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Human Identification Based on Extracted Gait Features

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Abstract. This paper presents a human identification system based on automatically extracted gait features. The proposed approach consists of three parts: extraction of human gait features from enhanced human silhouette, smoothing process on extracted gait features and classification by three classification techniques: fuzzy k-nearest neighbour, linear discriminate analysis and linear support vector machine. The gait features extracted are height, width, crotch height, step-size of the human silhouette and joint trajectories. To improve the classification performance, two of these extracted gait features are smoothened before the classification process in order to alleviate the effect of outliers. The proposed approach has been applied on SOTON covariate database, which comprises eleven subjects walking bidirectional in a controlled indoor environment with thirteen different covariate factors that vary in terms of apparel, walking speed, shoe types and carrying objects. From the experimental results, it can be concluded that the proposed approach is effective in human identification from a distance over various covariate factors and different classification techniques.

Keywords: human identification, gait analysis, Gaussian filter, covariate factors and classification.

1 INTRODUCTION

Human identification based on biometrics is to distinguish individuals based on their physical and/or behavioural characteristics such as face, fingerprint, gait, iris and spoken voice. Biometrics are getting significant and widely acceptable today because they are unique and one will not lose or forget them over time. Gait is a complex locomotion pattern which involves synchronised movements of body parts, joints and the interaction among them [1]. Basically, every individual has his/her own walking pattern. Thus, it can be considered as a unique feature for biometric. In 1973, psychological research from Johannson [2] has proved that human can easily recognise walking friends based on the light markers that are attached to them. Even since then, much research has been carried out on gait analysis and it has been proven that gait can be used to identify people. As a result, gait has become one of the latest promising biometrics.

Gait offers the ability to identify people at a distance when other biometrics are obscured. Furthermore, it does not require any intervention from the user and can be captured by hidden cameras or synchronised closed-circuit television (CCTV) cameras, which do not require any direct contact with feature capturing device unlike other biometrics. This is also motivated by the increasing number of CCTV cameras that have been installed in many major cities, in order to monitor and prevent crime by identifying the criminal or suspect.

The performance of gait as biometric can be affected by covariate factors, such as light illumination during video capturing, imperfect object segmentation from background, changes in the subject appearance, nature of ground and different camera viewing angle with respect to the subjects. This paper aims to concentrate on extracting gait features regardless of covariate factors such as apparel, carrying objects, shoe types and walking speed of subject.

The remainder of this paper is organised as follows. Section 2 describes the previous works on gait analysis and its classifying tools. Section 3 discusses the proposed system overview. Section 4 provides the details of gait features extraction and Linear LDA, Fuzzy KNN and Linear SVM model. Section 5 illustrates the experimental set up and Section 6 presents the experiment results. Finally, Section 7 concludes the paper.

2 PREVIOUS WORKS

Basically, gait analysis can be divided into two major categories, namely model-based approach and model-free approach. Model-based approach generally models the human body structure or motion and extracts the features to match them to the model components. It incorporates knowledge of the human shape and dynamics of human gait into an extraction process. The gait dynamics are extracted directly by determining joint positions from model components, rather than inferring dynamics from other measures (such as movement of other objects). Thus, the effect of background noise can be eliminated. Research examples of this approach are static body parameters [3], thigh joint trajectories [4], dual oscillator [5], articulated model [6], 2D stick figure [7] and elliptic Fourier descriptors [8] [9].

The advantages of this approach are the ability to derive dynamic gait features directly from model parameters. It is free from background noise as well as the effect of different subject's apparel or camera shooting viewpoint. However, it creates many parameters from extracted gait features and hence resulting in a complex model. Due to that reason, the computational time, date storage and cost are extremely high due to its complex searching and matching procedures.

