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A NOVEL APPROACH FOR THE RECOGNITION OF THE FACES OF EUNUCHS

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ABSTRACT: Face can be considered as multidimensional visual stimuli. Eunuchs are the special kind of human being regarding the gender and their faces are also different in nature since these faces do not belong to either male or female gender. In this paper, a modified Local Binary Pattern (LBP) technique is used for extracting feature of eunuch faces and neural network based algorithm is used for face recognition. Recognition is done by Multilayer Feed Forward Neural Network with back proapgation learning rule. Here real life face images of the eunuchs are taken from North East India people and performance evaluation metrics like acceptance ratio and execution time are calculated.

Keywords: Face recognition, modified Local Binary Pattern, Multilayer Feed Forward Neural Netwrok, back propagation learning rule.

I. INTRODUCTION

A number of biometric approaches have been proposed for personal identification in the past. Among the vision based ones, we can mention Face recognition, Fingerprint recognition, Iris Scanning and Retina Scanning [1 - 4]. Face Recognition is the most widely known among the vision based ones. Face is a behavioral biometric; it is based on physical properties of an individual. As such ones face may change over time but still it is unique and difficult to forge as the pattern. The face is a primary focus of attention in social life. Playing a big role in conveying identity and emotion. Human ability to recognize faces is remarkable but it is very difficult to recognize all faces of particular type of people which are similar in looks.Eunuchs are the special kind of human being addressed by various names: hijra, kinnar, transsexuals, the third sex, or the other sex. Eunuchs live in their own communities - a separate world of their own. Among these ostracized eunuchs, many of them are castrated, few are genetically born hermaphrodite, that is, they have genitals of both sexes, and few are transvestites that is, a female mind trapped in male body or vice versa [5]. Transgender communities have existed in most parts of the world with their own local identities, customs and rituals. As of date now face recognition done on either male or female faces but Eunuch faces are different in dimension as their faces are different from normal human being.Face recognition problem is concerned to determine whether a particular face belongs to a person, to decide if the record regarding the concerned person already exists or not. Computer recognition of face images involves two important aspects: facial feature extraction and classification. Before extracting features it is necessary to derive a set of features from original image that are to be used for describing faces. Features may or may not relate to intuitive notation such as eyes, nose, lips, and hair etc. If features used for recognition are not passable, even the best classifier will fail to achieve accurate recognition. Hence it requires extensive knowledge to select adequate feature that describe face. Adequate facial features are desired to have following properties [6-7]: first, they should be able to tolerate the within-class variations while discriminate different classes well; second, they can be easily extracted from the raw images to allow fast processing; and finally, the features should lie in a space with the low dimensionality in order to avoid computationally expensive classifiers.A number of studies based on various algorithms has been reported since long on face recognition. M.Turk *et al* proposed Principal Component Analysis [8] approach for automated face recognition aimed at to catch the total variation in the set of training faces and to explain the variation by a few variables. Linear Discriminant Analysis (LDA) [9], and Independent Component Analysis (ICA)[10] have been widely used for feature extraction and object recognition.Although these studies were made for the recognition of general human faces, no work on Eunuch Face Recognition using combination of various algorithm is found in available published or on time literature. Face recognition system generally includes a series of steps as follows: (i) image acquisition, (ii) face pre processing including localization, segmentation, and normalization (iii) feature extraction, and (iv) matching and classification, as shown in figure 1. Image acquisition is the first step in Eunuch Face Recognition System where a face image is captured, and the second step is pre processing and it includes localization, segmentation and normalization. The third step is the feature extraction to get the feature

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Vol. 2, Issue 7, July 2013

vector and Classifier used for matching and classification to obtain the recognition rate.This paper is organized as follows: Local Binary Pattern (LBP) and its variants are described in section 2. Proposed modified algorithm over LBP and feature extraction technique has been discussed in sectin 3. Section 4 has dealt with the application of proposed algorithm in order to classify the extracted features. Experimental results and discussion are given in section 5. Conclusion is incorporated in section 6.

