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Human Gait Recognition Using Silhouettes

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Abstract

This paper proposes a new algorithm to recognize the person using gait. Gait means the walking style of an individual. Current gait analysis involves numerous gait parameters for authentication. This work attempts to use angles at various points that are from head to neck, neck to torso, hip to knee of legs, knee to foot angle of legs. Height and width of every successive silhouette frame of an individual during the complete walking cycle is also considered. These six angles, height and width parameters are taken as the selective features for gait analysis to produce improved recognition rate. These features have a high discriminative power to recognize an individual. The features are trained with support vector machine and a person is recognized automatically. The proposed methodology achieves better performance with 91% recognition rate.

Keywords — Silhouettes, Gait Recognition, SVM classifier.

I . Introduction

Over a few decades, gait analysis is an emerging technology in computer vision community. Human gait is a complex action involving the motion of various parts of the body simultaneously in a three dimensional way. It refers to various activities like joint motion, swinging with linear and nonlinear motions, toe on, toe off, heel on and heel off. The combination of all these activities makes distinct walking style of an individual. Gait is a promising biometric modality that can be used for biometric authentication. Because gait parameters such as step length, gait cycle, angles of the hip, knee and joint rotation can be unique attributes of the human gait. Most commonly used recognition techniques involves face, iris and speech recognition, where as the gait based person recognition has an advantage that it can be observed without attention or cooperation of the person.

In general, gait analysis is classified into two groups. They are model based approach and model free approach. Model based methods employ templates to extract measurable gait parameters. Kim et al. [14] proposed a novel method for gait recognition from model based gait cycle extraction using prediction based hierarchical active shape model. The shape modeling process can be misled by illumination changes, shadows and strong occlusions. A model based method [27] extracts 73-dimensional measurement vectors for each gait sequence based on adaptive model and deformable contours was proposed by Liu and Wagg. To reduce the feature dimensionality, Guo and Nixon [15] have proposed a method for gait feature subset selection by Mutual Information (MI). MI evaluates statistical dependence between random variables. This method improves the classification accuracy with elimination of redundant data and selection of an optimal feature subset using MI. Amin and Hatzinakos [5] have proposed another method for generating gait signature from six different parts of the human body based on Empirical Mode Decomposition algorithm. Ron Zhang et al. tested the human gait recognition in CMU-MOBO database and USF gait challenge dataset with different training set [19].

A silhouette based gait representation for human identification using gait flow image was proposed by Toby et al. [11]. This paper is based on gait period detection and USF gait challenge dataset is used for experimentation. This has produced better recognition than gait energy images. Human gait recognition for Multiple views proposed by Yan- qiu Liu et al. [27] in which they have used Fourier transform of gait energy image to extract gait features and the nearest neighbor classifier for identification. Cross-view gait recognition based on human walking trajectory was proposed by Xin Chen et al.[1] from the projection of gravity center trajectory (GCT) gait period fluctuations. Gait recognition based on joint distribution of motion angles was proposed by Wei Lu et al.[2]. They have produced histogram for joint distribution angles. Hu Ng et al. evaluated the extraction of various angles as gait features with fuzzy K-means Nearest Neighbor (KNN) classifier. They have experiment the proposed methodology with wearing shoes, boots and walking with normal speed [16]. Rezaul et al. [21] proposed a method of automated gait classification involving young and elderly subjects from their respective gait pattern using Support Vector Machine (SVM) and improving classification to a superior classification performance with low error rate. An Efficient gait recognition system using Modified Independent Component Analysis was proposed by Pushpa Rani and Arumugam [12]. In this method, the gait video sequences were transformed into an equivalent parametric Eigen space vectors. Ashish Bhangale et al.[6] proposed a model for automatic extraction and description for gait recognition using K-Nearest Neighbour algorithm. Human gait recognition based on motion analysis was given by Han Su et al.[22], static and kinematic information were considered as a feature vectors. Gait Energy Image is represented with Gabor patch distribution feature for gait recognition was proposed by Dong Xu et al. [8]. Zongi Liu et al. proposed a new method to remove the noises, shadows in a silhouette using population based Hidden Markov Model coupled with an Eigen stance model to increase the recognition rate