Conversely, model-free approach generally differentiates the whole motion pattern of the human body by a concise representation such as silhouette without considering the underlying structure. Normally, its parameters are obtained from the static gait features like centroid, width and height of the silhouette. Research examples of this approach are self similarity Eigen gait [1], key frames analysis [10], spatial-temporal distribution characterization [11], kinematic features [12], unwrapped silhouette [13], higher order correlation [14], video oscillations [15] and gait sequences [16].

The advantages of this approach are speedy processing, low computational cost and small data storage. However, the performance of this approach is highly affected by the background noise and the changes of the subject's apparel.

Gait classification can be defined as human identification based on the variation and characteristics of a subject walking motion. From the gait classification research record, classifier that have been applied are: K-nearest neighbor (KNN) [1, 4, 5, 6, 8, 9, 10, 13, 15], back-propagation neural network algorithm [7], Baseline algorithm [11], Genetic algorithm [12], Fisher discriminant analysis [14], Hausdorff distance [16] and Support Vector Machine [16]. Most of the gait classification applied KNN. This is mainly due to its simplicity and ability to handle large data set.

Since gait includes both the physical appearance of body and dynamics of human walking stance [17], this paper presents a model-free silhouette based approach to extract the static gait features (height and width, step size) and dynamic gait features (joint trajectories). This concept of joint trajectory calculation is found faster in process and less complicated than the model-based method like 2D stick figure by Yoo et al. [7], articulated model by Wagg et al. [6] and elliptic Fourier descriptors by Bouchrika et.al. [8] [9]. As there are only a few studies on gait classification using the covariate database [8], [9],[11] [16], this research work aims to evaluate the recognition rate of the walking subjects with different covariate factors. In addition, three classifiers were employed to validate the consistency of the proposed approach.

3 OVERVIEW OF THE SYSTEM

This paper presents a model-free approach to extract the gait features by dividing human silhouette into six body segments and applying Hough transform to obtain the joint trajectories.

For the gait feature extraction, morphological opening is first applied to reduce background noise on the original images downloaded from SOTON covariate database provided by University of Southampton [18]. Each of the human silhouettes is then measured for its width and height. Next, each of the enhanced human silhouettes is divided into six body segments based on anatomical knowledge [19]. Morphological skeleton is later applied to obtain the skeleton of each body segment. The joint trajectories are obtained after applying Hough transform on the skeletons. Step-size, which is the distance between the bottom of both feet and crotch height, which is the distance between the subject's crotch and the floor, are also determined. The dimension of the human silhouette, step-size, crotch height and two joint trajectories from the body segments are then used as the gait features for classification.

To mitigate the effect of outliers, both thigh trajectory and crotch height are smoothened by Gaussian filter before their average values are applied in the classification process. Even though the smoothing process reduces the peak value of the data, it is not affecting the uniqueness of gait features. In addition, it also reduces the outlier of the data. This is proven as better gait recognition results have been obtained as compared to the results without smoothing. Fig. 1 summarizes the process flow of the proposed approach.

