Performance Comparison of SVM and kNN in Automatic Classification of Human Gait Patterns

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***Abstract*—:** Information fusion offers a promising solution to the development of a high performance classification system. In this paper multiple gait components such as spatial, temporal and wavelet are fused for enhancing the classification rate. Initially background modeling is done from a video sequence and the foreground moving objects in the individual frames are segmented using the background subtraction algorithm. Then gait representing features are extracted for training and testing the multi_class k-Nearest Neighbor models (kNN) and multi_class support vector machine models (SVM). We have successfully achieved our objective with only two gait cycles and our experimental results demonstrate that the classification ability of SVM is better than kNN. The proposed system is evaluated using side view videos of NLPR database.

***Keywords*—:** Biometrics, Gait recognition, Silhouette images, Video Surveillance.

I. Introduction

THE interest in gait as a biometric is strongly motivated by the need for an automated recognition system for visual surveillance and monitoring applications. Recently the deployment of gait as a biometric for people identification in surveillance applications has attracted researches from computer vision. The development in this research area is being propelled by the increased availability of inexpensive computing power and image sensors.

The suitability of gait recognition for surveillance systems emerge from the fact that gait can be perceived from a distance as well as its non-invasive nature. Although gait recognition is still a new biometric, it overcomes most of the limitation that other biometrics suffer from such as face, fingerprints and iris recognition which can be obscured in most situations where serious crimes are involved. As stated above, gait has many advantages, especially unobtrusive identification at a distance, so that unauthorized and suspicious persons can be recognized when they enter a surveillance area, and night vision capability which is an important component in surveillance. This makes gait a very attractive biometric for real time monitoring as well as for access control at sites of high risk. Information fusion technology offers a promising solution to the development of a superior classification system. It has been applied to numerous fields and new applications are being explored constantly.

The problem of multiple gait feature fusion has been addressed by [1]–[5]. Wang et al. [1] employed both static and dynamic features for recognition using the nearest exemplar classifier. The features were fused on decision level using different combination rules. Lam et al. [2] presented two gait feature representation methods, the motion silhouette contour templates (MSCTs) and static silhouette templates (SSTs), and performed decision-level fusion by summarizing the similarity scores. Bazin et al. [3] examined the fusion of a dynamic feature and two static features in a probabilistic framework. They proposed a process for determining the probabilistic match scores using intra and interclass variance models together with Bayes rule. Han and Bhanu [4] proposed a method to learn statistical gait features from real templates and synthetic templates to address the problem of lacking gallery gait data. A matching score fusion strategy was therefore applied to improve the recognition performance. Veres et al. [5] tried to fuse static and dynamic features to overcome the problem when the gallery and probe databases were recorded with a time interval.

The approaches of information fusion can be roughly classified into two categories: the decision-level fusion [1]–[11], [13], [15] and the feature level fusion [12], [14]. In the decision-level fusion system, multiple classifiers work in hierarchical [12], [15] or in parallel [1]–[11], [13], [14]. The outputs of the individual classifiers (subject labels, rank values, or match scores) are combined by some specific fusion rules to produce the final recognition result. Commonly applied fusion rules include majority voting, sum rule, product rule, and so on. Some details of these fusion rules can be found in [3] and [8]. While fusion at the decision level has been extensively studied, feature-level fusion is relatively understudied. Zhou and Bhanu [14] presented a summary of the recent work for the feature-level fusion and pointed out that feature concatenation was the most popular feature-level fusion methodology.

II. PROPOSED APPROACH

For obtaining optimal performance, an automatic person identification system should incorporate as many informative cues as available. There are many properties of gait that might

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serve as recognition features. Early medical studies suggest that there are 24 different components to human gait and if all movements are considered, gait is unique [16]. However from a computational perspective, it is quite difficult to accurately extract some of the components such as angular displacements of thigh, leg and foot using current computer vision system, and some others are not consistent over time for the same person. So precise extraction of body parts and joint angles in real visual imagery is a very cumbersome task as non-rigid human motion encompasses a wide range of possible motion transformations due to the highly flexible structure of the human body with hundreds of muscles and joints and to self occlusion. Furthermore clothing type, segmentation errors and different viewpoints post a substantial challenge for accurate joint localization. Hence, the problem of representing and recognizing gait turns out to be a challenging one. In this paper we developed a hybrid holistic approach which is computationally affordable for real-time applications.