[23]. Kohli and Verma [10] have experiment the detailed usage of SVM classifier. Yasushi Makihara et al. gave the OU-ISIR data set information with various walking speeds of large population, and different age group silhouettes [4]. Sudeep Sarkar et al. have tested the impact of shadows, discontinuity and correct the error using Eigen stance model and Hidden Markov Model to improve the performance with respect to human recognition [25]. Fujiyoshi and Lipton [26] have analyzed motion target in a video stream. The above said papers have discussed various approaches and algorithms to authenticate the person, which consider the parameters taken from head to ankle portion. Still there is a challenge in real time to improve the recognition rate. The proposed algorithm includes knee to toe angle which gives the additional information of ground meeting point of a person.

The proposed method contributes the absolute angle measurement which includes head to toe to improve the recognition rate. In a critical scenario, like the two persons are having the same height, width, and the angles from head to neck angle, neck to torso angle, hip to knee angle of both (right and left) and knee to ankle of two legs then the earlier algorithms are not sufficient to authenticate the right person. The inclusion of knee to toe angle gives the additional information about ground meeting point of individual person. As the ground meeting point is different for a person, the algorithm identifies the right person. SVM classifier with radial basis function as a kernel is utilized for better classification accuracy.

II. Proposed Methodology

This section describes the silhouette based approach for gait recognition. The flow of the proposed method is shown in Fig. 1.

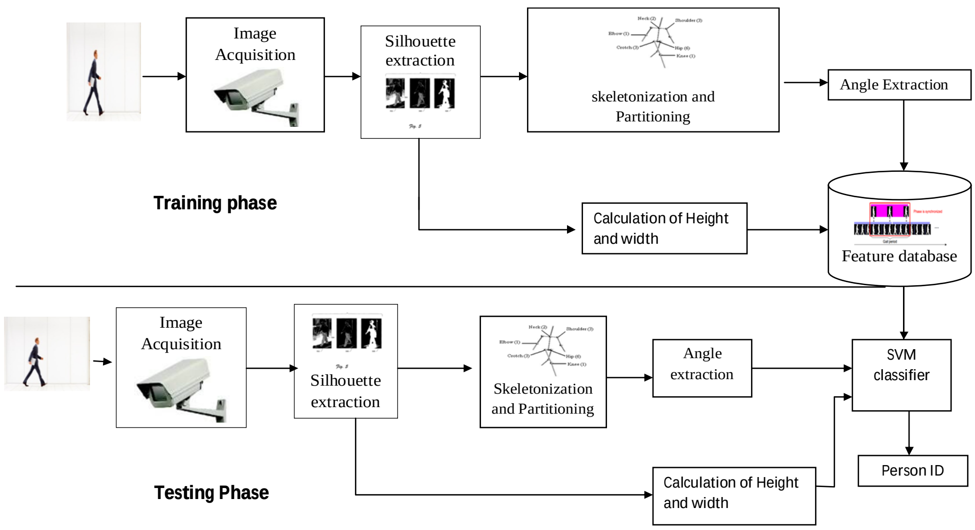


Fig.1. Block Diagram of the proposed method

The proposed methodology consists of two phases such as training phase and testing phase. In training phase, walking style (gait) is captured by camera. Silhouettes are extracted from the sequence of video frames. From each extracted silhouettes, skeleton is acquired and the angle features are extracted to form feature database. In testing phase, features are extracted as same as training phase. Support Vector Machine (SVM) classifier is used to recognize the person.

Feature Extraction

Performance of the gait based human recognition approaches are highly depends upon the feature extraction technique. The proposed methodology uses height and width, six angles such as head to neck, neck to torso, hip to knee of both legs, knee to foot angle of both legs computed from skeleton .