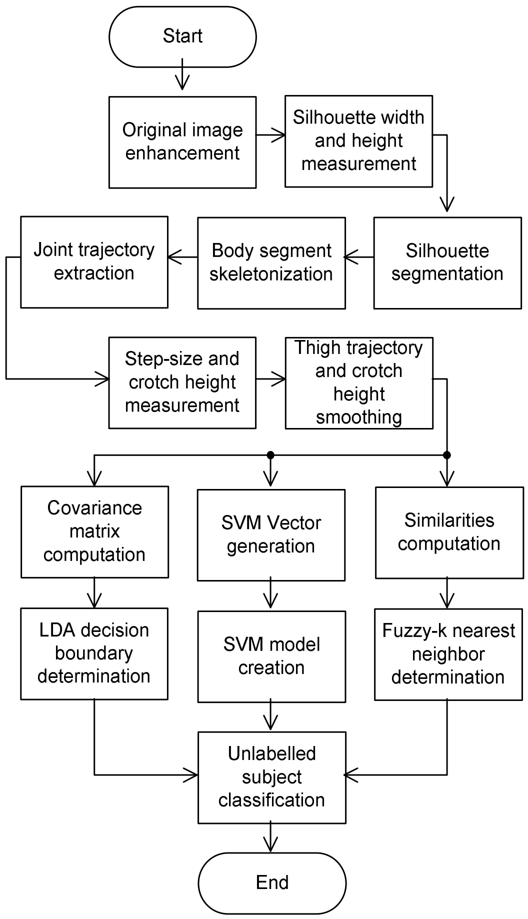


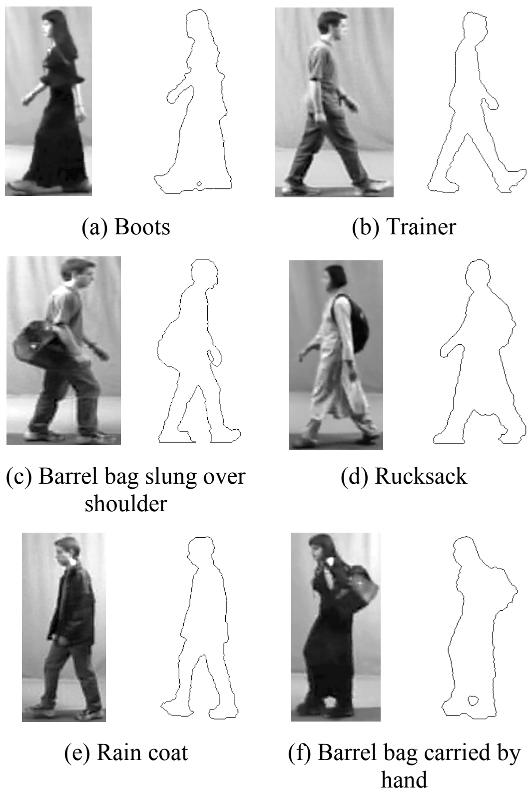
Fig.1. Flow chart of the proposed approach

4 EXTRACTING THE GAIT FEATURES

The original human silhouette images are obtained from the well-known SOTON covariate database [18]. It consists of eleven walking subjects walking bidirectional on an indoor track, with a green chroma-key backdrop.

The video was captured by CANON camcorders with 25 frames per second. Background subtraction approach has been applied to segment out the subject from the background. The generated silhouette images have the resolution of 720 x 576 (width x height) pixels.

There are a total of eleven subjects in the database: eight males and three females. All the males and one of the females are wearing trousers, whereas another two females are wearing attires that cover the legs, full blouse and shalwar kameez. These impose a challenge into this research, as there are occlusion at knee, thigh, and hip joints on their silhouettes. Each subject was captured wearing a variety of shoe types, apparel and carrying various objects. They were also recorded walking at different speed. This database was used to evaluate the recognition rate of the walking subjects with different covariate factors. The examples of subjects with different apparel, shoe types and carrying various objects can be found in Fig. 2.



(a) Boots (b) Trainer

(c) Barrel bag slung over shoulder (d) Rucksack

(e) Rain coat (f) Barrel bag carried by hand

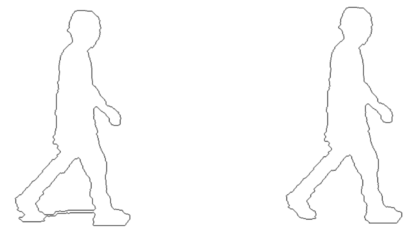
Fig.2. Subjects with different apparel, shoe types and carrying various objects. Left: original image. Right: silhouette image.

4.1 Original Image Enhancement

In most of the human silhouette images, shadow is found especially near to the feet. It appears as part of the subject body in the human silhouette image as shown in Fig. 2. The presence of the artifact affects the gait feature extraction and the measurement of joint trajectories. The problem can be reduced by applying a morphological opening operation with a 7×7 diamond shape structuring element, as denoted by

$$A \circ B = (A \ominus B) \oplus B) \qquad (1)$$

where A is the image, B is the structuring element, $\ominus$ represents morphological erosion and $\oplus$ represents morphological dilation. The opening first performs erosion, followed by dilation. Fig. 3 shows the original and enhanced images.



