A New Technique ForFace Recognition Using 2D-Gabor Wavelet Transform With 2D-Hidden Markov Model Approach

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Abstract— **A Discrete Gabor Wavelet Transform (DGWT) based 2D Hidden Markov Model (2DHMM) approach for Face Recognition (FR) is proposed in this paper. To improve the accuracy of the face recognition algorithm, a Gabor Wavelet Transform is used in obtaining the observation sequence vectors. We have conducted extensive experiments ORL database which shows that the proposed method can improve the accuracy significantly, especially when the face image dataset is large with limited training images. Unlike the pervious HMMs used for FR, we propose 2D HMM with Expectation-Maximization (EM)algorithm suitable for almost perfect estimation as feature vectors. This model of 2D HMM shows superior image segmentation for learning process. A recognition rate of 99% is achieved.**

Keywords—2D Hidden Markov Model (HMM); Discrete Gabor Wavelet Transform (DGWT); Expectation-Maximization (EM); Face Recognition (FR)

I. INTRODUCTION

Over the past two decades, numerous FR researches and studies have been carried out in the field of Computer Vision (CV) [1]. There are several real-time applications like biometrics, surveillance, security access, Human Computer Interaction (HCI), robotic vision that demand a robust, accurate and simply trainable face recognition systems. The availability of cheap and yet so competent systems have led to rapid development and commercialization of FR systems.

Face Recognition from static images and dynamic sequences is an active research area with numerous applications as stated above. An excellent attempt to survey FR was given in [1]. Despite many achievements, however, external parameters such as pose variation, discrepancy in illumination, facial expression, gender recognition and twins' recognition are still a paradox. In order to avoid these problems, a perspective based approach was initiated and developed [2]. This approach was carried out in two stages; the first process was to calculate the face images' orientation and alignment and the second step was to recognize these faces using a dataset of corresponding images.

The success of HMM in speech processing and recognition was well noted. The HMM when proposed in [3] had a very similar approach by nature. The architecture proposed in [3] was extended and refined by Nefian's work in [4]. In spite of implementing DCT as observational vectors the system had some flaws with respect to the effect of illumination, expression and pose. In this paper we propose a Discrete Wavelet Transform (DWT) approach. Wavelets are orthogonally normal function that escalated and transformed to the parent wavelet. The elementary idea behind a wavelet [5] is that each function can be perceived at intermediate levels and different resolution by spanning the function. The advantage of Wavelet Transform (WT) is that its ability to analyze the signal in both time and spatial domains. DWTs also have higher flexibility, better compression ratio and performance.

The core of this paper is based on this concept. We propose a DGWT for feature extraction and 2D HMM based FR system. The outline of this paper is as follows: Section I gives a brief Introduction about the proposed method.Section II deals with the literary survey and concurrent works. Section III describes the method of implementation. Section IV and V are the Results and Future work respectively.

II. RELATED WORK

There are several face recognition methods. Some common face recognition methods are Geometrical Feature Matching [6], Eigenfaces method [7,8], Bunch Graph Matching (BGM) [9], Neural Networks (NN) [10,11], Support Vector Machines (SVM) [12], Elastic Matching [8] and Hidden Markov Models (HMM) [4]. We briefly review some of the notable approaches.

The first approach, proposed by Kanade [6] in the 70's, were based on geometrical features. Geometrical Feature Matching techniques are based on the extraction of a set of geometrical features forming the picture of a face. Their system achieved 75% recognition rate on a database of twenty persons, using two images per person; one for training and the other for test. In summary, geometrical feature matching techniques do not provide a high degree of accuracy and also are rather time-consuming. The other approach, one of the well-known face recognition algorithms, is eigen faces method [7,8]. This method uses the Principal Component Analysis (PCA) to project faces into a low dimensional space. This method showed to be not very robust versus the variations of face orientation. In [7], the authors reported 90.5% correct recognition on ORL database. In summary, eigen faces method is a fast, simple and practical method. However, it generally does not provide invariance over changes in scale and lighting conditions. Neural Networks is one of the approaches which have been used in many pattern recognition tasks. The attractiveness of using neural networks could be due to their ability in nonlinear mapping. The paper [11] used Probabilistic

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Decision- Based Neural Network (PDBNN) for face recognition which had been capable to recognize up to 200 people and could achieve up to 96% correct recognition rate. In general, neural network approaches encounter problems when the number of face classes increases. The last approach is the stochastic modeling of non-stationary vector time series based on Hidden Markov Models (HMM) which has been widely used in recent years.

