CSA+DATER, for gait recognition based on gray-level average silhouettes over a gait cycle is performed. In the conventional PCA and LDA algorithms, the image matrix is concatenated into a vector, thus the image object is often represented in a very high dimensional feature space, whereas, in many recognition applications, the number of available training samples is small, typically resulting in the well-known curse of dimensionality and the small sample size problem. Furthermore, in real applications, the extracted feature of an object often has some specialized structure in the form of a second-order or even higher order tensor. For example, the gray-level average silhouette is a second-order tensor or matrix. Therefore, it would be highly desirable to uncover such underlying structure in gait recognition. Each sequence was represented as several gray-level average silhouette images, which correspond to gait cycles. A two-stage scheme called CSA+DATER has been employed for dimensionality reduction directly based on the matrix representations. The experiments on the standard USF HumanID Gait database demonstrate encouraging performance improvements over the state-of-the-art algorithms for human gait recognition.

Dr. D. Cunado [10] proposed a new method in which he modelled the leg as a pendulum. The method of identification was defined by calculating the difference between SHM and the motion of the subjects thighs. The gait signature was successfully extracted and could withstand differing amounts of noise and occlusion. This method achieved recognition rates of 100 on a database of ten subjects.

Dacheng Tao et al [11] introduced three new representations of the averaged gait images. These are the sum over directions of Gabor functions based representation (GaborD), the sum over scales of Gabor functions based representation (GaborS), and the sum over scales and directions of Gabor functions based representation (GaborSD). The most important benefit of these new representations is that the cost of computing them is low. This method focus on the representation and pre-processing of appearance-based models for human gait sequences. Two major novel representation models are presented, namely, Gabor gait and tensor gait, and some extensions of them are made to further enhance their abilities for recognition tasks. Gabor gait is based on the well-known Gabor functions. Three different approaches using Gabor functions are developed to reduce the computational complexities in calculating the representation, in training classifiers, and in testing. Tensor gait is also introduced to represent these Gabor gaits. To take the feature selection into account, the size of the tensor gait is reduced by the general tensor discriminant analysis (GTDA), which is based on a low rank approximation of the original data. Apart from reserving discriminative information, GTDA has another advantage - it significantly reduces the effects of under sampling on classification.

Dong Xu et al [12] proposed an effective method which yields better performance on the common databases, reduces computational complexity and improves the accuracy. This system is based on a new Patch Distribution Feature(PDF).To extract Gabor-PDF, each GEI is taken as a set of local augmented Gabor features from which the distribution is estimated by exploiting a two-stage approach to learn an image-specific GMM. Also developed a new classification method referred to as LGSR by enforcing both group sparsity and local smooth sparsity constraints. This method presents a systematic and comprehensive gait recognition approach, which can work just as fine as other complex published techniques in terms of effectiveness of performance while providing all the advantages associated with the computational efficiency for real-world applications.

3. Proposed Method

Existing systems were concentrating on model-based approaches, the human body structure is characterised using the model parameters fitted based on the extracted features. The parameters can be dynamic parameters (e.g., the stride length and speed) or static body parameters (e.g., the size ratios of various body parts).

- There is no way for compact representation to characterize the motion patterns of the human body.
- Computational and time complexity.
- Inaccurate recognition results.

A new methodology for extracting human gait features from a walking human based on the silhouette image is proposed. In this system it employs the silhouette shape similarity, the binary silhouettes over one gait cycle are averaged such that each gait video containing a number of gait cycles is represented by a set of gray-level average silhouette images [i.e., gait energy images (GEIs)]. Following are the various stages included in gait recognition. Figure 3.1 summarizes the main steps in the proposed human gait recognition system.

1. ROI selection by blob detection in the given silhouette image
2. Measuring the width and height of the human silhouette
3. Separating the enhanced human silhouette into six body segments
4. Applying morphological skeleton to obtain the body skeleton
5. Applying radon transform to obtain the joint angles from the body segment skeletons

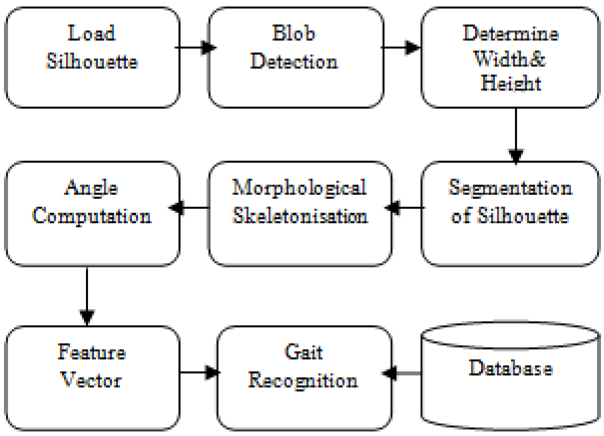

Figure 1: Main steps in the proposed Human Gait Recognition System

3.1 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. The presence of the artefact affects the gait feature extraction and the measurement of joint trajectories. The problem can be reduced by applying morphological erosion and dilation. The opening first performs erosion, followed by dilation. 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. These two features will be used for gait analysis in the later stages.

