International Journal of Innovative Research in Science and Engineering
Vol. No.2, Issue 09, September 2016
www.ijirse.com
ISSN (O) 2454-9665
ISSN (P) 2454-0663

LAPLACIAN BIDIRECTIONAL SCATTER DIFFERENCE CRITERION FOR GAIT RECOGNITION

Risil Chhatrala[1], Dattatray V. Jadhav[2]

[1]Research Scholar, Dept. of E&TC, Rajashri Sahu College of Engineering, Savitribai Phule Pune University, (India)

[2]TSSM Bhivarabai Sawant College of Engineering and Research, Narhe, Savitribai Phule Pune University, (India)

ABSTRACT

Extraction of discriminative features for robust human gait recognition is challenging due to inherent challenges involved in covariate factors such as carrying and clothing conditions, view angle and many more. The effect of covariate can be modeled as unknown fractional feature contamination problem, resulting in to conversion of useful or relevant feature in to irrelevant one. Conventional feature extraction and discriminant analysis methods show poor performance when considered in presence of covariates. In this paper, discriminative feature extraction method based on Laplacian Bidirectional Scatter Difference Criterion for gait recognition is proposed. It exploits benefit of weighted scatter difference instead of generalized Rayleigh quotient or fisher discriminant criterion as a class separability measure. When addressing small-sample-size problems, it avoids computation of inverse of within class scatter, thereby solving singularity problem of Linear Discriminant Analysis with preservation of discriminant feature extraction capability. It is extracting benefit from maximum margin criterion with a difference of weighing scheme of scatter matrices to achieve improvement in performance in presence of view angle as covariate condition.

Keywords: Gait Recognition; Feature Extraction; Biometrics;

I. INTRODUCTION

Physical biometrics like fingerprint, iris offers very good recognition rate but requires subject consent and co-operation under controlled environment. In contrast gait-as behavioral biometric allows flexibility to capture subject gait signature without consent and cooperation [HYPERLINK \l "SSa05" 1]2]. The working resolution requirement offered by gait is very low. These set of advantages offer gait as unique candidate for video surveillance application. Number of efforts made by researchers to improve recognition rate under experimental environment, but found to degrade performance in presence of diverse factor called as covariates. Thus robust human gait recognition offers unique challenge for extraction of discriminative features in presence of covariates. Different covariates [HYPERLINK "" \l "KBa10" 3] 4] can be classified as 1) Conditions that affect gait itself like shoes, injury, speed, pregnancy, affliction of the legs or feet, drunkenness and time i.e.

International Journal of Innovative Research in Science and Engineering
Vol. No.2, Issue 09, September 2016
www.ijirse.com
ISSN (O) 2454-9665
ISSN (P) 2454-0663

increase in age and 2). Conditions that affect features extracted from gait are carrying condition, clothing condition, view angle etc.

This paper presents a comprehensive strategy and techniques suitable at various at stages of processing gait video sequence. Generalized framework for gait recognition and human identification is described in Section 2 with prime focus on preprocessing of video sequence. Section 3 gives broad review of representation schemes for gait representation. To achieve effective and efficient representation, single template based approach is employed. The discrimination ability at reduced order and dimensions are explained in Section 4. Feature extraction scheme based on Laplacian Bidirectional Scatter Difference Criterion (LBSDC) is employed in Section 5. Experimental evaluation of proposed scheme is presented in Section 6 followed by Conclusion and discussion in Section 7.

II. OVERVIEW OF GAIT RECOGNITION

Basic block diagram showing processing of video sequence captured from CCTV is shown in Figure1.