III. THE METHODOLOGY

A. The 2D-HMM Training and Classificaion

The Hidden-Markov Models are a set of statistical models used to represent and characterize the statistical properties of a signal [13]. Every HM model consists of two correlated processes layers: (1) an underlying unobservable Markov chain with finite number of states, their transition probability matrix and an initial state probability distribution matrix and (2) a set of probability density function (PDFs) that are associated with each individual state.

1) Expectation-Maximization (EM) Algorithm

The EM algorithm is suitable for estimation of parameters of the 2D HMM model. We define the observed feature vectors set $O = \{o(i,j), i = 1,2, \ldots I; j = 1,2 \ldots J\}$and corresponding hidden state set $S = \{s(i,j), i = 1,2 \ldots I; j = 1,2 \ldots J\}$. The model parameters are defined as a set $\Theta = \{\Pi, \mathrm{A}, \mathrm{B}\}$ where $\Pi = \{\mu_m\}$ is the initial probability of states; $A = \{a_{m,n,k,l}\}$ is the set of state transition probabilities, $(m, n, k, , l \in \{1,2, \ldots M\})$; and B is the set of probability density functions (PDFs) of the observed feature vectors given corresponding states.

Define $F^{(p)}_{m,n,k,l}(i,j)$ as the probability of the state corresponding to observation $o(i-1,j)$is the state m, stae corresponding to observation $o(i-1,j-1)$ is state n, state corresponding to observation $o(i,j-1)$ is state k and the state corresponding to observation $o(i,j)$ is state 1, giventhe observation and model parameters,

$$F^{(p)}_{m,n,k,l} = P\left(\begin{matrix} m = s(i-1,j), n = s(i-1,j-1), \\ k = s(i,j-1), l = s(i,j) \end{matrix} \middle| O, \Theta^{(p)} \right), \tag{1}$$

And define $G^{(p)}_m(i,j)$ as the probability of the state corresponding to observation $o(i,j)$ is state m, then

$$G^{(p)}_m(i,j) = P\big(s(i,j) = m \big| O, \Theta^{(p)}\big) \tag{2}$$

We can get the iterative updating formulas of parameters of the proposed model,

$$\pi^{(p+1)}_m = P(G^{(p)}_m(1,1)|O, \Theta^{(p)}) \tag{3}$$

$$a^{(p+1)}_{m,n,k,l} = \frac{\sum_i^I \sum_j^J F^{(p)}_{m,n,k,l}(i,j)}{\sum_{l=1}^M \sum_i^I \sum_j^J F^{(p)}_{m,n,k,l}(i,j)} \tag{4}$$

$$\mu^{(p+1)}_m = \frac{\sum_i^I \sum_j^J G^{(p)}_m(i,j) o(i,j)}{\sum_i^I \sum_j^J G^{(p)}_m(i,j)} \tag{5}$$

$$\Sigma^{(p+1)}_m = \frac{\sum_i^I \sum_j^J G^{(p)}_m(i,j)(o(i,j) - \mu^{(p+1)}_m)(o(i,j) - \mu^{(p+1)}_m)^T}{\sum_i^I \sum_j^J G^{(p)}_m(i,j)} \tag{6}$$

In equations (1) – (6), $p$is the iteration step number. $F^{(p)}_{m,n,k,l}(i,j)$, $G^{(p)}_m(i,j)$, are the unknown in the above HMM. In order to estimate these unknowns we use the General Forward-Backward (GFB) algorithm.

2) The General Forward Backward (GFB) algorithm

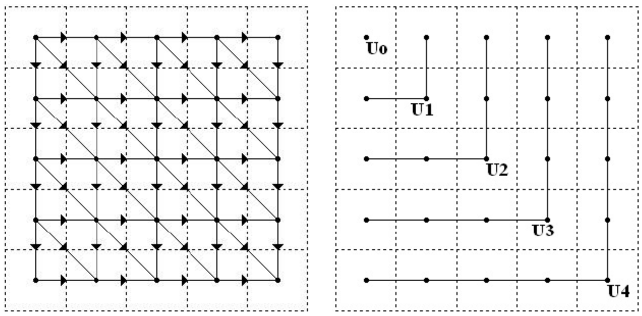
Forward-Backward algorithm was firstly proposed in [18] by Baum et al for 1D hidden Markov Model. Later, Jia Li et al. [19] proposed a similar Forward-Backward algorithm for their model. Here, we would like to generalize the Forward-Backward algorithm in [18][19] so that it can be applied to any HMM system, the proposed algorithm is called General Forward- Backward (GFB) algorithm.