3.2 Silhouette Segmentation

Segmentation of the image helps to determine regions for blobs. Then separate the correct blobs from accidental noise connecting blobs with existing detections, register new detections and removing ones that are not present any more. Blob Analysis is used to calculate statistics for labelled regions in a binary image. The block returns quantities such as the centroid, label matrix, and blob count and bounding box measurements. Thus the detected degraded pixels will be enclosed by means of bounding boxes.

Segmentation can be improved by building a model of the background pixel intensities. The model of the background can be built on a combination of statistical range and colour values for each pixel in the scene. If the background is continually changing gradually over a period of time, the model will have to be updated over time to reflect these changes. Various simplification assumptions can be made in controlled environments to enhance the performance of segmentation. As well as creating a better model of the background in the image, it is also possible to apply image filters to the foreground image map, which help to reduce noise (pixels which have been misclassified as foreground pixels) and classify pixels into groups. The enhanced human silhouette is divided into six body segments based on anatomical knowledge which represents head and neck, torso, right hip and thigh, right lower leg and foot, left hip and thigh and left lower leg and foot.

3.3 Skeletonization of Silhouette

Skeletonization plays an important role in digital image processing and pattern recognition, especially for the analysis and recognition of binary images. It has been widely used in gait recognition. The silhouette binary image is then subjected to skeletonization. The process can be viewed as a transformation to transform the width of a binary pattern into just one single pixel. Essentially, such transformation can be achieved by successively removing points or layers of outline from a binary pattern until all the lines or curves are of unit width. The resulting set of lines or curves is called the skeleton of the pattern. As we know, the purpose of skeletonization is to reduce the amount of redundant data embedded in a binary image and to facilitate the extraction of distinctive features from the binary image thereafter. Until now, thinning is still the most frequently used method to achieve the skeletonization goal and distortion. To remedy the problems produced by traditional thinning methods, a novel approach to skeletonize binary images with faster speed is proposed.

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.

3.4 Feature Extraction and Angle Computation

The skeleton image is useful for the extraction of features such as angle at joints. Before computing angle the skeleton image is partitioned into six parts. Each and every partitioned portion, with that of the corresponding portion from the reference frames are used for the angle computation. Gabor filter is basically a Gaussian with variances S_x and S_y along x and y directions modulated by a complex sinusoid with center frequencies F_x and F_y along x and y directions. Gabor filter selects the feature along a particular direction under consideration. This reduces the number of points for which radon transform need to be calculated. Even though Gabor filter consider less number of points, the computation requires more time reducing the overall speed. The Radon transform is the projection of the image intensity along a radial line oriented at a specific angle. The radial coordinates are the values along the x'-axis, which is oriented at θ degrees counter clockwise from the x-axis. The origin of both axes is the center pixel of the image. For example, the line integral of f(x,y) in the vertical direction is the projection of f(x,y) onto the x-axis; the line integral in the horizontal direction is the projection of f(x,y) onto the y-axis. The Radon transform of a 2-D function f(x, y) is defined as:

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

Where r is the perpendicular distance of a line from the origin and θ is the angle between the line and the y-axis. The Radon transform can be used to detect linear trends in images. The Radon transform along this direction usually has larger variations. Therefore, the variance of the projection at this direction is locally maximum.

To extract the joint trajectory for each body segment, Radon transform is applied on the skeleton. Radon 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.

3.5 Multisvm Model

After feature extraction, multiclass Support Vector Machine (SVM) is employed for classification. 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..., l where x_i € R^n and y_i € $1,-1^i$ (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 hyper plane to separate different classes by solving the quadratic optimization problem.

4. Experimental Results

In order to be able to perform recognition there needs to be a set of data which the query can be compared against and classified. Here the gait signatures of five different individual was recorded, each person had some video sequences taken at different times. The training data is created by choosing randomly one sequence of each of the different people (a total of six subjects) and storing the details. Queries are then compared against this database. First created a database by capturing walking data from 5 peoples. Each individual performs their walks of approximately same distance. Taking all the data for each subject, arms, legs, head, hip and knee joint locations are recovered. For each subject, there are approximately thirty sets of walking sequences, which are from left to right and vice-versa on normal track. In total, there are 154 walking sequences that are used for training and testing process. The underlying skeleton is connected through these joints joint angle trajectories are recovered. Then select randomly a walk sequence from the database to be a walking template and then we time-warp all the data to that template. After the signal normalization process, all the signals have the same footstep structure and same temporal length.

The USF HumanID gait database collected by Sarkar et al is currently the largest publicly available database for evaluating human gait recognition algorithms. Sarkar et al. also proposed a baseline algorithm to extract the binary silhouette, calculate the gait period length, and conduct final matching. In order to facilitate the subsequent research in this field, Sarkar et al. made the binary silhouettes and the gait period lengths publicly available in http://figment.csee.usf.edu/Gait Base line/.