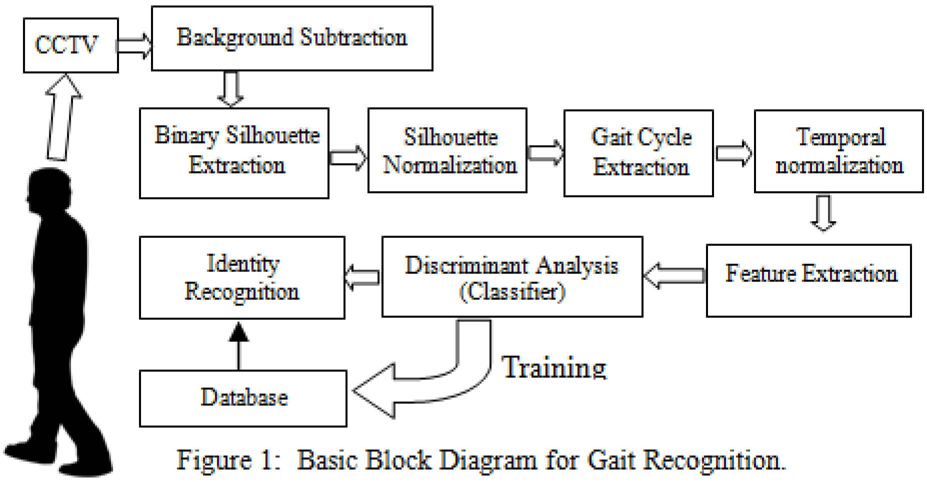


Figure 1: Basic Block Diagram for Gait Recognition.

The detection of human within images is achieved by background subtraction and silhouette extraction. The raw silhouettes so-obtained are further processed by silhouette normalization which makes silhouette invariant to variation in zoom angle and alignment. Gait cycle extraction allows us to extract one gait cycle video sequence from binary extracted silhouette. In model free approaches, video sequence of one complete gait cycle is being mapped to single template; the process is called as temporal normalization. Mapping of temporal information, on to single template improves computational efficiency. Features that can be used for recognition are extracted from gait template of walking person. Discriminant analysis and classifier is used to train the database and further used to recognize human identity. Recognition is achieved by comparison of extracted features with those features available in database.

2.1 Background Subtraction

Once moving subjects are captured by surveillance camera, individual from moving video sequence will be detected and separated from the background. The most widely used method is background subtraction, which attempts to separate objects from the difference between the modeled background and the current frame.

ISSN (O) 2454-9665
ISSN (P) 2454-0663

2.2 Binary Silhoutte Exatraction

Baseline algorithm proposed by Sarkar et. al [HYPERLINK "" \l "SSa05" 1] extracts the motion silhouette in each frame by background subtraction, within the semi-manually defined bounding boxes. For SOTON database5] the gait sequences are derived in the laboratory, aiming for near-perfect conditions to obtain the best possible silhouette. The dynamic signature [HYPERLINK "" \l "MNi06" 5] 6] is obtained by chroma-key subtraction in conjunction with a connected components algorithm followed by windowing. Liang Wang et.al [HYPERLINK "" \l "LWa03" 7] has adopted change detection based on background subtraction. The improved version of background subtraction procedure can be applied to any realistic scene to extract moving silhouettes of walking figures from the background. The silhouettes are made binary so as to remove the coloring, intensity and illumination variation.

2.3 Silhoutte Normalization

The raw silhouettes so-obtained are further processed by size normalization (proportionally resizing each silhouette image so that all silhouettes have the same height) and horizontal alignment (centering the upper half silhouette part with respect to its horizontal centroid) 1].

2.4 Gait Cycle Extraction

Human walking can be considered as periodical motion [HYPERLINK "" \l "JLi98" 8] and period detection in gait sequence allow us for preservation of temporal information. Sarkar et. al 1] had detected gait periodicity by a counting the number of foreground pixels Nf (t) mostly from leg region from bottom half of the silhouette in each frame over time. Gait period is estimated by computing averaging median of the distances between minima, skipping every other minimum. Chen wang et.al [HYPERLINK "" \l "Wan10" 9] has proposed to use degree of the individual's two legs apart from each other to represent regular human walking. Height normalization and alignment normalization 10] is used to improve gait period detection.

III. GAIT REPRESENTATION APPROACHES

Much progress has been made in computer vision-based human motion analysis. It is only recently that human identification (Human ID) from gait has received attention and become an active area of computer vision. In recent years, various techniques have been proposed for human recognition by gait. Most of the gait recognition methods focus on gait representation approaches in order to make it robust against covariate conditions and computationally efficient. A good representation of gait should be able to discriminate, be robust to noise and changing covariate conditions, be space efficient and be easy to compute and manipulate. Based on the way gait is represented, the existing gait recognition approaches can be divided into two categories: model based and model free approaches.

Model Based Approach

The approach represents gait using the parameters of a model of the body configuration [HYPERLINK "" \l "Mao11" 2]. 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). Model based approach has inferior performance due to requirement of high resolution images as input and sensitivity to image noise, self-occlusion, shadows and view changes. The requirement of higher computational cost is major challenge.