For GFB to be applied, a the state sequence of the HMM system should satisfy the following:

"The probability of all states sequences S can be decomposed as products of probabilities of conditional-independent subset sequences U_o, U_1, ... "

$$P(S) = P(U_0)P(U_1/U_0) \ldots P(U_i/U_{i-1}) \tag{7}$$

whereU_o, U_1, ... U_i... are subsets of all-state sequence in the HMM system. Subset-state sequences for our model are shown in Figure 1.



a b

3) Forward and Backward Probability

The Forward-Backward probability is defined as below:

The forward probability $\alpha_{U_u}(u), u = 1,2, \ldots$ is the probability of observing the observation sequence $O_v (v \leq u)$ corresponding to subset state sequence $U_v (v \leq u)$ and having state sequence for u-th product component as U_u, given the model parameters Θ.

$$\alpha_{U_u}(u) = P\{S(u) = U_u, O_v, v \leq u | \Theta\} \tag{8}$$

The iterative updating process is given by:

$$\alpha_{U_u}(u) = \left[\sum_{u-1} \alpha_{U_{u-1}} P\{U_u | U_{u-1}, \Theta\}\right] P\{O_u | U_u, \Theta\} \tag{9}$$

The backward probability$\beta_{U_u}(u), u = 1,2, \ldots$is the probability of observing the observation sequence$O_v (v > u)$ corresponding to subset state sequence $U_v (v > u)$ given state sequence for u-th product component as $U_u$and model parametersΘ.

$$\alpha_{U_u}(u) = P\{O_v, v > u | S(u) = U_u, \Theta\} \tag{10}$$

The iterative updating process is given by:

$$\beta_{U_u}(u) = \sum_{u+1} P(U_{u+1}|U_u, \Theta)\, P(O_{u+1}|U_{u+1}, \Theta) \beta_{U_{u+1}}(u+1) \quad (11)$$

The estimation formulas of $F^{(p)}_{m,n,k,l}(i,j)$, $G^{(p)}_m(i,j)$, are as below:

$$G_m(i,j) = \frac{\alpha_{U_u}(u)\beta_{U_u}(u)}{\sum_{u:U_{u(i,j)}=m} \alpha_{U_u}(u)\beta_{U_u}(u)} \quad (12)$$

$$F^{(p)}_{m,n,k,l}(i,j) = \frac{\alpha_{U_{u-1}}(u-1)P(U_u|U_{u-1},\Theta)P(O_u|U_u,\Theta)\beta_{U_u}(u)}{\sum_U \sum_{U-1}[\alpha_{U_{u-1}}(u-1)p(U_u|U_{u-1},\Theta)P(O_u|U_u,\Theta)]} \beta_{U_u}(u) \quad (13)$$

The HMMs generally work on sequences of symbols called observation vectors, while an image usually is represented by a simple 2D matrix. In the case of using a one dimensional HMM in face recognition problems, the recognition process is based on a frontal face view where the facial regions like hair, forehead, eyes, nose and mouth come in a natural order from top to bottom. In this paper we divided image faces into seven regions which each is assigned to a state in a left to right one dimensional HMM. Figure 2 shows the mentioned seven face regions.

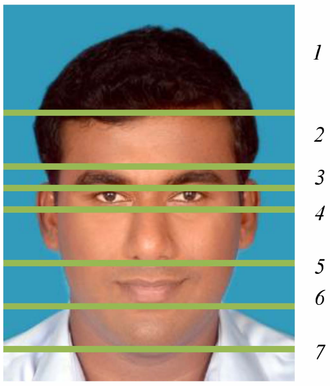


Figure 2. Seven Segememts of the face

B. Feature Extraction –Gabor Wavlets

This section is very important for our FR system. Here the face image is processed with Gabor wavelets and in the process features are extracted. A set of frequencies are chosen to represent the image at each of the above mentioned seven segments of the face.