Height and Width Calculation

Maximum height (H) and maximum width (W) can be measured from silhouettes. When a person moves towards the camera, the height value is increased. Similarly, when a person is away from the camera, the frame height continuously decreases. Variation of height and width can be evaluated by defining the bounding box and the centroid point for each observed body is calculated. The height and width of box alters in a gait cycle.

Let H_1, H_2, ….H_N be the height of skeleton in a gait cycle. Then the maximum height of the person in the entire silhouettes is denoted as H_{max} = max (H_1, H_2, ….H_N).

The variation of the width is important cue for gait analysis, as it contains structural and dynamical information about the gait. When the person is in middle stance position, the space between the two legs is small and hence the width is minimum. The maximum width is attained, when a person walks by swinging his arms. Let W1, W_2, ….W_N be the width of skeleton in a gait cycle. Then the maximum spacing between two legs for a person is denoted as W_{max} = max (W_1, W_2, ….W_N).

The centroid ($X_{c,}Y_c$) of the human silhouette is calculated by using the following equations

$$X_c = \frac{1}{N}\sum_{i=1}^{N} X_i \tag{1}$$

$$Y_c = \frac{1}{N}\sum_{j=1}^{N} Y_i \tag{2}$$

where ($X_{c,}Y_c$)represents the average contour pixel position.($X_{i,}Y_i$) represents points on the human blob, N- Total number of points on the contour.

Skeletonization and Angle calculation

Skeleton of the input silhouette A is defined as $S(A)$ in terms of erosions and openings.

$$S(A) = \bigcup_{k=0}^{K} S_k(A) \tag{3}$$

With $S_k(A) = (A\Theta kB) - (A\Theta kB)oB$ (4)

B is the structuring element and $(A\Theta kB)$ indicates k successive erosions of A

$$(A\Theta kB) = (....((A\Theta B)\Theta B)\Theta B.....)\Theta B \tag{5}$$

The operation should be performed k times and K is the last iterative step before A erode to an empty set in other words

$$K = \max\{k|(A\Theta kB) \neq 0\} \tag{6}$$

In order to calculate angles, the skeleton of the silhouette is partitioned into six portions like head to neck, neck to torso, hip to knee (both legs), knee to foot (both legs) depicted in fig.2. The angles are measured in terms of deviation of reference partitioned planes between the given divided skeleton planes.

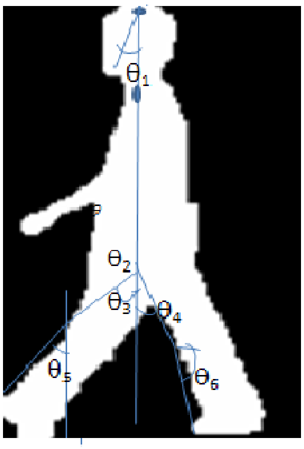


Fig.2. Six angles: θ_1 - angle between head to neck, θ_2 - angle between neck to torso, θ_3 - angle between hip to knee of left leg, θ_4 - angle between hip to knee of right leg, θ_5 - angle between knee to foot of left leg, θ_6 - angle between knee to foot of right leg.

The angles are calculated by the following procedure. The input silhouettes are applied into Fourier transform. The resultant Fourier coefficients are given to Radon transform, to produce a rotation invariant image features. By applying Radon transform, it is possible to establish a mapping between (x, y) domain to the radon domain of (r,θ). During human walking, a large variation exists at leg portion. Since the variation is higher, the output of the Radon coefficients are also higher in its value, and it is very suitable to act as feature vectors.

The radon transform of a skeleton image $f(x, y)$ denoted as $\mathrm{R}(r,\theta)$ where r defined by a normal distance from the origin, θ as a normal angle.
Radon transform point

$$R(r,\theta)[f(x, y)] = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x, y)\delta(r - x\cos\theta - y\sin\theta)dxdy \tag{7}$$