International Journal of Innovative Research in Science and Engineering
Vol. No.2, Issue 09, September 2016
www.ijirse.com
ISSN (O) 2454-9665
ISSN (P) 2454-0663

3.1 Model-Free Approach

The approach constructs gait descriptor from motion dynamics of human bodies and/or static shape information of silhouettes in compact form. This presentation is more robust to noise, insensitive to the quality of silhouettes and has the advantage of low computational costs. However, they are usually not robust to viewpoints and scale.

IV. SINGLE TEMPLATE BASED GAIT RECOGNITION APPROACH

The approach converts video sequence into a single image template and provides compact representation of gait. A gait cycle represented using a single image offers unique advantage of low computational complexity and robustness for noise in silhouette extraction. However, they are vulnerable to appearance changes of the human silhouette.

4.1 Average Silhouette Representation

The average silhouette proposed by Liu and Sarkar 1] has been used as a choice of representation for gait by many researchers. The representation captures the shape of the template and, to a lesser extent, the temporal dynamics of gait.

Let be the silhouette sequence which is partitioned into subsequences of gait period length, denoted by. For each subsequence the silhouettes are averaged to arrive at a set of average silhouettes,

Let $S = \{S(1), \mathrm{L}\ S(M)\}$ be the silhouette sequence which is partitioned into subsequences of gait period length, denoted by $S_{pk} = \{S(k), \cdots, S(k + N_{pk})\}$. For each subsequence the silhouettes are averaged to arrive at a set of average silhouettes,

$$AS(i) = \frac{1}{N_{Gait}} \sum_{k=iN_{Gait}}^{(i+1)N_{Gait}-1} S(k) \qquad (1)$$

4.2 Gait Energy Image

A more popular version of average silhouettes is the Gait Energy Image (GEI) proposed by Han and Bhanu [HYPERLINK "" \l "BBh06" 11]. GEI represents gait averaged over a complete cycle in a single grey scale image. Given preprocessed binary gait silhouette images at time t in a sequence, the grey level gait energy image (GEI) is defined as

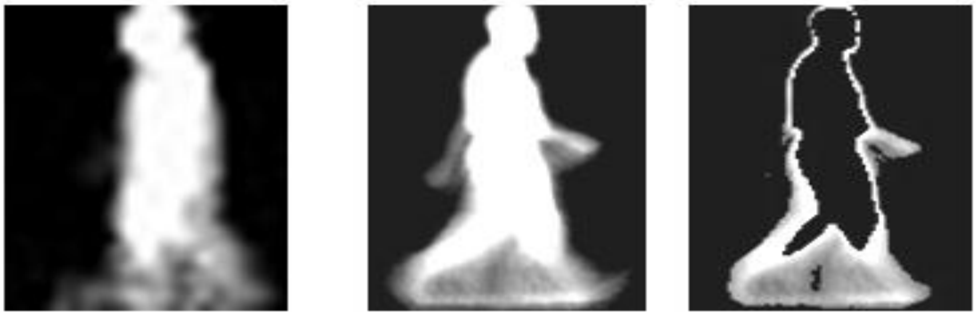
$$G(x, y) = \frac{1}{N} \sum_{t=1}^{N} B_t(x, y) \qquad (2)$$

This simple representation loses the dynamical variation between successive frames but has useful properties. (1) No silhouette alignment is required. (2) Space efficient compact representation of gait. (3) Reduced effect of noise because of the averaging procedure.

GEI representation captures explicitly the shape and dynamics of the subject. Pixels with high intensity values in a GEI correspond to body parts that move little during a walking cycle (e.g. head, torso), while pixels with low intensity values correspond to body parts that move constantly (e.g. lower parts of legs and arms). This explicit

International Journal of Innovative Research in Science and Engineering
Vol. No.2, Issue 09, September 2016
www.ijirse.com
ISSN (O) 2454-9665
ISSN (P) 2454-0663

representation of shape makes the average silhouette (GEI) representation of gait vulnerable to appearance changes of the human silhouette caused by common conditions such as clothing and carrying.



(a) Average Silhouette **(b) Gait Energy Image** **(c) Masked Gait Energy Image**

Figure 3: Single Template Representation

4.3 Masked GEI

As GEI captures dynamics and shape of object, the object which remains stationery over gait cycle appears with high intensity in GEI and leg region which has most of movement appears with low intensity. In order to capture only dynamic part and remove effect of occlusion, mask is used to suppress high intensity component from GEI. This image is called as masked GEI. Simple threshold detection is used to obtain masked GEI.

