate the performance of the silhouette joint detection technique on multiple covariate factors gait database, six experiments have been performed on the complete 11 subjects from Small DB: Experiment 4 (Exp. 4) consists of 921 walking sequences at different speeds (slow, normal and fast); Experiment 5 (Exp. 5) consists of 1164 walking sequences with a variety of footwear (flip flops, bare feet, socks, boots, own shoes and trainers); Experiment 6 (Exp. 6) consists of 1127 walking sequences with various objects carrying (hand bag, barrel bag slung over shoulder or carried by hand, and rucksack); Experiment 7 (Exp. 7) consists of 689 walking sequences with various type of clothes (normal or with rain coat, trenchcoat); Experiment 8 (Exp. 8) consists of 241 walking sequences from normal walking condition wearing own shoes and own cloth without carrying any object; Experiment 9 (Exp. 9) consists of 3178 walking sequences from the entire 15 covariate factors as stated above.

Since SVM with RBF kernel gave the best recognition rate during the experiments in view invariant analysis, the experiments for covariate analysis were carried out using only SVM with RBF kernel. The overall results are summarized in Figure 11.

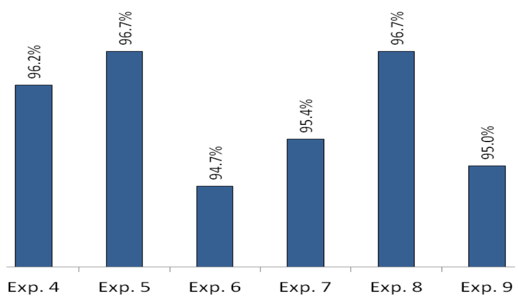


Figure 11. Correct classification rates for covariate analysis.

Table 1 shows the comparison with other approaches using Small DB. The highest CCR (96.0%) from Exp. 9 outperforms the results obtained by [7, 19] that have been tested on the same database. The poorer result in [7] may be due to the requirement to manually label model template to describe joints' motion. Conversely, our results are better than [19] as we do not involve the selection 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 [7] (10 subjects, 11 covariate factors and 440 sequences) and [19] (10 subjects, 4 covariate factors and 180 sequences).

Table 1. Comparison with other approaches employing small DB.

	Bouchrika et. al.[7]	**Pratheepan et. al.[19]**	**Our Approach**
CCR (%)	73.4	86.0	96.0
No. of subjects	Ten	Ten	Eleven
Covariate factors	Eleven	Four	Fifteen
No. of walking sequences	440	180	3178
Feature extraction technique	Elliptic Fourier Descriptor	Dynamic Static Silhouette Template	Silhouette Joints Detection
Classification technique	k-NN	SVM	SVM

5. Conclusions

A new multi-view gait analysis technique based on the perspective correction has been developed to automatically extract gait features based on joint angular trajectories. This method is found to be more effective as it is capable of identifying the body joints even from self-occluded silhouettes or those occluded by apparels. In addition, the high CCRs also show that the proposed method is robust and can perform well either in gait databases with oblique view or various covariate factors. Nevertheless, this method was only validated using SOTON Small DB and oblique DB.

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