(a) Original image (b) Enhanced image

Fig.3. Original and enhanced images after morphological opening

4.2 Measurement of Width and Height

The width and height of the subject from each frame during the walking sequences are measured from the bounding box of the enhanced human silhouette, as shown in Fig. 4(a). These two features will be used for gait analysis in the later stages.

4.3 Dividing Enhanced Human Silhouette

Next, the enhanced human silhouette is divided into six body segments based on anatomical knowledge [19] as shown in Fig. 4(b). Where *a* represents head and neck, *b* represents torso, *c* represents right hip and thigh, *d* represents right lower leg and foot, *e* represents left hip and thigh and *f* represents left lower leg and foot.

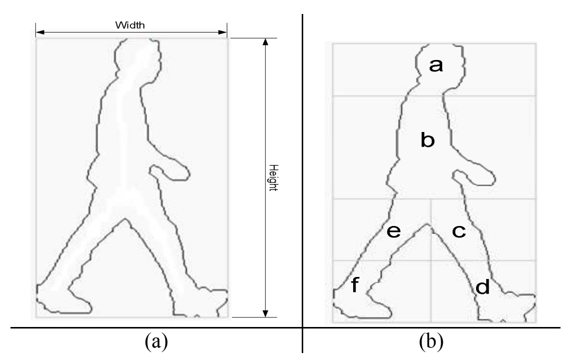


Fig. 4. (a) Width and height of human silhouette. (b) Six body segments.

4.4 Skeletonization of Body Segments

To reduce the segments to a simpler representation, morphological skeleton is used to construct the skeleton from all the body segments. Skeletonization involves consecutive erosions and opening operations on the image until the set differences between the two operations are zero. The operations are given as:

Erosion	Opening	Set differences	
$A \ominus kB$	$(A \ominus kB) \circ B$	$(A \ominus kB) - ((A \ominus kB)) \circ B$	(2)

where A is an image, B is the structuring element and k is from zero to infinity. Fig. 5 shows some examples of skeleton of the body segments.

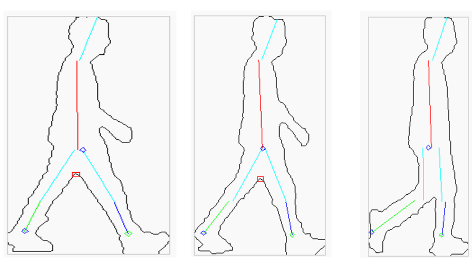


Fig. 5. Example of skeleton of the body segments from a series of frames

4.5 Joint Trajectory Extraction

To extract the joint trajectory for each body segment, Hough transform is applied on the skeleton. Hough transform maps pixels in the image space to straight lines in the parameter space. The skeleton in each body segment, which is the most probable straight line, is indicated by the highest intensity point in the parameter space.

4.6 Measurement of Step-size and Crotch Height

To obtain the step-size of each walking frame, Euclidean distance between the bottom ends of both feet are measured. To obtain the crotch height, the distance between the subject's crotch and the floor is measured. If the crotch height is lower than the knee height, it will be deduced to 0. Fig. 6 shows all the gait features extracted from a human enhanced silhouette, where θ_3 is the thigh trajectory, calculated as:

$$\theta_3 = \theta_2 - \theta_1 \qquad (3)$$

where θ_2 is the front knee trajectory and θ_1 is the back knee trajectory

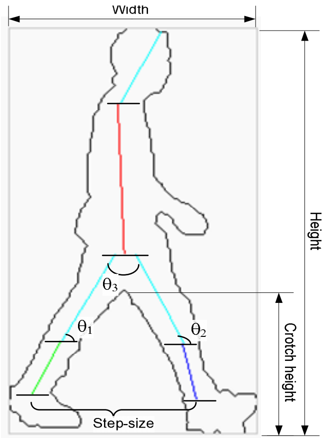


Fig. 6. The entire extracted gait features

4.7 Smoothing Technique

It can be observed from the collected gait features that the changes in crotch height and thigh trajectory are sinusoidal over time. However, the curves for crotch height and thigh trajectory are uneven due to the presence of outliers. Fig. 7 shows an example of the original thigh trajectory over time. Therefore, smoothing is required to reduce the effect of these outliers.