V. LAPLACIAN BIDIRECTIONAL SCATTER DIFFERENCE CRITERION

The method proposed is straight forward extension of image projection method based on Laplacian Bidirectional Maximum Margin Criterion (LBMMC) proposed by Wankou Young et al [12]. It has advantage of consideration of structural information without mapping image in to vector. Thus employing low dimensional feature space reducing computation complexity. Let X is image of size $m \times n$ and Y is feature matrix of size $k_{col} \times k_{row}$ then feature matrix Y is obtained from X by following projection.

$$Y = W_{col}^{T} \times X \times W_{row} \qquad (k_{col} \ll m, k_{row} \ll n) \qquad (3)$$

Where W_{col} and W_{row} is column and row projection matrix respectively. Let $X = [X_1, X_2, \cdots X_N]$ is set of N sample gait image templates taken from $m \times n$ dimensional image space. The similarity between two samples as defined in [12] is given as $S_{ij} = \exp(-\|x_i - x_j\|^2 / t)$ (4)

Where x_i is the vector of image X_i with the constraint that for any x_i and x_j , parameter t, $0 \le S_{ij} \le 1$ always hold. It is important to note that similarity function is strictly monotonically decreasing causing heavy penalty when Euclidean distance between two samples is too large.

Similarity matrix between any two samples in same class is defined as

$$H_{ij} = \begin{cases} S_{ij} & \text{if } x_i \text{ and } x_j \text{ belong to same class} \\ 0 & \text{Otherwise} \end{cases} \qquad (5)$$

Image total scatter matrix, within class scatter matrix, between class scatter matrix and image total Laplacian scatter matrix along row and column direction is given in table 1. Image total Laplacian scatter matrix uses sample similarity weight as defined in equation (4).

Table1: Scatter Matrices along Row and Column

Along Row	Along Column
$S_t^{row}=\sum_{i=1}^{N}\sum_{j=1}^{N}\left(X_i-X_j\right)^T\left(X_i-X_j\right)$ $S_W^{row}=\sum_{k=1}^{c}\sum_{i=1}^{l_k}\sum_{j=1}^{l_k}\left(X_k^i-X_k^j\right)^T\left(X_k^i-X_k^j\right)$ $S_b^{row}=S_t^{row}-S_W^{row}$	$S_t^{col}=\sum_{i=1}^{N}\sum_{j=1}^{N}\left(X_i-X_j\right)\left(X_i-X_j\right)^T$ $S_W^{col}=\sum_{k=1}^{c}\sum_{i=1}^{l_k}\sum_{j=1}^{l_k}\left(X_k^i-X_k^j\right)\left(X_k^i-X_k^j\right)^T$ $S_b^{col}=S_t^{col}-S_W^{col}$
$LS_t^{row}=\sum_{i=1}^{N}\sum_{j=1}^{N}S_{ij}\left(X_i-X_j\right)^T\left(X_i-X_j\right)=X^T\left(L\otimes I_m\right)X$ $LS_W^{row}=\sum_{k=1}^{c}\sum_{i=1}^{l_k}\sum_{j=1}^{l_k}H_{ij}\left(X_k^i-X_k^j\right)^T\left(X_k^i-X_k^j\right)=X^T\left(L_w\otimes I_m\right)X$ $LS_b^{row}=LS_t^{row}-LS_W^{row}$	$LS_t^{col}=\sum_{i=1}^{N}\sum_{j=1}^{N}S_{ij}\left(X_i-X_j\right)\left(X_i-X_j\right)^T=X\left(L\otimes I_m\right)X^T$ $LS_W^{col}=\sum_{k=1}^{c}\sum_{i=1}^{l_k}\sum_{j=1}^{l_k}H_{ij}\left(X_k^i-X_k^j\right)\left(X_k^i-X_k^j\right)^T=X\left(L_w\otimes I_m\right)X^T$ $LS_b^{col}=LS_t^{col}-LS_W^{col}$

The objective function based on image Laplacian bidirectional scatter difference criterion along row and column direction is defined in (6) and (7). It has simple assumption that between class Laplacian scatter should be maximum for the samples coming from different classes and have minimum within class Laplacian scatter for samples from same class. The objective function proposed, is similar to LBMMC with the difference of tuning parameter Λ_{row} and Λ_{col} , which contributes largely towards fast convergence.

$$J_{row}\left(W\right)=tr\left(W_{row}^T\left(LS_b^{row}-\Lambda_{row}*LS_w^{row}\right)W_{row}\right) \quad (1) \text{ and } \quad J_{col}\left(W\right)=tr\left(W_{col}^T\left(LS_b^{col}-\Lambda_{col}*LS_w^{col}\right)W_{col}\right) \quad (2)$$

Where $\Lambda_{row}=tr\left(LS_b^{row}-LS_w^{row}\right)$ and $\Lambda_{col}=tr\left(LS_b^{col}-LS_w^{col}\right)$

Since there is no closed form solution exists for simultaneous maximization of two objective functions in (6) and (7), iterative scheme is proposed in algorithm in Table II.