One of the most important measures in the whole project, as it is the aim of the project is the recognition rates, for the various measures. A comparative analysis of the proposed approach for gait recognition with LGSR classifier was performed using the images available in the database. For the techniques adopted for comparison, Recognition rate of each individuals was calculated and the results are tabulated in Table 1. The corresponding graph is depicted in Figure 2.

Table 1: Comparison of LGSR and MultiSVM Classifier

Person	LGSR Classifier		MULTISVM Classifier	
	Recognition Rate	End Time	Recognition Rate	End Time
Person 1	66.6667	10.1198	80	2.3665
Person 2	62.4554	12.4436	83.3333	2.6557
Person 3	37.5000	23.4153	70.8333	3.4837
Person 4	45.8333	13.0543	62.6667	5.4546
Person 5	37.7833	13.4980	76.3333	5.5076

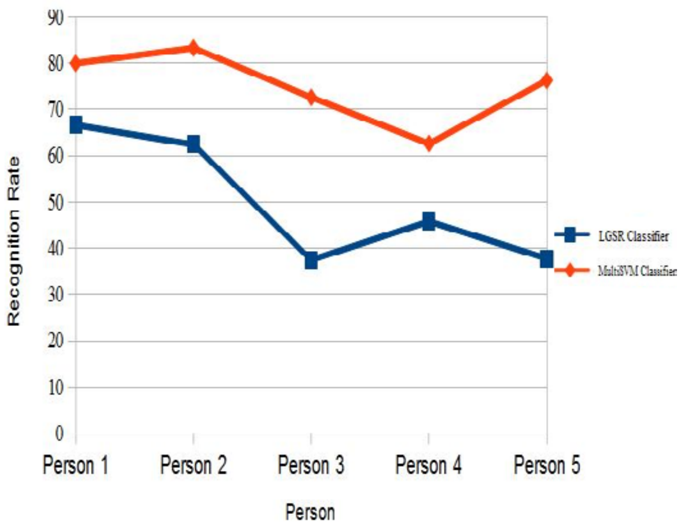

Figure 2: Performance analysis based on Recognition Rate

From the graph, it is evident that the proposed system outperforms the normal gait recognition system that employs LGSR classifier for gait recognition. Thereby, the proposed approach for gait recognition can serve as an effective tool for human identification.

5. 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 angles are obtained after applying Radon transform on the skeleton. To extract features (Gabor-Patch distribution features), each GEI is taken as a set of local augmented Gabor features from which the distribution is estimated by exploiting a two-stage approach to learn an image-specific GMM. Also developed a new classification method using multisvm classifier which presents a systematic and comprehensive gait recognition approach, which can work just as fine as other complex published techniques in terms of effectiveness of performance while providing all the advantages associated with the computational efficiency for real-world applications. The resulting gait recognition system yields better performance on the common databases, reduces computational complexity and improves the accuracy.

References

[1] Hu Ng, Hau-Lee Tong, Wooi-Haw Tan, Timothy Tzen Vun Yap, Pei-Fen Chong, and Junaidi Abdullah, "Human Identification Based on Extracted Gait Features", International Journal on New Computer Architectures and Their Applications (IJNCAA) 1(2):358-370.

[2] Dr.Vincent Huang, "Gait Recognition by combined PCA and CA", http://www.isis.ecs.soton.ac.uk/image/gait/vincent-huang/index.php3.

[3] James J.Little and Jeffrey E.Boyd, "Recognising people by their gait: the shape of motion", MIT Press Journal Videre, 1996.

[4] Ju Han, and Bir Bhanu, "Individual Recognition Using Gait Energy Image".
[5] Chiraz BenAbdelkader, Ros Cutler, Harsh Nanda and Larry Davis, "Eigen Gait: Motion based Recognition of People using Image Self-Similarity".
[6] Jyoti Bharti, and M.K.Gupta, "Gait Recognition with Geometric Characteristic and Fuzzy Logic", Canadian Journal on Image Process, and Computer Vision Vol. 3 No. 1, March 2012.
[7] Aaron F.Bobick, and Amos Y.Johnson, "Gait Recognition Using Static, Activity-Specific Parameters".
[8] N.Boulgouris and Z.Chi, "Gait recognition using radon transform and linear discriminant analysis", IEEE Trans. Image Process., vol. 16, no. 3, pp. 731740, Mar. 2007.

[9] D.Xu, S.Yan, D.Tao, L.Zhang, X.Li, and H.Zhang, "Human gait recognition with matrix representation" , IEEE Trans. Circuits Syst.Video Technol., vol. 16, no. 7, pp. 896903, Jul. 2006.
[10] Dr.David Cunado, "Model based gait recognition variation in hip inclination", http://www.isis.ecs.soton.ac .uk/images/gait /david-cunado/index.php3.
[11] Dacheng Tao, Xuelong Li, Xindong Wu, and Stephen J. Maybank, "General Tensor Discriminant Analysis and Gabor Features for Gait Recognition".
[12] Dong Xu, Yi Huang, Zinan Zeng, and Xinxing Xu, "Human Gait Recognition Using Patch Distribution Feature and Locality-Constrained Group Sparse Representation", IEEE Transactions on image Processing, vol. 21, no. 1, Jan 2012.