In this paper we are concerned with only side view videos and normal gait. This is because gait of a person is easily recognizable when extracted from side view of the person and majority of the people have normal walk. Also we avoid uncontrollable conditions such as illumination changes, movement of other objects such as swaying trees and moving vehicles and also varied weather conditions.

We perceive the problem of gait representation as that of the representation of approximately periodic spatio_temporal nature in an efficient manner, preferably using only a few parameters. After careful analysis we group the features under three categories spatial, temporal and wavelet components.

Our Biometric Classification system is schematically shown in Fig.1. The input to our system is a gait video sequence captured by a static camera. Once the video is captured, binary silhouettes of the walker are generated by using a background subtraction process which includes two important steps background modeling and foreground extraction. Then the features are extracted as numerical information. All the above steps are repeated for multiple video sequences and mean of feature values are stored in the database along with the identity of the walker. Then pattern recognition classifiers are trained with the created database in training phase. During testing phase, binary silhouette of the test video is generated as in training phase and the individual is recognized by comparing the obtained features with the ones previously stored in the database by the classifier.

The remainder of this paper is organized as follows. Section III describes the modules of our system, section IV provides experimental results and section V contains conclusion.

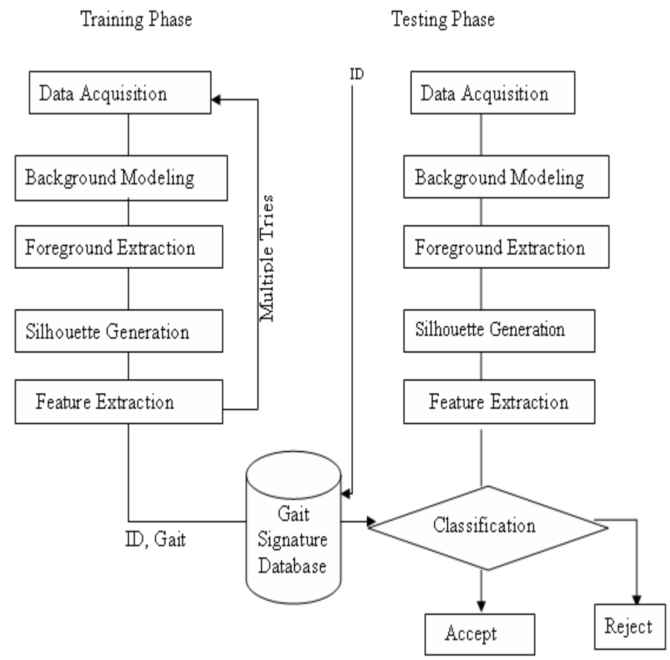


Fig.1 Human Gait Recognition System.

III. MODULES DESCRIPTION

As almost all recent approaches for gait recognition system, our algorithm consists of three basic modules Background subtraction, Feature extraction and Recognition which are described in the subsections below. First module is to segment the moving foreground object and to extract the binary silhouette. Second module is to extract the features to represent human gait and finally third module is to determine the person's identity. This proposed approach is examined with two classifiers namely kNN and SVM.

A. Background Subtraction

Identifying moving objects from a video sequence is a fundamental and critical task in many computer vision applications. A common approach is to perform background subtraction, which identifies moving objects from the portion of a video frame that differs significantly from a background model. Implementation of this module contains three steps namely background modeling, foreground extraction and binary silhouette generation. First background of the video must be modeled from the frames of the captured video. Many background modeling techniques are available in the literature. But we found that Median value computation is comparatively faster than others. So in our approach we used it to model the background by the equation given below.

$$B(x,y) = median[P_1(x,y), P_2(x,y) \dots Pn(x,y)] \quad (1)$$

Where P represents a video sequence with N frames and B(x,y) is the background brightness in the pixel location (x,y).

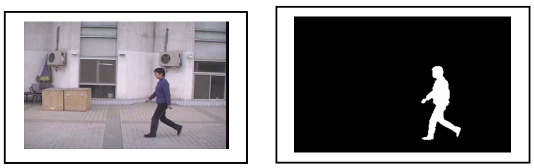
After the background is modeled, it is subtracted from the original frames to obtain moving foreground object by the equation given below.

$$D_k(x, y) = | P_k(x, y) - B(x, y) | \qquad (2)$$

In order to be robust to changes of clothing and illumination it is reasonable to consider the binarized silhouette of the object as in Fig.2. This can be obtained by thresholding the difference image with a suitable threshold value T.

$$D_k(x, y) = \begin{cases} 0 \; Background \quad if \;\; D_k(x, y) > T \\ 1 \; Foreground \quad else \end{cases} \qquad (3)$$

The primary assumption made here is that the camera is static, and the only moving object in video sequences is the walker.