Where $-\infty < r < \infty, 0 < \theta < \pi$

Classification

In general, SVM classifier is considered as suitable classifier for real world classification problems. The main reason for choosing SVM is more robust against noisy data, less computational complexity and provides good performance in high dimensional feature space. SVM is a discriminative classifier formally defined by a separating hyper plane. For a given labeled training data, new samples are classified based on an optimal hyper plane that gives the largest minimum distance to the training samples. The optimal hyper plane can be represented in an infinite number of ways by scaling of β and β_0. The possible representations of the hyper plane, the one chosen is

$$\left|\beta_0 + \beta^T x\right| = 1 \tag{8}$$

Where β is weight vector, β_0 is bias

The distance between the point of x and the hyper plane β, β_0 is defined as

$$\text{Distance} = \frac{\left|\beta_0 + \beta^T x\right|}{\|\beta\|} \tag{9}$$

In a particular canonical hyperplane the magnitude of the numerator is equal to one and hence the distance to support vector defined by the equation

$$\text{Distance}_{\text{support vectors}} = \frac{\left|\beta_0 + \beta^T x\right|}{\|\beta\|} = \frac{1}{\|\beta\|} \tag{10}$$

$$M = \frac{2}{\|\beta\|} \tag{11}$$

where, M is margin. The requirement of the hyper plane is to maximise the margin is equalent to the problem of minimising the error function L(β) subject to some constraints. The constrained model, the requirement for the hyperplane, is to classify correctly all the training persons x_i where i = 1,2….N, N denotes no of training persons

$$\min_{\beta,\beta_0} L(\beta) = \frac{1}{2}\left\|\beta^2\right\| \tag{12}$$

subject to y_i $(\beta^T x_i + \beta_0) \geq 1$ $\forall$ i , y_i represents each of the labels of the training examples.

III. Experimental Analysis

In this section, the effectiveness of the proposed methodology is analyzed by investigating experiments using the standard datasets CASIA and OU-ISIR.

Dataset Description

CASIA gait dataset

CASIA dataset consists of four subsets: Dataset A is a standard dataset contains 19139 images; Dataset B is a large gait dataset which has 124 subjects. Waking style of each subject in the form silhouettes were captured from 11 views and three variations namely viewing angle variation, different clothing styles and different luggage carrying conditions, with the changes in personality. Dataset C was collected using an infrared camera with four different walking styles: normal walking, slow walking, fast walking, and normal walking with a bag. It contains 153 subjects. Dataset D consists the gait of 88 subject and its corresponding footprints. In this paper, CASIA data set B with 34 persons have been taken for experimentation.

1. OU-ISIR (Osaka University -The Institute of Scientific and Industrial Research) database

   OU-ISIR database is the world's largest gait database. This database has four subsets: Treadmill dataset A is composed of gait silhouette sequences of 34 subjects from side view with speed variation from 2 km/h to 10 km/h at 1 km/h interval. Treadmill dataset B is the collection of gait silhouette sequences of 68 subjects from side view with clothes variation up to 32 combinations. Treadmill dataset C is in under preparation. Treadmill dataset D is constructed by gait silhouette sequences of 185 subjects from side view with various gait fluctuations among periods. Gait fluctuations are measured by Normalized Auto Correlation (NAC) for the temporal axis of size-normalized gait silhouette images. Data set A and B with 34 persons have been considered for training and testing.