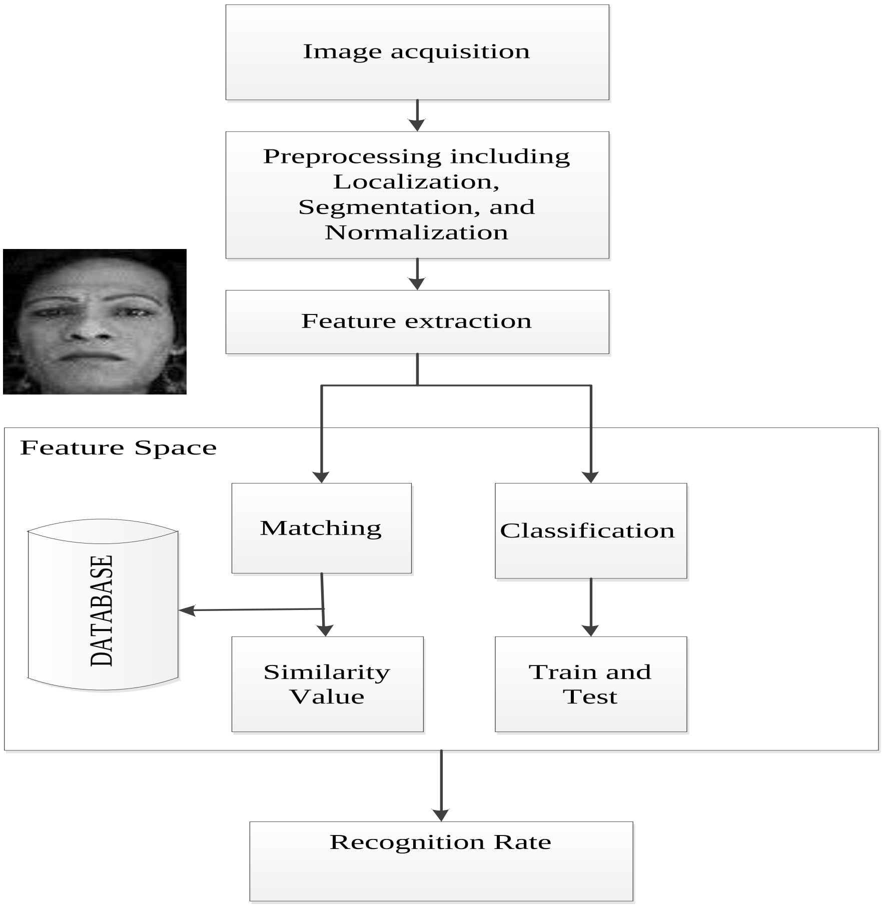

Fig. 1 General Structure of Eunuch Face Recognition System

II. LOCAL BINARY PATTERN METHOD: A BRIEF REVIEW

Local Binary Pattern (LBP) is an efficient method used for feature extraction and texture classification [11]. In this section, we introduce the original LBP operator as well as several extensions like multi-scale LBP, uniform LBP and variants Extended LBP and Census LBP

A. Original LBP

The original Local Binary Pattern (LBP) operator is a non-parametric 3x3 neighbourhood operator which summarizes the local spatial structure of an image. It was first introduced by Ojala et al. [12] who showed the high discriminative power of this operator for texture classification. Each pixel with the 3x3 neighbourhood centre value and considering the results as a binary number, of which the corresponding decimal number is used for labelling. The derived binary numbers are called Local Binary Patterns or LBP codes.

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120	115	170
125	**140**	155
155	175	135

Subtraction

-20	-25	30
-15		15
15	35	-5

Binary Intensity

0	0	1
0		1
1	1	0

Binary : 00110110
Decimal 54

Fig. 2: Basic LBP operator

The decimal form of the resulting 8-bit word (LBP code) can be expressed as follows:

$$\mathrm{LBP}(xc, yc) = \sum_{n=0}^{7} S(i_n - i_c) 2^n$$

where n = Number of neighbour with respect to centre pixel

i_n = Pixel intensity of n^{th} neighbouring pixel

i_c = Intensity of center pixel.

r = Maximum number of neighbours surrounding the center pixel.

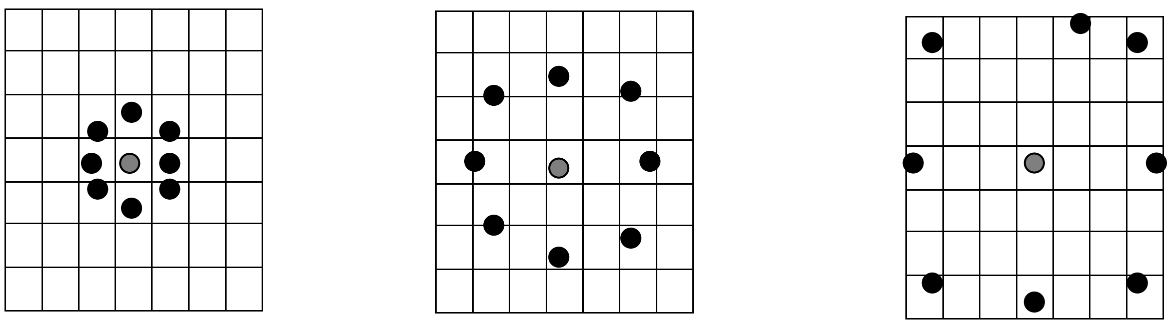
Here r = 8 and function s(x) that denoted binary intensity of each cell is defined as:

$$S(X) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases}$$

By the definition above, the LBP operator is invariant to the monotonic gray-scale transformations which preserves the pixel intensity order in local neighborhoods. The histogram of LBP labels calculated over a region can be exploited as a texture descriptor. The limitation of the basic LBP operator is that its small 3x3 neighborhood cannot capture the dominant features with large scale structures. As a result, to deal with the texture at different scales, the operator requires extension to use neighborhoods of different sizes.

B. Multiscale LBP

Multi-scale LBP [13] is an extension to the basic LBP, with respect to neighborhood of different sizes. In Multiscale-LBP, a circle is made with radius R from the center pixel. P sampling points on the edge of this circle are taken and compared with the value of the center pixel.. Fig.3 shows some examples of Multiscale LBP operator, where the notation *(P, R)* denotes a neighborhood of *P* sampling points on a circle of radius of *R*.



LBP (8,1) LBP (8,2) LBP(8,3)

Fig. 3 : Multiscale LBP operator

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Vol. 2, Issue 7, July 2013

C. Uniform LBP

The LBP operator *LBP(P, R)* produces 2^P different output values, corresponding to 2^P different binary patterns formed by the *P* pixels in the neighborhood. It has been shown that certain patterns contain more information than the others [13]. It is possible to use only a subset of the 2^P binary patterns to describe the texture of the images. Ojala *et al*. named these patterns as uniform patterns [13]. A local binary pattern is called uniform if it contains at most two bitwise transitions from 0 to 1 or vice versa when the corresponding bit string is considered circular. 11111111, 00000110 or 10000111 are for instance uniform patterns.

D. Extended LBP

Huang *et al*. [14] reported that LBP can only reflect the first derivative information of images, and cannot represent the velocity of local variations. So they proposed an extended LBP by applying the LBP operators to both the gradient magnitude image and the original image. For that purpose, they simply applied kernels $LBP^{u2}_{(8,1)}$, $LBP^{u2}_{(8,2)}$ and $LBP^{u2}_{(8,3)}$ both to the original image and the gradient image. Approximately at the same time when the original LBP operator was introduced by Ojala [12], Zabih and Woodfill [26] proposed a very similar local structure feature. This feature, called Census Transform, also maps the local neighborhood surrounding a pixel to a bit string. With respect to LBP, the Census Transform only differs by the order of the bit string.

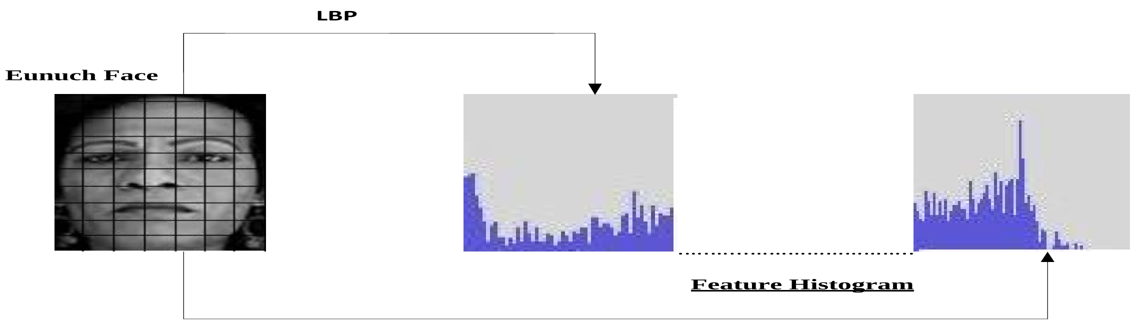

Fig 4 : A face image with small LBP regions and concatenated feature histogram

III. FEATURE EXTRACTION USING MODIFIED LBP

Feature extraction is presented in order to reduce the input face data and transfers it to feature vector. If the features extracted are carefully chosen, it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input face image. A face image can be seen as a composition of micro-patterns which are described by LBP. The histogram of LBP computed over the whole face image encodes only the occurrences of the micro-patterns without any indication about their locations. To consider the shape

Information of faces, Ahonen *et al*. [15] proposed to divide face images into *m* local regions to extract LBP histograms and concatenate them into a single, spatially enhanced feature histogram (Fig 4). 8 main facial components such as eyebrow, eye, pupil, nose and face boundary have been selected as spatial templates shown in Fig. 5 to preserve information about shape of
facial component.