(a) (b)
Fig. 2 a) Original Image b) Binarized silhouette

Before the process of feature extraction, we first place a bounding box around the binary silhouette to estimate the gait cycle and thereby to estimate the number of frames in a gait cycle. Knowing the number of frames in a gait cycle, the sequence of binary silhouettes is divided into subsequences of gait cycle length. We then consider frames in two gait cycles in order to extract the characteristic feature vector. This reduces the processing time considerably. The process of gait cycle estimation is briefly described below.

B. Feature Extraction

1) Gait Cycle Estimation

Human gait is treated as a periodic activity within each gait cycle. A single gait cycle can be regarded as the time between two identical events during the human walking and usually measured from heel strike to heel strike of one leg. There are two main phases called as stance phase and swing phase in the gait cycle. During stance phase, the foot is on the ground, whereas in swing phase that same foot is no longer in contact with the ground and the leg is swinging through in preparation for the next foot strike.

Considering the motion of the left foot, its heel strike starts its stance phase, which is characterized by a sequence of events. To bring the left foot onto the ground the ankle exes, and as a result, the body weight is transferred onto it. The right leg then swings through in front of the left leg as the left heel lifts off the ground; this is referred to "heel off". As the body weight moves onto the right foot, the supporting left knee exes, the stance phase ends, when the remainder of the left foot, which is now behind, lifts off the ground. This is referred to as "toe-off" and it occurs before the swing phase. As a result of the toe off, the weight is transferred onto the right leg and the left leg swings forward to strike the ground in front of the right foot. The swing phase ends with the heel strike of the left foot. A stance and a swing phase form a cycle referred to as the gait cycle which is illustrated in Fig. 3.

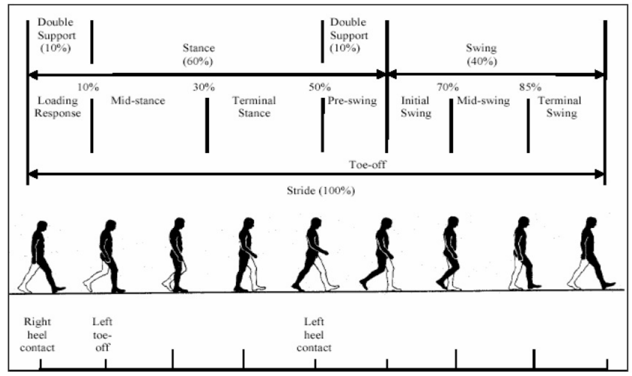


Fig.3. Gait cycle of a person

The computation of gait period and cycle partitioning are crucially important steps for gait recognition algorithms. Several methods have been proposed to estimate gait periodicity as it provides essential information for the extraction of gait features. To estimate the gait cycle the aspect ratio of the silhouettes bounding box is used in [17]. In our method width of the bounding box is used as it is periodic and the bounding box will be larger and shorter when the legs are farthest apart and thinner and longer when the legs are together.

2) Spatial Component Computation

Bounding rectangle's mean height, mean width, mean angle and mean aspect ratio are considered as spatial components. Bounding rectangle's mean height H is the representative height value for a person [18]. It is obtained by averaging the difference between upper and bottom points on y axis at each time instant t given by

$$H = \frac{\sum_{i=1}^{N} [Y_{up}(t) - Y_{bp}(t)]_i}{N} \qquad (4)$$

where Y_{up} is the upper point on y axis, Y_{bp} is the bottom point on y axis and N is the number of frames in the gait cycle.

Similarly bounding rectangle's mean width W is the representative width value of a person. It is obtained by averaging the difference between right and left points on axis x at each time instant t given by

$$W = \frac{\sum_{i=1}^{N} [X_{rp}(t) - X_{lp}(t)]_i}{N} \qquad (5)$$

where X_{rp} is the right point on x axis, X_{lp} is the left point on x axis and N is the number of frames in the gait cycle.