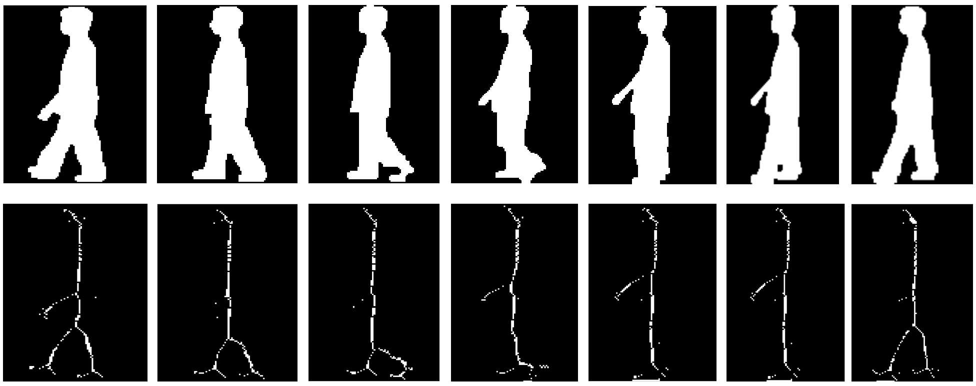
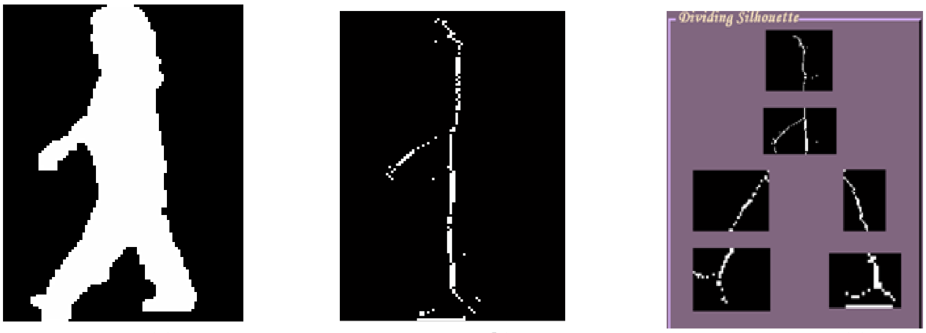


Fig. 4. Sequence of silhouettes and its concern skeletons of half gait cycle for a person

In this section, the qualitative and quantitative results are shown and analyzed to prove the efficient performance of the proposed methodology. In Fig. 4, Silhouette and its corresponding skeleton generated by the proposed methodology is shown. The silhouette is partitioned into six parts such as head to neck, neck to torso, hip to knee (both legs), knee to foot (both legs) as shown in fig. 5.



(a) (b) (c)

Fig.5. (a) silhouette of a person (b) Skeleton (c) partitioned skeleton

The angle variations of six portion of the skeleton in a gait cycle (100 frames of silhouette) of three different persons are shown in figure 6. It is observed that the various angles calculated from six parts of a skeleton are having unique pattern, hence the prediction of the individual person is possible.

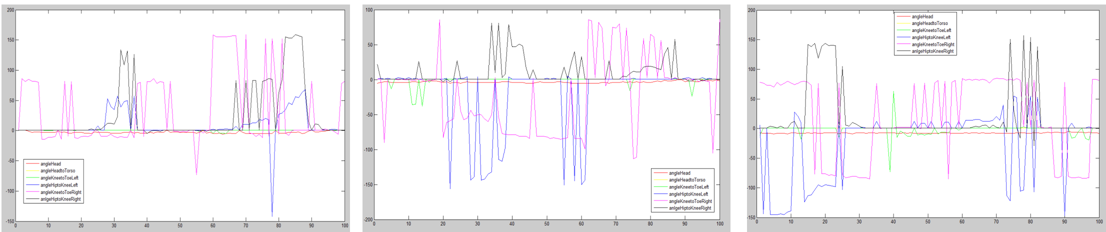


Fig. 6. Angle variations of six portions of silhouette in a gait cycle (100 frames) of three different persons

The table I shows various recognition percentage of 10 different persons with two different speeds. The algorithm has produced 100% as a maximum recognition and 71.71% as a minimum. The performance of the proposed methodology is evaluated in terms of recognition rate. The recognition rate is calculated as shown in equation (11).

$$\text{Recognition rate} = \frac{\text{Number of correctly recognized image of a person}}{\text{Total number of images tested of the person}} \times 100 \qquad (11)$$

For experimentation, we have taken OU-ISIR Treadmill dataset A and Treadmill dataset B. We have taken only 100 frames (one gait cycle) of silhouette for training a person. The recognition rate for Treadmill dataset A with varying speed is shown in table I. The table II shows recognition rate of 10 different persons with various clothing styles, the performance of the algorithm is independent on cloth variation.