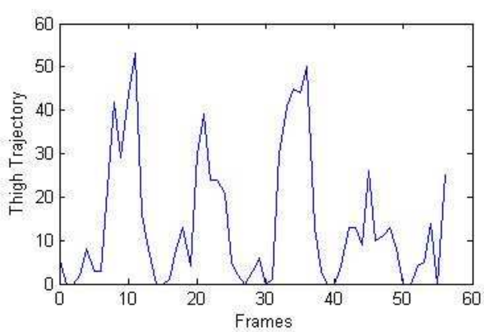


Fig. 7. Changes in original thigh trajectory over time

Therefore, Gaussian filter has been applied to overcome those outliers. It is designed to give no overshoot to a step function input while minimizing the rise and fall time. It generates a bell-shaped curve after the smoothing process. The operation is shown as:

$$y_j' = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y_j-\mu)^2}{2\sigma^2}} \quad (4)$$

where parameters μ and σ^2 are the mean and the variance, and y is the raw data. Fig. 8 shows the smoothed thigh trajectory by using Gaussian filter with σ of 1.4.

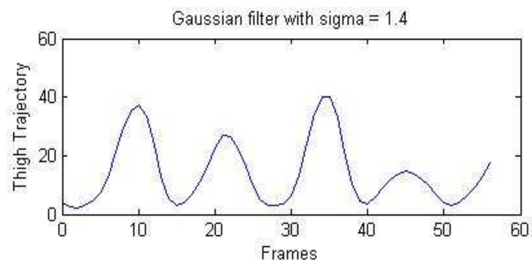


Fig.8. Smoothed thigh trajectory over time by using Gaussian filer with σ of 1.4

4.8 Support Vector Machine Model

After feature extraction, multiclass Support Vector Machine (SVM) is employed for classification. For the SVM technique used in this paper, we refer to the description by C.J.C. Burges [20] and implement the SVM experiments using the LIBSVM package [21].

SVM is based on structural risk minimization principle, which optimises the training data to create machine learning model. Given a training set of instance-label pairs: (x_i, y_i) , $i = 1, 2\ldots, l$ where $x_i \in R^n$ and $y_i \in \{1,-1\}^i$ (n and l denote the space dimensions and size of training set). In this case if x belongs to positive category then y_i =1; if x belongs to negative category then y_i = - 1.

Basically SVM is a classifier that focuses on finding an optimal hyperplane to separate different classes by solving the following quadratic optimization problem:

$$\text{Minimise: } \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}\xi_i \qquad (5)$$

Subject to $y_i(w \bullet x_i) + b \geq 1 - \xi_i, \xi_i \geq 0$.
Where, w, b and ξ_i denote weight vector for learned decision hyperplane, model bias and slack variable. Parameter C is penalty factor which keeps the balance of classification accuracy.

SVM classifies the test instance, X based on the following decision function:

$$f(x) = \text{sign}\left(\sum_{x_i \in sv} \alpha_i y_i K(x_i, x) + b\right) \qquad (6)$$

where sv, α_i and $K(x_i, x)$ represent support vectors, Lagrange multipliers and kernel function. The value of $f(x)$ denotes the distance of the test instance from the separating hyperplane and the sign indicates the class label. For this paper, we applied linear SVM, where $K(x_i, x)$ is equal to $x_i \bullet x$. Furthermore, different values of C were tested in the experiment.