Bounding rectangle's mean angle A is the representative diagonal value of a person. It is obtained by averaging the difference in degrees between axis x and the diagonal as in "(6)," at each time instant t and aspect ratio AR can be obtained by dividing Height H by Width W as in "(7),".

$$A = \frac{\sum_{i=1}^{N}\left[\tan^{-1}\left(\frac{H(t)}{W(t)}\right)\right]_i}{N} \qquad (6)$$

$$AR = \frac{\sum_{i=1}^{N}[H(t)/W(t)]_i}{N} \qquad (7)$$

3) Temporal Component Computation

Step length, Stride length, Cadence and Velocity are considered as temporal components. Step length and stride lengths are computed by finding the number of frames in a step and stride which is shown in Fig. 4. Cadence is number of steps /minute and velocity is calculated by the equation given below.

$$Velocity = stridelength \times 0.5cadence \qquad (8)$$

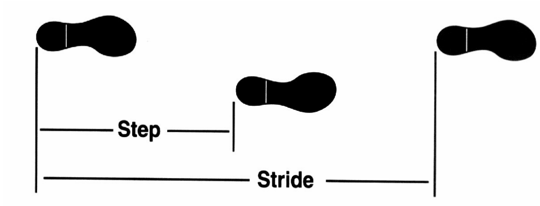


Fig. 4 Step and Stride length

4) Wavelet Energy Component Computation

Studies have shown that human gait is quasi periodic and there are slight changes in the fundamental frequency and amplitude over time. Discrete Wavelet Transform (DWT) is used to perform such analysis due to its robustness against rotation, translation and scaling. Wavelet transform belongs to the multiresolution transformation, performing the decomposition of the signals on different levels. In distinction to the Fourier transform applying the sinusoidal basis functions, the wavelet transformation uses wavelet functions and the scaling functions, both forming the orthogonal or biorthogonal family of basis functions. Wavelet descriptors are a compact representation for digitized silhouette that contain sufficient shape information to allow for reliable recognition. Even when silhouettes were described with only 1/32th (level-5 WD) of their original data, recognition rates did not significantly degrade and also wavelet descriptors are insensitive to individual walking style variations [19]. Wavelet functions have good localization abilities in both time and frequency. Because of its great time and frequency localization ability, DWT can reveal the local characteristics of the input patterns, enabling good representation of the local features of the patterns. From this point of view, the wavelet descriptors are better than Fourier, since they are able to catch small differences between patterns.

Among the various wavelet bases, the Haar wavelet is the shortest and simplest basis and it provides satisfactory localization of signal characteristics in time domain. Therefore, Haar wavelet was chosen as the mother wavelet in this work. The procedure of a two-level wavelet decomposition of a signal x(n) is illustrated in Fig. 5. As shown in the figure a high pass filter g(n) and a low pass filter h(n) are employed in the decomposition process. The symbol $\downarrow 2$ represents downsampling the filtered signal by two. The detail D1 and the approximation A1 represent the downsampled signal of the first level decomposition using the high-pass and the low-pass filters respectively. Following the first level of decomposition, the approximation A1 is further decomposed in the second level using the same filters.

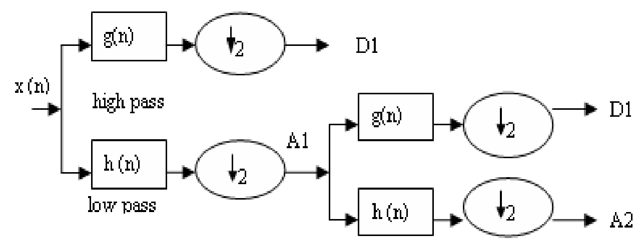


Fig. 5 Subband decomposition with two-level discrete wavelet transform

The silhouette area of each frame is decomposed by 2-D DWT using Haar wavelet kernel. From the low frequency subband we got one coefficient and from the detailed frequency subband we got two coefficients. Then mean and standard deviation is calculated as in "(9)," and "(10)," for all energy coefficients of each subband. Therefore the dimension of wavelet feature is six.

$$\mu = \frac{1}{N}\sum_{i=1}^{N} a_i . \qquad (9)$$

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(a_i - \mu)^2} . \qquad (10)$$

where μ is mean, σ is standard deviation, N is number of frames in the gait cycle, and a_i represents the different wavelet coefficients.

C. Human Recognition

Gait Recognition is a traditional pattern classification problem which can be solved by calculating the similarities between instances in the training database and test database. Let the spatial feature vector be S, the temporal feature vector be T and the wavelet feature vector be W. By fusing all these features at feature level, the feature vector H is represented as as in "(11),".

$$H = [S, T, W] \qquad (11)$$

This H is used to train kNN and SVM models to classify human gait and the models are explained in the following subsections.