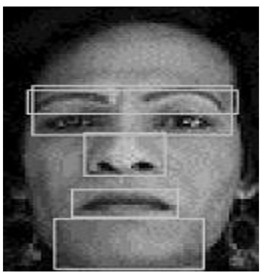

Fig. 5: Eunuch face with spatial templates region

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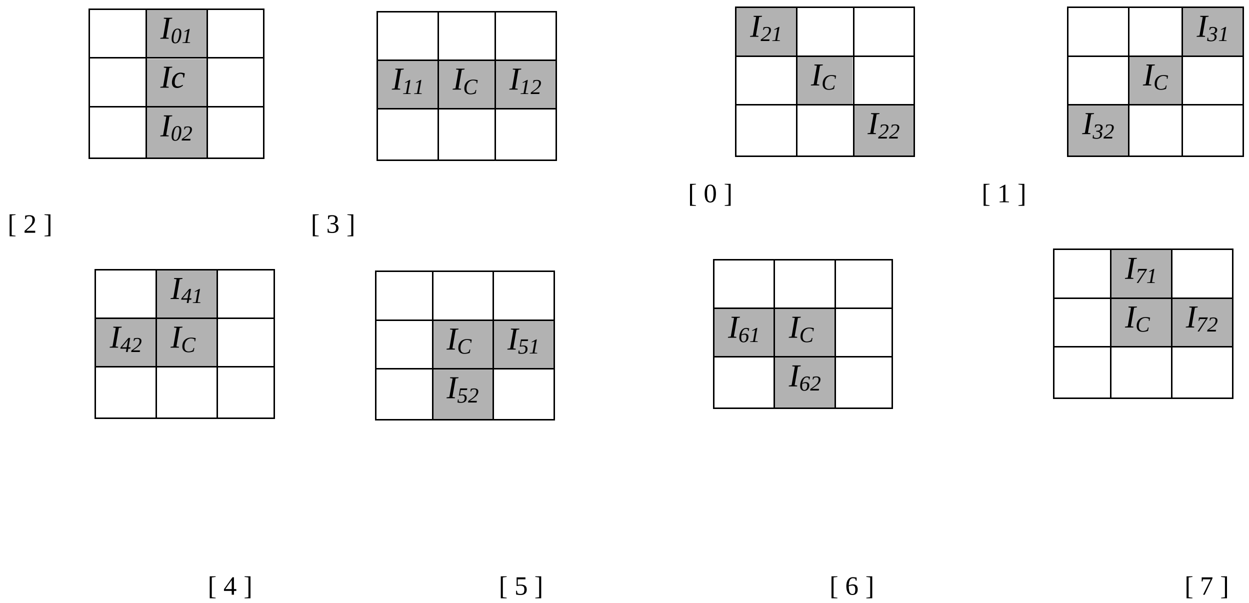

Fig. 6 : Spatial templates for face description

With only those spatial templates, all facial components can be described; for example, nose can be described by a union of templates 0, 5 and 6. However, both spatial information and local texture the information can be combined to improve the capacity of describing faces. Here instead of considering the central pixel P_C only with its each neighborhood pixel as original LBP operator did, we use each pair of two neighborhood pixels (Pi_1,Pi_2) according to spatial templates to compare with the central pixel P_C. Eight spatial templates form 8 binary digits of modified LBP number [15, 16]. So new LBP operator produces 256 different modified LBP values. Function (1) gives the computation of modified LBP number.

$$\text{modified LBP} = \sum_{i=0}^{7} S_i(x)2^i \qquad (1)$$

$$S_i(X) = \begin{cases} 1 & (P_C > P_{i1}) \text{and} \ (P_C > P_{i2}) \\ 0 & \textit{Otherwise} \end{cases} \qquad (2)$$

Where S_i(*x*) denotes i^{th} binary digit of modified LBP number.