4.9 Fuzzy k-Nearest Neighbour Model

Fuzzy k-Nearest Neighbour (KNN) is based on the identification of the k-nearest neigbhours in the feature space. The relationship between the training and testing data is determined by using fuzzy membership function as defined by:

$$u_n(\bar{x}) = \frac{\sum_{x \in KNN} u_n(x)\left(\frac{1}{\|\bar{x} - x\|^{\frac{2}{m-1}}}\right)}{\sum_{x \in KNN}\left(\frac{1}{\|\bar{x} - x\|^{\frac{2}{m-1}}}\right)} \qquad (7)$$

where m, $\bar{x}$, x and $u_n(x)$ represent the scaling factor, unlabelled subjects, labelled subjects and x's membership of class n.

The membership value of 1 denotes the nearest of all k-neigbhours while the membership value near 0 denotes poor k-neigbhours. Integration of fuzzy with KNN reduces the bias of the classification for certain classes.

Through the fuzzy component, the KNN will label the appropriate class to the testing subjects by summing up the similarities between training subjects. The flow of the technique for the identification of the subjects is:

Step 1: Compute the Euclidean distance between the unlabelled subjects and all labelled or training subjects. The distance between a testing subject, x_i and training subject, x_j is defined as:

$$D(x_i, x_j) = \sqrt{\sum_{j=1}^{k}(x_i - x_j)^2} \qquad (8)$$

Step 2: Sort the subjects based on the similarity and identify the k-nearest neighbors, where k-nearest neighbors, KNN $= \{x_1, x_2, ..., x_k\}$

Step 3: Compute the membership value for every class based on Eq. 7.

Step 4: Classify the unlabelled subject to the class based on the maximum sum of membership values for the nearest neigbhours as shown in Fig. 9 for five nearest neighbourhoods. The membership values on the lines represent the similarities between unlabelled and labelled subjects. The sum of the membership values for Class A, $u_n(x_A)$ = 0.9 and for Class B, $u_n(x_B)$ = 0.8. Since $u_n(x_A)$ is more than $u_n(x_B)$, so the unlabelled subject is classified into Class A.

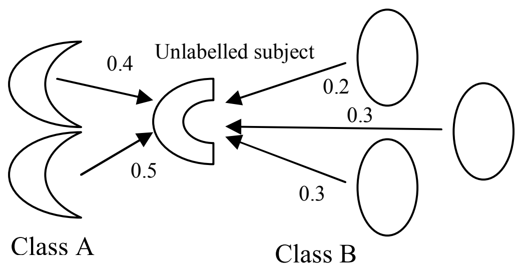


Fig. 9. An illustration for KNN with k = 5

4.9 Linear Discriminant Analysis Model

For a set of sample patterns: $\{x_1, x_2, \ldots, x_N\}$, each of which is annotated to their respective class, Linear Discriminant Analysis (LDA) computes a transformation that maximises the between-class scatter, S_{bc} and minimises the within class scatter, S_{wc}:

$$\text{Maximize: } \frac{\det(S_{bc})}{\det(S_{wc})} \qquad (9)$$

The S_{bc} and S_{wc} are defined in Eq. 10 and 11 respectively.

$$S_{bc} = \sum_{i=1}^{C} (\mu_i - \mu)\ (\mu_i - \mu)^T \qquad (10)$$

$$S_{wc} = \sum_{i=1}^{C} \sum_{j=1}^{N_i} (x_j - \mu_i)(x_j - \mu_i)^T \qquad (11)$$

Where, μ denotes mean of the entire data; μ_i denotes mean vector of class i = 1,2…,C; N_i denotes number of samples in class i.