1) kNN Classifier

In pattern classification, kNN is a method for classifying objects based on closest training examples in the feature space. It is the simplest of all algorithms for predicting the class of a test example. This algorithm contains following three steps to classify objects.

- Calculate distances of all training vectors to test vector.
- Pick k closest vectors.
- Calculate average/majority.

If k = 1, then the object is simply assigned to the class of its nearest neighbour. The best choice of k depends upon the data; generally, larger values of k reduce the effect of noise on the classification, but make boundaries between classes less distinct. A good k can be selected by various heuristic techniques, for example, cross validation. Choosing an appropriate k is essential to make the classification more successful. The special case where the class is predicted to be the class of the closest training sample (i.e. when k = 1) is called the nearest neighbour algorithm. To calculate distances of all training vectors to test vector, distance measures such as Euclidean distance, Cityblock distance, Cosine distance, Correlation, Hamming distance can be used. The most common distance function is Euclidean distance. The accuracy of the kNN algorithm can be severely degraded by the presence of noisy or irrelevant features, or if the feature scales are not consistent with their importance.

The training process for kNN consists only of storing the feature vectors and class labels of the training samples. One major problem to using this technique is the class with the more frequent training samples would dominate the prediction of the new vector, since they more likely to come up as the neighbor of the new vector due to their large number. To address this problem, in our experiment, we use the same number of videos for each class.

2) SVM Classifier

Recently, Support Vector Machines (SVM), proposed by Cortes and Vapnik in 1995 has emerged as a powerful supervised learning tool for general purpose pattern recognition. It has been applied to classification and regression problems with exceptionally good performance on a range of binary classification tasks [20]. In SVM the original input space is mapped into a high dimensional dot product space called feature space, and in the feature space the optimal hyper plane as shown in Fig.6 is determined to maximize the generalization ability of the classifier. The primary advantage of SVM is its ability to minimize both structural and empirical risk leading to better generalization for new data classification even when the dimension of input data is high with limited training dataset.

The standard soft-margin SVM is a binary classifier, which is mapping to a class and can identify an instance belonging to the class or not. This can be defined as

$$\theta = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2) \ldots (\mathbf{x}_i, y_i)\}\}$$
$$\mathbf{x}_i \in \Re^n$$
$$y_i = \{1, -1\}$$

Where $\mathbf{x}_i$ are feature vectors and y_i are the corresponding class labels. The SVM formulation is essentially a regularized minimization problem leading to the use of Lagrange Theory and quadratic programming techniques. The formulation defines a boundary separating two classes in the form of a linear hyperplane in dataspace where the distance between the boundaries of the two classes and the hyperplane is known as the margin of the hyperplane.

There are two kinds of multi-class SVM system, one-against-all(OAA) and one-against-one(OAO). The OAA SVM must train k binary SVMs where k is the number of classes. The i^{th} SVM is trained with all samples belonging to i^{th} class as positive samples, and takes other examples to be negative samples. All the k SVMs could be trained in this way, and then k decision functions are generated. A test sequence is labeled according to maximum output among the k classifiers as in "(12),".

$$Cls = \max(w_i . x + b) \cdot \tag{12}$$

where Cls is class of input data x and i = 1 to k, the number of classes.

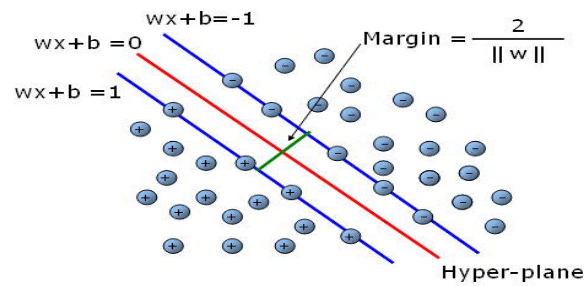


Fig. 6 Support Vector Machine.

The OAO SVM is that for every combination of two classes i and j, it must train a corresponding SVM_{ij} . Therefore, it will train k(k − 1)/2 SVMs and get k(k−1)/2 decision functions. For an input data, a voting strategy is used to decide which class it belongs to. If sign($w_{ij} \cdot x + b_{ij}$) shows x belongs to i^{th} class, then the vote for the i^{th} class is added by one. Otherwise, the j^{th} class is added by one. Finally, x is predicted to be the class with the largest vote. This strategy is also called the "Max Wins" method. There is no theoretic proof that which kind of multi-class SVM is better, and they are often compared by experiment.