As we use wavelets to represent the features from the image, we define Lower bound and Upper bound frequencies given by:

$$f_{LB} = \frac{1}{x_1\sqrt{2}} \text{ and } f_{UB} = \frac{1}{x_2\sqrt{2}} \quad (14)$$

The values of x_1 and x_2 are chosen such that $x_1 > x_2$. A set of frequencies to be used at each wavelet point is obtained by starting at f_{LB} and multiplying by 2 until f_{UB} is reached. The number of frequencies is given by P.

For each frequency, a set of orientations is chosen ranging from to −π to π. The step size between any two θ is 2π/n; where n is chosen appropriately. The number of orientations is given by Q.

The segments are denoted by (c_x,c_y) as per the 2D co-ordinates. The number of wavelet points is given by R. Now ∀ frequencies f and orientations θ, we obtain the wavelet point for each of the seven segments.

Assume $N = P \times R \times Q$;

When the input image I is represented by the variable x and y in the 2D coordinate system ranging over the values of height and width of the input image.

Under these conditions we can define the family of N-Gabor wavelet function as $\Psi = \{\psi_{1,1,1} \ldots \psi_{P,Q,R}\}$ as below:

$$\Psi_{i,j,k}(x,y) = \frac{f_i^2}{2\pi} \exp\left\{-0..5 f_i^2 \left[(x - c_{xk})^2 + \left(y - c_{yk}\right)^2\right]\right\} * \sin\{2\pi f_i[(x - c_{xk})\cos\theta_j + \left(y - c_{yk}\right)\sin\theta_j]\} \quad (15)$$

where f_i denotes the frequencyand θ_j denoted alignment. The Gabor wavelet function can be normalized to give its unit vector as:

$$\widehat{\Psi_{\iota,J,k}} = \frac{\Psi_{i,j,k}}{\|\Psi_{i,j,k}\|} \quad (16)$$

The parent and subsequent wavelet $\Psi_{1\ldots n}$ is given by the scalar product of I and $\widehat{\Psi_{(\iota,J,k)1}}$ as in below:

$$w_u = I_u \cdot (\widehat{\Psi_{\iota,J,k}}) \quad (17)$$

The final reconstructed image is given by:

$$\hat{I} = \sum_{u=0}^{N-1} w_u \cdot (\widehat{\psi_{\iota,J,k}})\,; for\ 1 \le u \le N \quad (18)$$

Where $w_u \cdot (\widehat{\psi_{\iota,J,k}})$ is the intermediate reconstructed image for each wavelet.

In this section we describe a reconstruction process by obtaining a set of weights. From a set of all weights the n highest weights are suitably selected along with their corresponding set of θ orientations are the observation vectors.

The proposed Face Recognition system requires seven face image vector blocks to be fed as the input to the HMM. In order to extract the feature vectors we implement a DGWT.

A 2D J-level wavelet decomposition on an image vector I[H×W] represents the image by (3J+1) sub-bands $\left[a_j, \{d_j^1, d_j^2, d_j^3\}_{j=1\ldots,J}\right]$, where a_j is the approximation of a low resolution original image, and d_j^k are specific image containing the details of images at intermediate level (2^j) and alignment (k). Wavelet coefficients in $d_j^1, d_j^2, and\ d_j^3$ correspond to vertical high frequencies (horizontal edges), horizontal high frequencies (vertical edges), and high frequencies in both directions, respectively. A typical DWT coefficient for the left eye is shown in figure 3.

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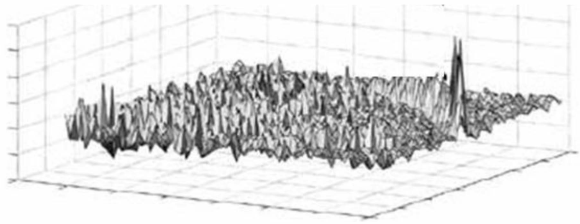

Figure 3. Typical DWT coefficient for a left Eye

Figure 4 shows the 2-level wavelet decomposition of an eye feature vector. For this multi-level decomposition fifteen sub-bands $[a_2, d_1^1, d_1^2, d_1^3, d_1^4, d_1^5, d_1^6, d_1^7, d_2^1, d_2^2, d_2^3, d_2^4, d_2^5, d_2^6, d_2^7]$are generated.