For LDA, all classes are assumed to have their own identical covariance matrices. The discriminant functions for LDA are defined by

$$d_i(x) = \ln \pi_i - \frac{1}{2} \mu_i^T \sum\nolimits_{pooled}^{-1} \mu_i + x^T \sum\nolimits_{pooled}^{-1} \mu_i \qquad (12)$$

where, x is the new data point to be classified, π_i is the estimated prior probability of class i and $\sum_{pooled}^{-1}$ is the estimated inverse pooled covariance matrix. From Eq. 12, the new data point, x is classified by the classification rule as specified by Eq. 13.

$$cf(x) = \arg\max_i d_i(x) \qquad (13)$$

The resulting LDA decision boundaries between classes are linear.

5 EXPERIMENTAL SET UP

The experiment was carried out for eleven subjects walking parallel to a static camera, with thirteen covariate factors. Each subject was captured wearing a variety of footwear (flip flops, bare feet, socks, boots, own shoes and trainers), clothes (normal or with rain coat) and carrying various objects (barrel bag slung over shoulder or carried by hand, and rucksack). They were also recorded walking at different speeds (slow, fast and normal speed).

For each subject, there are approximately twenty sets of walking sequences, which are from left to right and vice-versa on normal track. In total, there are 2722 walking sequences that are used for training and testing process.

In order to obtain the optimised results, four gait features were adopted. Firstly, maximum thigh trajectory,

$\theta_3^{\max}$ was determined from all the thigh trajectories collected during a walking sequence. When $\theta_3^{\max}$ was located, the corresponding values for the step-size, S and width, w and height, h were determined as well. To improve the recognition rate, additional features were used. These features were the average of the local maxima detected for width (A^W), smoothed crotch height (A^{HS}) and smoothed thigh trajectory (A^{TS}).

The experiment was performed on a computer with Intel Pentium 4 (2.9 GHz) microprocessor and 1 Gigabytes of RAM. The duration of extracting gait features from each walking sequence was approximately 80 seconds. The duration for the smoothing process and classification was less than five minutes for each classification technique.

6 EXPERIMENT RESULTS

For the classification, two-folds cross validation was applied by partitioning all the feature vectors into two disjoint subsets. By performing the cross validation, each disjoint subsets will be used in training and testing. This is to ensure that every feature vector will be trained and tested in order to evaluate the results appropriately. The results obtained from the two-folds cross validation are then normalised to produce a sole recognition rate.

To evaluate the experimental results by smoothing process, different sigma values (σ) of Gaussian filter have been used during the smoothing process. The overall results are summarised in Tables 1, 2 and 3. The highest recognition rate for each Gaussian filter sigma value under each classification technique is shown in Fig. 10.

Table 1. Recognition rates by LDA

	Recognition rate (%)						
σ	0	1	1.2	1.5	1.6	1.7	2.0
	78.2	80.6	80.5	81.1	81.2	81.3	80.4

Table 2. Recognition rates by Fuzzy KNN

	Recognition rate (%)						
k \ σ	0	1	1.2	1.5	1.6	1.7	2.0
5	80.1	82.2	81.7	81.8	82.1	82.0	82.2
6	80.5	82.0	81.9	82.1	82.2	81.9	81.7
7	80.9	81.7	81.6	82.4	82.5	82.6	82.2
8	81.3	82.1	82.2	82.6	82.7	82.6	82.3
9	81.2	82.3	82.4	82.6	82.9	82.8	82.4
10	81.2	82.2	82.3	82.8	82.9	83.2	82.4
11	81.0	81.8	82.0	82.7	82.4	82.8	82.1
12	80.7	81.5	82.3	82.7	82.9	82.6	82.4

Table 3. Recognition rates by Linear SVM

	Recognition rate (%)						
C \ σ	0	1	1.2	1.5	1.6	1.7	2.0
0.5	80.6	82.8	82.5	82.8	83.5	83.4	81.4
1	80.5	82.8	82.5	82.7	83.7	83.7	81.8
2	80.6	83.0	82.5	82.9	83.6	83.8	81.9
4	80.4	83.2	82.4	83.0	83.5	84.0	81.7
8	80.4	83.1	82.5	82.9	83.2	83.4	81.7
16	79.9	82.6	82.5	82.8	82.9	83.3	81.4