We adopt OAA SVM method to fulfill the multi-class gait classification since it is less complex. To build an SVM classifier user can choose kernel functions such as Linear, Polynomial, and Radial Basis Function(RBF) whose mathematical formula is given in Table 3. RBF is by far the most popular choice of kernel types used in SVM. This is mainly because of their localized and finite responses across the entire range of real x-axis. As kNN Classifier, we train SVM classifier with the extracted spatial, temporal and wavelet features, for different kernel functions and the results are discussed in the next section.

Table 3.
Kernel Functions in SVM Classifier

Kernel Function	***Mathematical Formula***
Linear	$K(x_i, x_j) = \langle x_i, x_j \rangle$
Polynomial	$K(x_i, x_j) = (\langle x_i, x_j \rangle + 1)^d$
Radial Basis Function	$K(x_i, x_j) = \exp\left(-\frac{\lVert x_i - x_j \rVert^2}{2\sigma^2}\right)$

The notation ‹.,.› indicates an inner product, d degree of polynomial, σ width of RBF function.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

We have used strong computing software called Matlab to develop our work because Matlab provides image Acquisition and Image Processing Toolboxes which facilitate us in creating a good GUI and an excellent code. Extensive experimentation has been carried out to portray the effectiveness of the proposed system and a detailed comparative analysis and discussion on the results are presented in the sub-sections below.

1) Data Acquisition

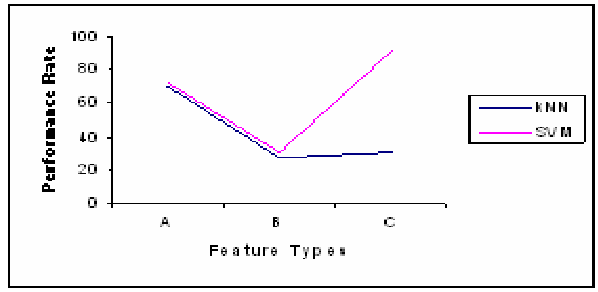
The experimentation of the proposed gait recognition system is performed with images publicly available in the National Laboratory of Pattern Recognition gait database. It contains 240 sequences from 20 different subjects and four sequences per subjects in three different views. The properties of the images are: 24-bit full color, capturing rate of 25 frames per second and the original resolution is 352 × 240. The length of each sequence varies with the time each person takes to traverse the field of view.

2) Results and analysis

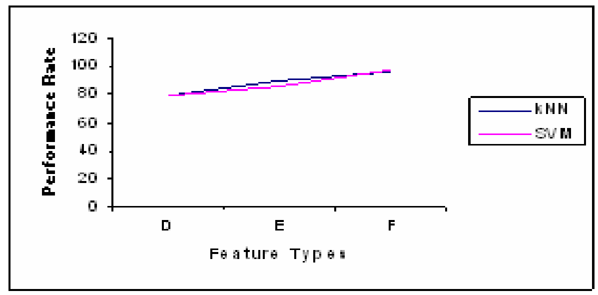
For each side view videos of NLPR gait database, we first generate silhouette images using background subtraction algorithm and then spatial, temporal and wavelet features are extracted in the manner described in section 3. Then we trained two classification models kNN and SVM by the feature vector H, and the gaits are classified by the trained models at last.

We first compare the identification performance of spatial, temporal & wavelet features separately for the three models. Then the performance of different combinations of features types are compared and shown in Fig. 7. Experimental results in Table 4 proves that though temporal features gives poor performance while using separately, improves performance rate when fused with other features.

We see that in our experiments, for the two models, the recognition rate is found to be increased when all the three feature types are fused together. The recognition rate of kNN, and SVM models are summarized in Fig. 8, from which it can be seen that the recognition performance based on SVM classifier is better than kNN.