Table I. Percentage of recognition rate of Treadmill Data set A (OU-ISIR), Speed Variation (2Km/h, 5Km/h)

Persons	**Recognition rate (%)**	
	Speed 1(2 Km/h)	**Speed 2 (5 km/h)**
Person1	100	87.43
Person2	85.71	72.85
Person3	85.75	100
Person4	100	100
Person5	71.71	78.14
Person6	100	79.86
Person7	100	100
Person8	100	100
Person9	100	100
Person10	77.28	100
Average	92.05	91.83

Table II. Recognition rate of Treadmill B dataset with five different cloth variations of ten person

Persons	**Recognition rate (%) (Cloth variation)**				
	Set1	**Set2**	**Set3**	**Set4**	**Set1**
Person 1	82.86	84.56	83.32	87.67	98.33
Person 2	94.28	85.23	82.23	90.53	83.89
Person 3	88.57	89.54	84.65	94.63	90.54
Person 4	91.43	83.67	90.21	95.32	91.86
Person 5	82.56	92.23	83.66	90.54	87.87
Person 6	91.43	83.67	90.71	89.69	90.56
Person 7	88.57	94.33	90.56	82.43	96.46
Person 8	91.52	83.88	96.56	93.5	89.87
Person 9	97.14	89.45	93.54	91.64	90.86
Person10	88.57	88.43	96.76	98.87	93.57
Average	89.7	87.5	89.2	91.5	91.4

Table III. Percentage of recognition rate in a CASIA data set (multi view)

Persons	Recognition rate (%)	
	ϴ=00	**ϴ=1800**
Person1	94.5	93.8
Person2	98.5	94.6
Person3	100	96.7
Person4	99.3	97.0
Person5	90.6	89.1
Person6	89.9	89.0
Person7	97.9	95.6
Person8	96.6	95.6
Person9	93.0	91.6
Person10	95.0	94.1
Average	95.5	93.7

Table 3 shows the recognition rate of ten persons .The dataset taken from CASIA. The algorithm yields a good recognition rate.

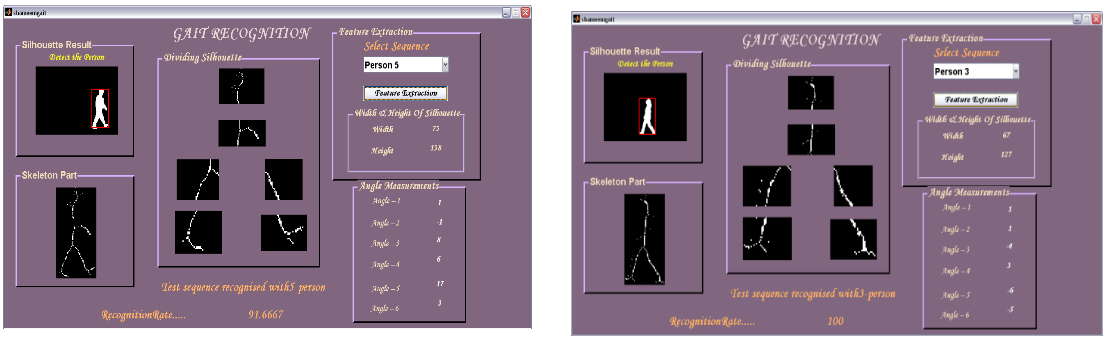


Fig.7. Sample Graphical User Interface for proposed Algorithm

IV. Conclusion

We present an automated approach for human identification from low resolution silhouettes. The algorithm has utilized exhaustive head to toe angles, height and width as feature vectors. The gait characteristic features are based on kinematics. The SVM is employed to classify the gait features. Experimental results demonstrate the feasibility of our approach. In future, we will pay more attention to the feature space for describing and recognizing the human gait on more subjects. SVM classifier has produced a high recognition rate around 91% in OU-ISIR data set and CASIA dataset. The algorithm includes the meeting point of ground with toe as added information it distinguish the person correctly. In future, the challenging problems like occlusion, shadows and noises in silhouettes can be overcome by modifying this proposed algorithm.

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