Table2: Algorithm for Discriminant Feature Extraction for Gait Recognition

1. Preprocess video sequence to obtain binary silhouette and normalized single template based on block diagram shown in figure 1.
2. Compute similarity matrix S and H using equation (4) and (5)
3. For itn =1: max_itern
4. If itn=1 Compute $\Lambda_{row}^{itn}=tr\left(\left[LS_b^{col}\right]^{itn}-\left[LS_w^{col}\right]^{itn}\right)$ $\Lambda_{row}^{itn}=tr\left(\left[LS_b^{row}\right]^{itn}-\left[LS_w^{row}\right]^{itn}\right)$

   Else $\Lambda_{row}^{itn+1}=tr\left(W_{row}^T*\left[LS_b^{col}\right]^{itn}-\left[LS_w^{col}\right]^{itn}*W_{row}\right)$ $\Lambda_{col}^{itn+1}=tr\left(W_{col}^T*\left[LS_b^{row}\right]^{itn}-\left[LS_w^{row}\right]^{itn}*W_{col}\right)$

   End if

   Perform eigen decomposition of $LS_b^{row}-\Lambda_{row}*LS_w^{row}$ and $LS_b^{col}-\Lambda_{col}*LS_w^{col}$

   Use Eigen vectors corresponding to eigen values in descending order to obtain W_{row} and W_{col}

International Journal of Innovative Research in Science and Engineering
Vol. No.2, Issue 09, September 2016
www.ijirse.com
ISSN (O) 2454-9665
ISSN (P) 2454-0663

If $\left\|W_{col}^{itn} - W_{col}^{itn-1}\right\| < \varepsilon$ and $\left\|W_{row}^{itn} - W_{row}^{itn-1}\right\| < \varepsilon$ or number of iteration is over then stop for loop

5. Compute row projection matrix W_{row}
6. Compute column projection matrix W_{col}
7. Obtain features in reduced dimension space by using $Y = W_{col}^{T} \times X \times W_{row} \quad \left(k_{col} \ll m, k_{row} \ll n\right)$
8. Compute Euclidean distance between features of gallery and probe sequence
9. Classify based on k-nearest neighbor rule and compute recognition rate

Column Eigen vectors corresponding to first k_{row} largest eigen values is selected to construct column projector

$$W_{row} = \left[w_1^{row}, w_2^{row}, \cdots, w_{k_{row}}^{row}\right] \qquad (8)$$

The optimal projection axes $w_1^{col}, w_2^{col}, \cdots, w_k^{col}$ is selected as orthonormal eigen vectors corresponding to first k largest eigen values $\lambda_1, \lambda_2, \cdots \lambda_k$

i.e. $\left(LS_b^{col} - \Lambda_{col} * LS_w^{col}\right) w_j = \lambda_j w_j$ where $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_k$

VI. EXPERIMENTS

To evaluate performance of the proposed scheme of representation and processing of gait video sequence; followed by discriminative feature extraction algorithm as explained in Table II, rank 1 and rank 5 recognition rates are computed for standard gait benchmark databases. The Rank 1 performance means the percentage of the correct subjects ranked first while the Rank 5 performance means the percentage of the correct subjects appeared in any of the first five places in the rank list. We also report the average performance by computing the ratio of correctly recognized subjects to the total number of subjects

6.1 Experiment on USF database

The walking sequence in the USF dataset was captured in an outdoor environment. The dataset contains 122 subjects and a total of 1870 gait sequences. The USF dataset contains a number of subsets offering a range of variables. In the USF data set, there are five different variations—view points, surface, shoe, carrying condition and time. The walking sequences are divided in to 13 different subsets: 1 gallery set and 12 probe sets. For training purpose, as explained by sarkar et. al. [1], gallery is used as training set. Gait energy image is computed with size 32X 22 pixels in grayscale, for each sample video sequence and this GEI template is used for discriminative feature extraction step in training. For testing purpose each probe sequence is processed with same algorithm as explained in Table II with same size 32X 22 pixels in grayscale. is set to be in our case. The projection matrices as computed in training, is used for discriminative feature extraction and dimensionality reduction. In testing phase, Euclidean distance is calculated between training set and testing set by reshaping tensors in to vectors. K-NN classifier is used to estimate 1-closest neighbor for rank-1 recognition rate and 5-closest neighbor for rank-5 recognition rate.