(a)

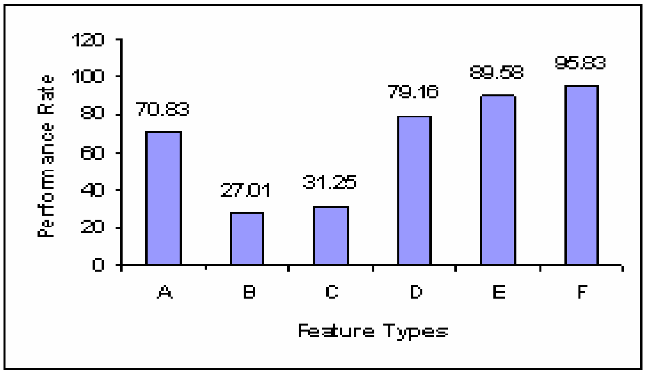


(b)

Fig. 7 Performance Comparison of kNN and SVM. A) Individual feature type b) Combined feature type

Table 4.
Comparison of Performance Rate of Individual Features

Feature Type	No. of Features	% of Performance	
		kNN	SVM
Spatial Features (A)	4	70.83	72.9
Temporal Features (B)	4	27.01	31.33
Wavelet Features (C)	6	31.25	91.66
Spatial & Temporal Features (D)	8	79.16	79.17
Spatial & Wavelet Features (E)	10	89.58	85.43
Spatial, Temporal & Wavelet Features (F)	14	95.83	97.92



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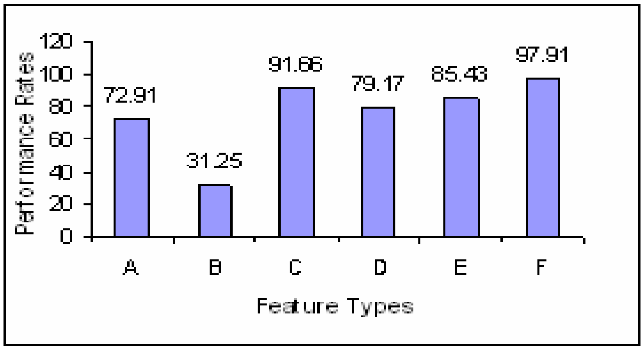

(b)

Fig. 8 Performance rate of all feature types. a) kNN b) SVM

We compared the proposed method with other well cited gait recognition approaches using NLPR gait database and is given in Table 6. From the Table it is clearly seen that the proposed approach gain a better performance rate.

Table 6
Comparison with State _of_ the Art Algorithms on NLPR database in the Canonical View

Methods	Performance Rate (%)
Collins (2002)	71.25
BenAbedelkader (2002)	82.50
Phillips (2002)	78.75
Wang (2003)	88.75
Su (2006)	89.31
Lu (2006)	82.50
Geng (2007)	90.00
Bo Ye (2007)	88.75
Sungjun Hong (2009)	90.00
Proposed Method	97.92

In this work apart from Performance rate (Accuracy), other measures such as Precision, Recall, and F-measure which are more appropriate for comparison are also considered and the values are tabulated in Table 7. The formulas for the above performance measures are given below.

$$\mathrm{Precision} = \frac{TP}{TP + FP} \quad (13)$$

$$\mathrm{Recall} = \frac{TP}{TP + FN} \quad (14)$$

$$F\_Measure = \frac{2 \times \mathrm{Precision} \times \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}} \quad (15)$$

where TP is True Positive, FN is False Negative and FP is False Positive. These measures are calculated using confusion matrix of classification.

Table 7
Comparison of Different Performance Measures

Performance Measures	kNN	SVM
Accuracy	95.83%	97.92%
Precision	96.66%	98%
Recall	95.83%	98%
F-Measure	96.24%	98%

In SVM, experiments were conducted with three kernel types for various values of regularization parameter (c) and other parameters such as degree of polynomial (d) in Polynomial Kernel and width of RBF function (σ). We found that classification performance of SVM depends on the selection of regularization parameter because it is the penalty parameter for misclassification. So it has to be carefully selected to achieve maximum classification accuracy. When compared across different kernels with various parameter values, RBF was found to perform the best in recognizing gait patterns. Best classification outcomes for different kernels are represented using accuracy rates and are tabulated in Table 8. Table 9(a) and 9(b) emphasizes that optimal value of c could be different for different feature types and has to be selected by trial and error method. Although the results are encouraging, evaluations on a large database still need to be further investigated in future work in order to be more conclusive.