The above mentioned modified LBP histogram is used to represent a face. But some parts of human faces can be occluded by sun glasses, human body parts or other complex objects. If we only use single LBP histogram for the whole face candidate image, occlusion will affect matching algorithm seriously. In general, human face has two most important parts: the upper part from nose up to forehead and the lower part from nose down to neck which includes the top of nose, mouth, lips, chin and neck. So we should calculate each part by individual histogram. And these two histograms are connected sequentially to create one mixed 255 x 2 histogram representing to face candidate image. By this way, we can reduce effectively the influence of occlusion. Fig. 7 shows gray image sample, its modified LBP image and histogram.

(i) (ii) (iii)

Fig. 7: (i) Face Image ii) modified LBP image iiii) modified LBP image histogram

IV. PROPOSED ALGORITHM

The main objective of the proposed algorithm is to combine the advantages of both Statistical and Neural Network features in order to build a hybrid system depending upon the advantages of both methods. In this paper a modified algorithm is proposed using LBP and histogram properties as a statistical approach for feature extraction and the use of Multilayer Feed Forward Network classifiers as a neural network approach for classification [8, 17, 18]. This Multilayer Feed forward network works on the basis of Back Propagation learning rule. Once the features are extracted using both LBP and Histogram properties, a face image is transformed into a feature vector which is applied to Multilayer Feed forward network classifier for classification. Multilayer Feed Forward Neural network consist of neurons that are ordered into layers. The first layer is called the input layer , the last layer is called the output layer and the layers between them are hidden layers. The mapping function Γ assigns for each neuron i *a* subset $\Gamma(i) \subseteq V$ which consists of all ancestors of the given neuron. Each neuron in a particular layer is connected with all neurons in the next layer. The connection between the i^{th} and j^{th} neuron is characterized by the weight co-efficient $\mathbf{w_{ij}}$. The value of the output neuron is considered as one pattern class. The Multilayer Feed Forward Neural network operates in two mode viz Training and Test mode [27]. Training mode begins with arbitrary values of the weights and process iteratively. In each iteration the network adjusts the weights in the direction that reduces error by applying Back Propagation learning rule [28]. In Testing mode information flows forward direction through the network from inputs to outputs. The network producing an estimate of the output value(s) based on the input values and then finds similarity between the test image and trained images stored in database.The present output value with all existing pattern classes which are formed during training period.The proposed Multilayer Feedforward Network is shown in Fig.8

The Algorithm for the proposed method is as follows

Step 1: Upload pre-processed input image

Step 2: Extract face feature components such as nose, eyes etc using proposed modified LBP algorithm and its Histogram properties to obtain feature vector

Step 3: The Feature vectors extracted using modified LBP is than fed into Multilayer Feed forward Network Classifier.

- Set the Target value for accepting classifier performance.
  ≈ +1 for acceptance

Step 4: The training and testing phase for the Classifier –

- Selecting the suitable value of number of neuron in input layer.
- Selecting number of hidden layer and number of neuron in each hidden layer.
- Selecting suitable transfer functions like “tansig” “traingdm” from one layer to another.
- Selecting learning rate($\mathbf{l_r}$) value that to be set under testable condition
- Selecting number of epochs.
- Apply Back propagation learning algorithm for each epoch

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Vol. 2, Issue 7, July 2013

Back propagation Algorithm for learning

- Input = A set of training pairs $\{(x^{(k)},d^{(k)})|k=1,2,\ldots,p\}$
  $x^{(k)}$ = feature vector
  p = Total no. of training patterns

- ***Processing Steps:***
- Step 0: (Initialization) Choose $\eta>0$ and E_{max}, set E=0 and k=1.
- Step 1: (Training Loop) Apply k^{th} input pattern to the input Layer.
- Step 2: (Forward Propagation) Propagate the Signal forward through the Network.
- Step 3: (O/p error Measure) Compute the error
- value $E=1/2 \sum (d_i^{(K)} - y_i^{(K)})^2 + E$
- Step 4: (Error propagation) Propagate the errors backward to update weights.
- Step 5: (One epoch Looping) If K < P then K=K+1, goto Step 1.
- Step 6: (Total error checking) Check whether the current total error is acceptable. If $E < E_{max}$ then terminate the training process and o/p the final weights, otherwise E=0, K=1 and goto Step 1.