International Journal of Innovative Research in Science and Engineering
Vol. No.2, Issue 09, September 2016
www.ijirse.com
ISSN (O) 2454-9665
ISSN (P) 2454-0663

6.2 Results

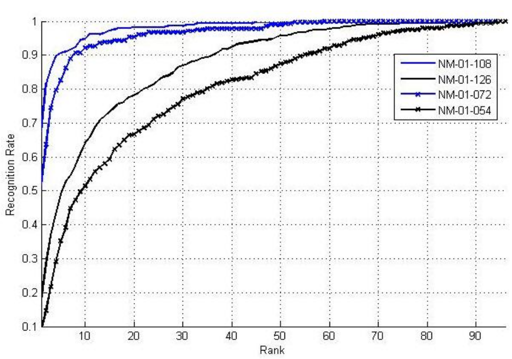
Table III shows results for proposed algorithm on USF dataset for rank 1 and rank 5 recognition rates. Recognition Rate on USF database

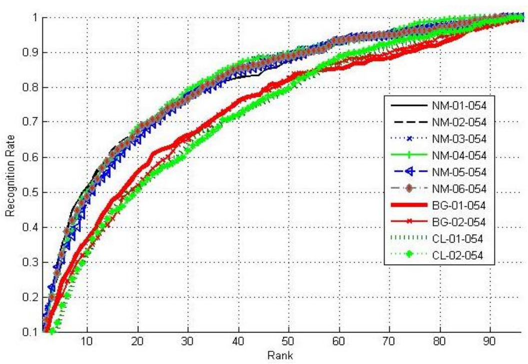
Probe	Variation	Total Objects	Covariates Difference	Recognition Rate	
				Rank 1	Rank 5
A	(G, A, L, NB, t_1)	122	View	85	95
B	(G, B, R, NB, t_1)	54	Shoe	75	87
C	(G, B, L, NB, t_1)	54	View, Shoe	65	79
D	(C, A, R, NB, t_1)	121	Surface	32	65
E	(C, B, R, NB, t_1)	60	Surface, Shoe	28	54
F	(C, A, L, NB, t_1)	121	Surface, View	25	45
			Average	51.6	70.83

6.3 Experiment on CASIA database

CASIA Gait Database is provided by the Institute of Automation Chinese Academy of Sciences. In the CASIA Gait Database there are three datasets: Dataset A, Dataset B (multiview dataset) and Dataset C (infrared dataset). Dataset A has 20 persons. Each person has 12 image sequences, 4 sequences for each of the three directions, i.e. parallel, 45 degrees and 90 degrees to the image plane. The length of each sequence is not identical for the variation of the walker's speed, but it must ranges from 37 to 127.

In order to evaluate performance of our proposed algorithm, extensive experiments are carried out on Dataset B of CASIA database. Published literature claims that maximum information is embodied in gait video sequence when captured at 90 degree view angle. Hence, NM-01-090 gait sequence is selected as training sequence and all other are used as testing sequence. View angle 054, 072, 090, 108, 126 are tested for different carrying and clothing conditions. Figure 5.a demonstrates acceptable rate for 72 and 108 degrees and poor performance for 54 and 126 degrees. This shows that as view angle deviates largely from training view angle, recognition rate falls sharply.