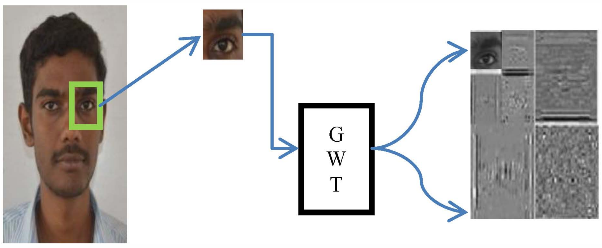

Figure 4. The observation vector extraction process

C. *Training the Face*

The face images of every subject in the database is identified by a HMM face model. A dataset of seven image vectors representation different instances of the same face image are put to train each of the 7-level HMM.

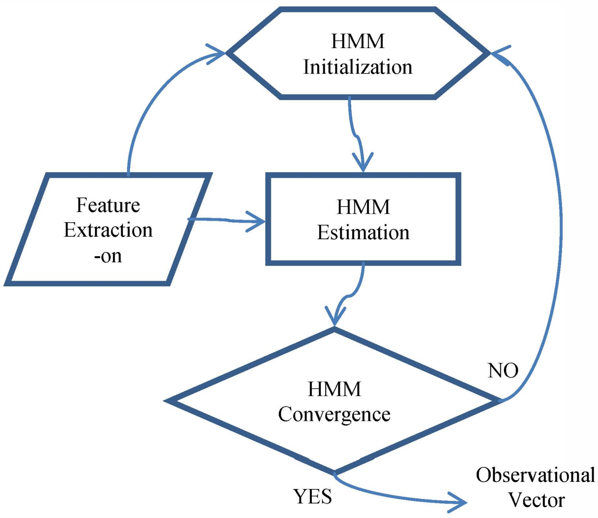

Figure 5. Schematic representation of HMM Training

The HMM 'λ' is initialized. The training data is segmented in N=7 states and the observation vectors associated with each individual state are used to obtain the initial estimation of matrix **'B'**. The initial values of matrix 'A' and '∏' are assumed to given the sliding window structure of the model. This process is shown as a flow diagram in figure 5. The next step is to re-estimate the face model using Expectation-Maximum algorithm [14] to increase the probability. This iterative process is terminated after the convergence is achieved.

D. *Face Recognition*

The recognition system works as the algorithm described in figure 6. After extracting the observational vectors from the training phase, the probability of the observational vector is computed.

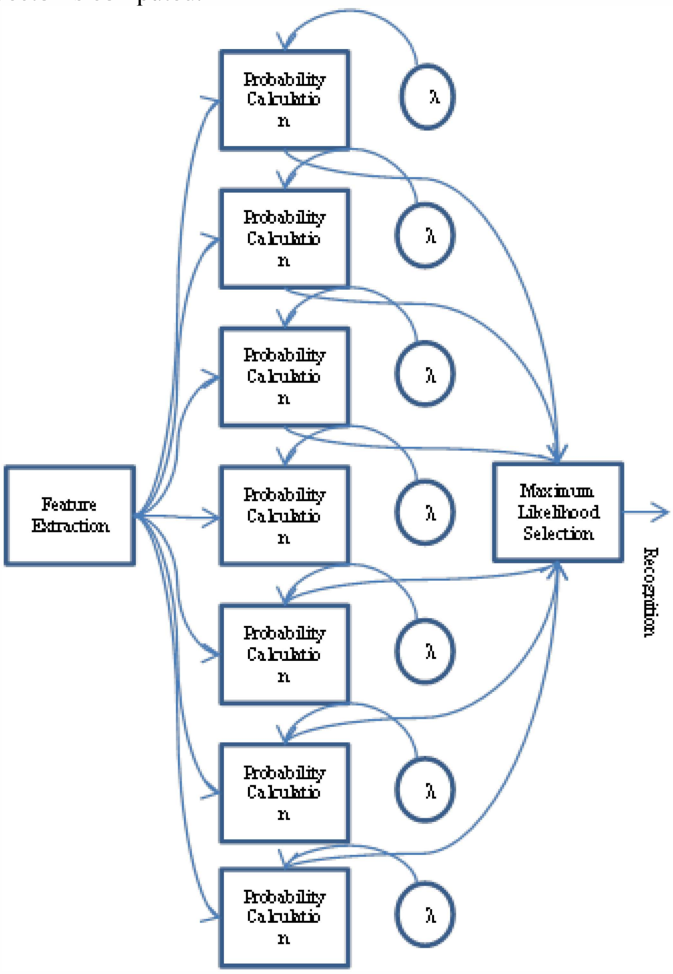

Figure 6. HMM Recognition

IV. Experimental Results

The proposed algorithm is developed in MATLAB environment using an Intel Core i7 processor @ 3.40 GHz. The proposed FR system was tested on the Olivetti Research Laboratory (ORL) face database. The database has 10 different face images per subject. In order to reduce the overall complexity of the system we resize the images to 32×32 PNG format.