Table 8
Performance rate for various SVM kernels

SVM Kernel types	% of Performance
Linear	77.08
Polynomial	77.08
Radial Basis function	97.92

Table 9(a)
Performance of RBF kernels for different regularization parameter(c), width of RBF (σ) and feature types

Kernel	Parameters		Features				
	σ	**C**	A	B	D	E	F
Gaussian RBF	σ = 1	1	54.16	16.66	62.50	54.17	56.25
		5	64.58	16.66	66.67	60.42	62.50
		10	64.58	18.75	66.67	60.42	62.5
		15	64.58	18.75	66.67	60.42	62.50
		50	64.58	18.75	66.67	60.42	62.50
Gaussian RBF	σ = 2	1	75.00	14.58	68.75	83.33	83.33
		5	77.08	22.92	75.00	85.42	89.58
		10	77.08	22.92	75.00	83.33	89.58
		15	77.08	22.92	75.00	83.33	89.58
		50	77.08	22.92	75.00	83.33	89.58
Gaussian RBF	σ = 3	1	77.08	16.66	77.08	87.50	91.67
		5	77.08	22.92	77.08	87.50	93.75
		10	77.08	25.00	77.08	87.50	93.75
		15	77.08	25.00	77.08	87.50	93.75
		50	77.08	25.00	77.08	87.50	93.75
Gaussian RBF	σ = 4	1	75.00	16.66	77.08	85.42	93.75
		5	77.08	22.92	77.08	87.50	93.75
		10	77.08	25.00	77.08	87.50	93.75
		15	77.08	27.08	77.08	87.50	93.75
		50	77.08	27.08	77.08	87.50	93.75
Gaussian RBF	σ = 5	1	77.08	18.75	79.17	81.25	93.75
		5	77.08	21.92	77.08	85.42	95.83
		10	77.08	27.08	77.08	89.58	95.83
		15	77.08	25.00	77.08	89.58	95.83
		50	77.08	27.08	77.08	89.58	95.83
Gaussian RBF	σ = 6	1	77.08	16.66	79.17	83.33	93.75
		5	72.92	25.00	79.17	89.58	95.83
		10	77.08	31.25	79.17	87.50	95.83
		15	79.17	31.25	79.17	87.50	95.83
		50	79.17	31.25	79.17	87.50	95.83
Gaussian RBF	σ = 7	1	77.08	14.58	81.25	87.50	91.67
		5	77.08	25.00	79.17	87.50	97.92
		10	75.00	31.25	79.17	89.58	97.92
		15	77.08	31.25	79.17	87.58	97.92
		50	79.17	31.25	79.17	87.58	97.92

Table 9(b)

Performance of Polynomial and linear kernels for different regularization parameter(c), order of polynomial (d) and feature types

Kernel	**Parameters**		**Features**					
	d	**c**	A	B	C	D	E	F
Polynomial	d=0	1	39.58	29.17	35.42	56.25	75.00	77.08
		5	47.92	25.00	33.33	41.67	58.33	77.08
		10	41.67	31.25	43.75	41.67	58.33	77.08
		15	43.75	31.25	45.83	41.67	58.33	77.08
		50	52.08	22.92	43.75	41.67	58.33	54.17
Polynomial	d=1	1	39.58	29.17	35.42	56.25	75.00	77.08
		5	47.92	25.00	33.33	41.67	58.33	77.08
		10	41.67	31.25	43.75	41.67	58.33	77.08
		15	41.67	31.25	45.83	41.67	58.33	77.08
		50	50.00	22.92	43.75	41.67	58.33	54.17
Polynomial	d=3	1	54.17	18.75	35.42	52.08	58.33	77.08
		5	54.17	18.75	35.42	52.08	58.33	77.08
		10	54.17	18.75	35.42	52.08	58.33	77.08
linear		1	41.67	25.00	35.42	56.25	75.00	77.08
		5	45.83	25.00	37.50	41.67	58.33	77.08
		10	41.67	31.25	43.75	41.67	58.33	77.08
		15	41.67	31.25	45.83	41.67	54.17	77.08
		50	41.67	22.92	41.67	41.67	54.17	77.08

V. CONCLUSION

With mounting demands for visual surveillance systems, human identification at a distance has recently emerged as an area of significant interest. Gait is being considered as an impending behavioral feature and many allied studies have illustrated that it can be used as a valuable biometric feature for human recognition. It is found that this proposed method can effectively capture the gait characteristics and the performance of SVM classifier with RBF Kernel is better than kNN classifier for side view videos. But in realistic surveillance scenarios, however it is unreasonable to assume that a person could always present a side view to the camera and hence the algorithm need to be extended to work in a situation where the person walks at an arbitrary angle to the camera.

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