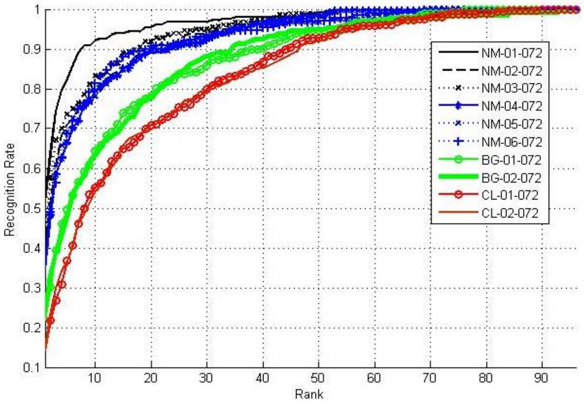


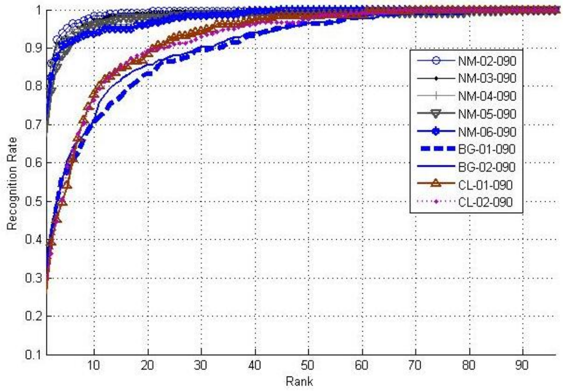


(a) For view angles. 054,072,108,126

(b) View angle: 090 for Training, 054 testing. For various clothing and carrying condition

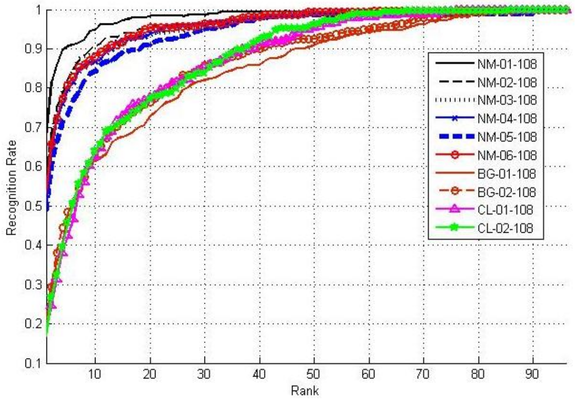
International Journal of Innovative Research in Science and Engineering
Vol. No.2, Issue 09, September 2016
www.ijirse.com
ISSN (O) 2454-9665
ISSN (P) 2454-0663

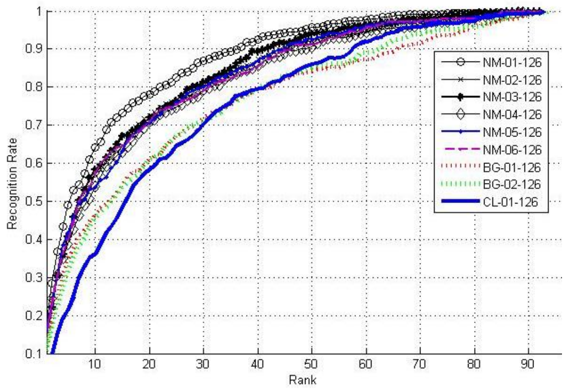




c) View angle: 090 for Training, 072 testing For various clothing and carrying condition

d) View angle: 090 for Training, 090 Testing. for various clothing and carrying condition





e) View angle: 090 for Training, 108 Testing. For various clothing and carrying condition

f) View angle: 090 for Training, 126 Testing. For various clothing and carrying condition

Figure 4.b to 4.e shows that when training view angle is set as 90 degree, and tested for 54, 72, 90, 108 and 126 degrees with various carrying and clothing condition, recognition rate is acceptable for normal conditions nm-01 to nm-06 but drops rapidly with carrying and clothing conditions bg-01 to cl-02.

VII. CONCLUSION AND DISCUSSION

In this paper, discriminative feature extraction method based on Laplacian Bidirectional Scatter Discriminant Criterion for gait recognition is proposed. The evaluation of performance on USF and CASIA data set shows better performance in comparison with conventional supervised learning based on fisher criterion called linear discriminant analysis.

Even though recognition rate posed is acceptable for experimental set up, gait based human identity recognition is still far away from making it suitable for real life applications. Important set of challenges which requires deep thought and promising directions for future research are outlined as follows

1. Just like other biometrics, gait is also affected by image noise and changing lighting conditions.
2. All existing methods assume experimental set up for capturing gait sequence. However, humans may walk in a complex background, which means feature extraction from video captured from visual surveillance cameras poses new set of limitation for segmentation.

ISSN (O) 2454-9665
ISSN (P) 2454-0663

3. Most of existing techniques assumes fixed view, however subject may be tested for different view angle. Hence, view-invariant methods need to be explored to improve the performance of gait recognition.
4. It was observed that large number of covariate exist that may affect persons gait degrading recognition rate and this is totally unexplored area where large amount of research needs to be carried out so as to make gait as suitable candidate for identity recognition without consent.