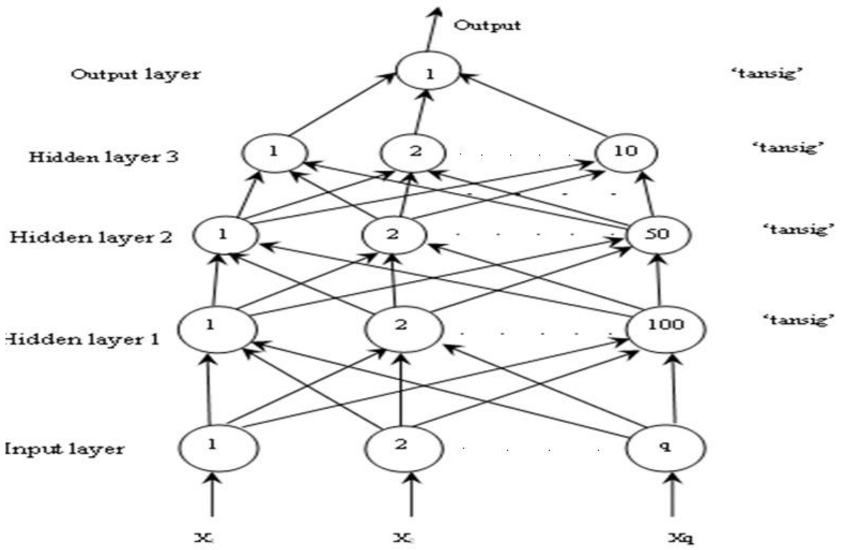

Fig. 8 : Proposed Multilayer feed forward network

V. EXPERIMENTAL RESULT AND DISCUSSION

We implement the proposed method and conduct experiments to evaluate its effectiveness. For our result we choose face images of eunuch and pre process before applying proposed method. The proposed method is implemented using MATLAB version 10.0 on Intel core *i3* Processor PC with 4 GB of RAM memory. The changes of Multilayer feed forward network classifier parameters have a high effect on the classification results. After setting different numbers of neuron in each layer we found that the classifier works best with 3 hidden layers with each layer having number of neurons 100, 50, 10 respectively. With the number of trials made by keeping the number of hidden layer at three it has been found by the experiment that recognition rate is optimum when the number of input neurons in the input layer is 10.The number of hidden layer had been kept at the value of three for reducing hardware of the system as well as to reducing the propagation time of the input variable to a minimum.The saving in the computational time (which include both training and testing time) would lead towards saving of cost also. Different learning rate parameters like *lr, mc, goal* have been used in order to get best Learning rate with 800 epochs. Fig 9 shows that recognition rate increased with the same set of Test images using more and more input image for same class during training period of the network. Our best recognition rate is found to be 97.35%. Recognition rate = ((No.of recognised face / No. of test face) *100). The results obtained by the proposed algorithm have been compared with those obtained by using orginal LBP operator alongwith feed forward neural network and the both were applied to the faces of eunuch faces obtained from the real life residence of India. It has been found out that the proposed algorithm outperforms the results obtained by applying the previous algorithm.

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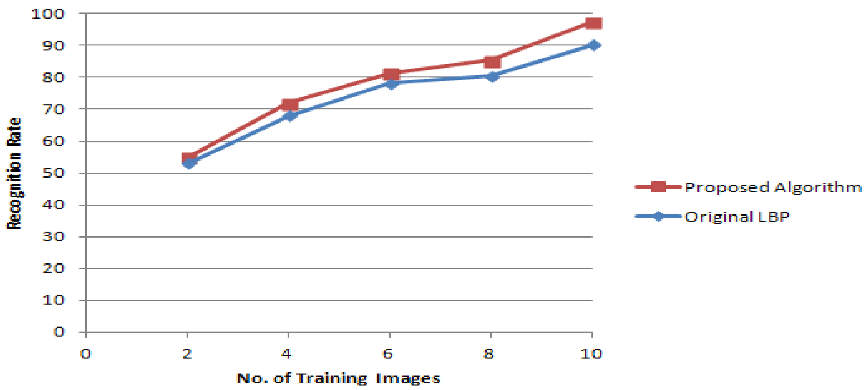

Fig. 9: Variation of recognition rate with number of training images

VI. CONCLUSION

Face recognition has provided many important applications and a large number of approaches has been proposed during the past several years. There are several techniques which have been proposed for identification of general human being but so far no work has been done on eunuch faces to categorise their gender. In this paper, we proposed a hybrid method by merging two different methods one for feature extraction and another for classification. This hybrid method produces a good result with high recognition rate for eunuch identification and verification. We presented a modified LBP technique for extracting some important features of eunuch face and making them into feature vector which reduces computational cost for classification. Finally, we used Multilayer feed forward network for classification with optimised performance achieve through successive trials.

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