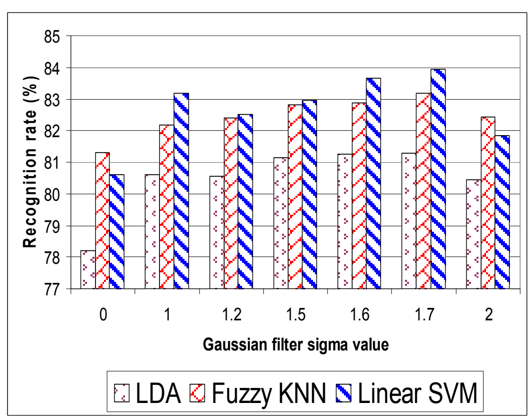


Fig.10. Highest recognition rate for each classification technique over Gaussian filter sigma value

From Fig. 10, the highest recognition rate of 81.3%, 83.2% and 84.0% for each classification technique are obtained with σ = 1.7. It is also shown that the recognition rates for each Gaussian filter sigma value outperform recognition rates without smoothing. Hence, it is proven that the smoothing process for crotch height and thigh trajectory has significant contribution.

The extended analysis for the result of σ = 1.7 was conducted by using the Cumulative Match Scores (CMS) as initiated by Philips et. al. [22]. CMS shows the probability of correct identification versus relative rank *k*. It depicts the recognition rate for the correct subject with respect to top *n* matches.

By referring to Fig. 11, it can be observed that most of the subjects are correctly classified at rank 3, which achieved near to 98%. The recognition rate reached 100% at the rank 7, which indicated all the subjects can be correctly identified within top seven matching.

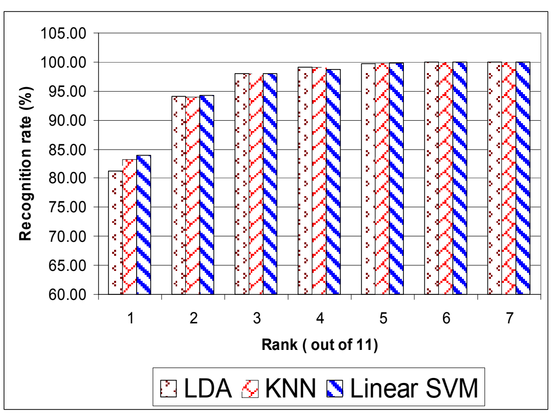


Fig. 11. Cumulative Match Scores of top seven matches for 11 subjects

For comparison with other approaches that use the same SOTON covariate database, our approach performed better than the recognition rate of 73.4% as reported by Bouchrika et. al. [9]. Even though the recognition rate achieved by Pratheepan et. al. [16] is 86%, we believed that our approach is better after comparing the number of subjects, covariate factors and walking sequences that were used for experiment. Table 4 summarises the comparison.

Table 4. Benchmark with other approaches on SOTON covariate database

	Bouchrika et. al. [9]	Pratheepan et. al. [16]	Our approach
Recognition rate (%)	73.4	86	84.0
Number of subjects	10	10	11*
Number of covariate factors	11	4#	13
Number of walking sequences	440	180	2722

* Subjects include one female wearing long blouse, (tested on the entire eleven subjects from SOTON covariate database)

Without covariate factors on shoe types and walking speed

7 CONCLUSION

A novel model-free approach for extracting the gait features from enhanced human silhouette image has been developed. The gait features are extracted from human silhouette by determining the skeleton from body segments. The joint trajectories are obtained after applying Hough transform on the skeleton. Both crotch height and thigh trajectory had been smoothened before their average values were applied for classification by LDA, fuzzy KNN and linear SVM. The results show that the proposed method can perform well regardless of walking speed, carrying objects and apparel of subject. In addition, it performs consistently well on three different classification techniques. For future development, experiments on other gait databases will be performed.

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