REFERENCES

[1] S. Sarkar, et al., "The HumanID Gait Challenge Problem: Data Sets, Performance, and Analysis," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 27, no. 2, pp. 166-177, Feb. 2005.

[2] Z. Zhang, M. Hu, and Y. Wang, "A Survey of Advances in Biometric Gait Recognition," in CCBR, 2011, pp. 244-251.

[3] K. Bashir, "Robust Gait Recognition Under variable Covariate conditions ," PhD Thesis, Queen Marry University of London, London, 2010.

[4] K. Bashir, T. Xiang, and S. Gong, "Gait Recognition Using Gait Entropy Image," in IEE International Conference on Imaging for Crime Detection and Prevention, London, U.K., 2009.

[5] M. Nixon and J. Carter, "Automatic Recognition by Gait," IEEE Transaction on Image and Video Processing, vol. 94, no. 11, pp. 2013-2024, Nov. 2006.

[6] S. D. Mowbray and M. S. Nixon, "Automatic gait recognition via Fourier descriptors of deformable objects," in AVBPA, 2003, pp. 566-573.

[7] L. Wang, T. Tan, W. Hu, and H. Ning, "Automatic Gait Recognition based on Statistical Shape Analysis," IEEE Transaction on Image processing , vol. 12, no. 9, Sep. 2003.

[8] J. Little and J. Boyd, "Recognizing People by Their Gait: The Shape of Motion," Journal of Computer Vision Research, vol. 1, no. 2, 1998.

[9] C. Wang, J. Zhang, J. Pu, X. Yuan, and L. Wang, "Chrono-Gait Image: A Novel Temporal Template for Gait Recognition," Springer Computer Vision – ECCV 2010, vol. 6311, pp. 257-270, 2010.

[10] C. BenAbdelkader, "Gait as a Biometric for person identification in video," PhD Thesis, University of Maryland, 2002.

[11] J. Han and B. Bhanu, "Individual Recognition Using Gait Energy Image," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 28, no. 2, pp. 316-322, Feb. 2006.

[12] W. Yanga, et al., "Feature extraction based on Laplacian bidirectional maximum margin criterion," Pattern Recognition, vol. 42, pp. 2327-2334, 2009.

[13] Y. Makihara, R. Sagawa, Y. Mukaigawa, T. Echigo, and Y. Yagi, "Gait Recognition using a View Transformation Model in the Frequency Domain," in European Conference on Computer Vision (ECCV2006), 2006.

[14] J. Wang, M. She, S. Nahavandi, and A. Kouzani, "A Review of Vision-based Gait Recognition Methods for Human Identification," Digital Image Computing: Techniques and Applications, pp. 320-327, 2010.

[15] Q. Xiao, "Technology review - Biometrics-Technology, Application, Challenge, and Computational Intelligence Solutions," Computational Intelligence Magazine, IEEE, vol. 2, no. 2, pp. 5-25, May 2007.

ISSN (O) 2454-9665
ISSN (P) 2454-0663

[16] Y. Liu, R. Collins, and S. Lee, "Shape Variation-Based Frieze Pattern for Robust Gait Recognition," in CVPR, 2007, pp. 1-8.

[17] T. H, W. L. n, K.H.Cheung, and J. N.K.Liu, "Gait Flow Image:A silhouette-based Gait Representation for Human Identification," Pattern Recognition, vol. 44, pp. 973-987, 2011.

[18] D. Tao, X. Li, X. Wu, and S. Maybank, "General Tensor Discriminant Analysis and Gabor Features for Gait Recognition," IEEE Transaction on Pattern Analysis and Machine Intelligence, vol. 29, no. 10, pp. 1700-1715, Oct. 2007.

[19] A. K and K. L, "A Review On Linear And Non - Linear Dimensionality Reduction Techniques," Machine Learning and Applications: An International Journal (MLAIJ) , vol. 1, no. 1, pp. 65-76, Sept 2014.

[20] R. Xu and Y.-W. Chen, "Generalized N-dimensional principal component analysis (GND-PCA) and its application on construction of statistical appearance models for medical volumes with fewer samples," Neurocomputing, vol. 72, no. 10, pp. 2276-2287, 2009.

[21] D. Xu, S. Yan, and L. Zhang, "Concurrent Subspaces Analysis," in IEEE Computer Society Conference on Computer Vision and Pattern Recognition, CVPR 2005, 2005.

[22] S. Yan, et al., "Discriminant analysis with tensor representation," in Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on, vol. 1, 2005, pp. 526-532.