We create a dataset of five face images of each subject for training and the remaining five is used for testing the FR system as shown in figure 7.

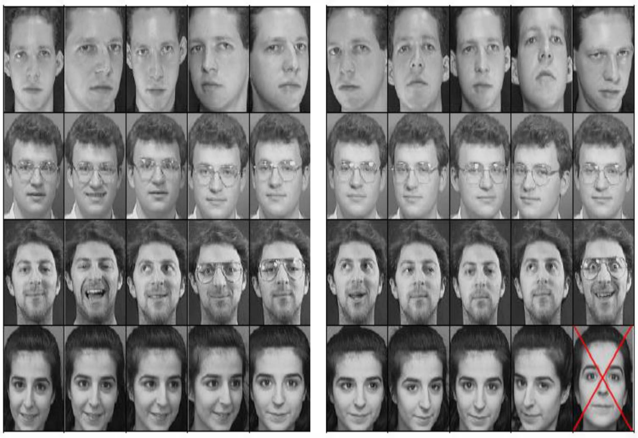

Figure 7. Training and testing dataset from ORL Database.

As seen from figure 7 the incorrect classification is crossed out which almost makes this FR system perfect. As a novel point, the increase in recognition rate is due to more information for the learning system and resizing of face images. Table 1 shows the comparison between the proposed system and the other previously developed techniques.

TABLE I. Comparative results on ORL DB

Method (Learning algorithm + Feature Extraction)	Percentage of Error (%)	Reference
Sliding HMM + Grey tone	13%	[21]
Eigenface	~10%	[7]
Pseudo 2D HMM + Gray tone	5%	[30]
EBGM	<20%	[8]
PDNN	5%	[11]
Continuous n-tuple classifier	~3%	[18]
Up-Down HMM + DCT`	16%	[31]
Correlation matching	15%	[19]
Ergodic HMM + DCT	>0.5%	[32]
P2D HMM + DCT	0-0.1%	[33]
SVM + PCA	3%	[12]
ICA	15%	[20]
Gabor filter + rank	~9%	[22]
Markov Random Fields	13%	[23]
2D HMM + DGWT	1%	-

In the below, figure 8, represents a sample set of seven-segmented- recognition results.

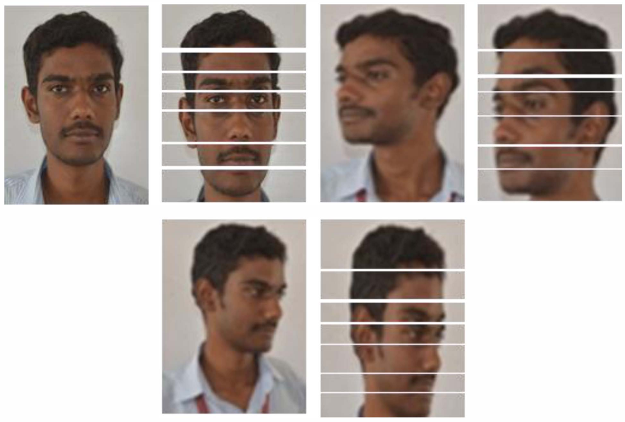

Figure 8. Recognition Results

V. CONCULSION

A novel 2D-DGWT based 2D HMM has been proposed for face recognition. We have categorically achieved our goal of recognizing face image from a large dataset with few set images. The exhausting tests conducted on the proposed method explicitly convey that this system is more stable, efficient and robust than the benchmark algorithm when compared. A significant augmentation in the accuracy of recognition has been clearly observed through the experiment. The tests run on the ORL database stand a testimony to this fact. A recognition rate of ~99% is obtained through the experiments.

VI. FUTURE WORK

The HMM modeling of human face images appears to be an encouraging method for FR under a wide spectrum of constraints such as pose, illumination, and expression. Our future work will be to improve the learning algorithm by testing on much larger databases. We believe that advanced feature extraction techniques with competent learning algorithms can handle large and complex face images.

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