A Preliminary Study and Analysis on Hidden Markov Model (HMM) Using PCA Techniques for Face Recognition

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ABSTRACT

Nowadays preparing an effective model for face recognition is difficult task. Face is a critical and complex multidimensional visual model. However in this Article, we present a method for face recognition based on Hidden Markov Model (HMM) and it has been widely used in various fi elds such as in speech recognition, gesture recognition and so on. We proposed this approach basically current face recognition techniques are dependent on issues like background noise, lighting and position of key features (i.e. the eyes, lips etc.).Moreover the face patterns are divided into numerous small-scale states and they are recombined to obtain the recognition result. Our experimental results shows that the proposed method has been achieved 96.5% recognition accuracy for 400 patterns of 40 Subjects i.e. 40 classes of which each class contains 10 patterns each. Apart from these results we did some comparative analysis with PCA. Over observations stated that the performance of HMM based face-recognition method is better than the PCA for face recognition.

Keywords **–** Pattern Recognition, preprocessing, Hidden Markov Model, PCA Based Face Recognition.

I. INTRODUCTION

Face identification is a fundamental part of many face recognition systems. The task of detecting and locating human faces in arbitrary images is complex due to the variability present across human faces, including skin color, pose, expression, position and orientation, and the presence of 'facial furniture' such as glasses or facial hair. Differences in camera gain; lighting conditions and image resolution further complicate the situation. Various parameters choices are investigated to confirm an optimal set of operational parameters. We identified limitations, which leading to small but significant improvements. The recognition rate was increased from 29% to 44% on the first test set, and from 44% to 96% on the second test set, at the expense of an increase in the number of false positives.

As we move on nowadays the Pattern recognition is a modern day machine intelligence problem with numerous applications in a wide field, including Face recognition, Character recognition, Speech recognition as well as other types of object recognition. Face recognition, although a trivial task for the human brain has proved to be extremely difficult to imitate artificially. It is commonly used in applications such as human-machine interfaces and automatic access control systems. Face recognition involves comparing an image with a database of stored faces in order to identify the individual in that input image. The related task of face detection has direct relevance to face recognition because images must be analyzed and faces identified, before they can be recognized. Detecting faces in an image can also help to focus the computational resources of the face recognition system, optimizing the systems speed and performance.

The rest of the article is organized as follows: II. Present Statistical pattern reorganization concepts. III. Hidden Markov Model (HMM) for Face Recognition. IV. While with PCA based Face Recognition. V. Comparative analysis of HMM With PCA and finally VI. Presents Conclusion.

II. STATISTICAL PATTERN REORGANIZATION CONCEPTS

In case of statistical pattern recognition, a pattern is represented by a set of dimensional attributes or features viewed as a "d" dimensional feature vector. Here Theory of Statistical decision is utilized to establish decision boundaries between pattern classes. The recognition system is operated in two modes: Training (learning) and Classification (Testing). The main objective of preprocessing module is to segment the pattern of interest from the background, remove noise, normalize the pattern, and any other operation which will contribute in defining a compact representation of the pattern.

Furthermore concerning the common methods, there have been proposed many methods in which frontal image was used. This caused a problem, in this recognition rate was decreased for the slight angle profile face images when the common method was used. In this paper in order to solve this problem, I present a method to recognize non registered frontal facial images. Finally, the effectiveness of the proposed method is verified by a recognition experiment done.

A formal method of classifying faces was first proposed by Francis Galton in 1888 [1, 2]. During the 1980's work on face recognition remained largely dormant. Since the 1990's; the research interest in face recognition has grown significantly as a result of the following facts:

1. The increase in emphasis on civilian/commercial research projects.
2. The re-emergence of recognition classifiers with emphasis on real time computation and adaptation.
3. The availability of real time hardware.
4. The increasing need for surveillance related applications due to drug trafficking, terrorist activities, etc.

Although it is clear that people are good at face recognition, it is not at all obvious how faces are encoded or decoded by the human brain. Developing a computational model of face recognition is quite difficult, because faces are complex, multi-dimensional visual stimuli. Therefore, face recognition is a very high level computer vision task, in which many early vision techniques can be involved. The general representation of Face recognition classifier is as follows:

The first step of human face identification is to extract the relevant features from facial images. Research in the field primarily intends to generate sufficiently reasonable familiarities of human faces so that another human can correctly identify the face. The question naturally arises as to how well facial features can be quantized. If such a quantization if possible then a computer should be capable of recognizing a face given a set of features. Investigations by numerous researchers [3, 4, and 5] over the past several years have indicated that certain facial characteristics are used by human beings to identify faces. There are three major research groups which propose three different approaches to the face recognition problem. The largest group [6, 7, 8] has dealt with facial characteristics which are used by human beings in recognizing individual faces. The second group [9, 10, 11, 12, 13] performs human face identification based on feature vectors extracted from profile silhouettes. The third group [14, 15] uses feature vectors extracted from a frontal view of the face.

The second method is based on extracting feature vectors from the basic parts of a face such as eyes, nose, mouth, and chin. In this method, with the help of deformable templates and extensive mathematics, key information from the basic parts of a face is gathered and then converted into a feature vector. L. Yullie and S. Cohen played a great role in adapting deformable templates to contour extraction of face images. So our method of HMM based face recognition belongs to extracting feature vectors of triplet i.e. combination of the following set of states:

1. Hidden States.
2. Transition probabilities.
3. Observations.
4. Emission probabilities.
5. Initial state Probabilities.

III. HIDDEN MARKOV MODEL (HMM):

Since the coding is crucial for the subsequent learning, here take a moment to elaborate on it further. The strategy used to obtain the data sequence from a face image consists of two steps: scanning and feature extraction, respectively.

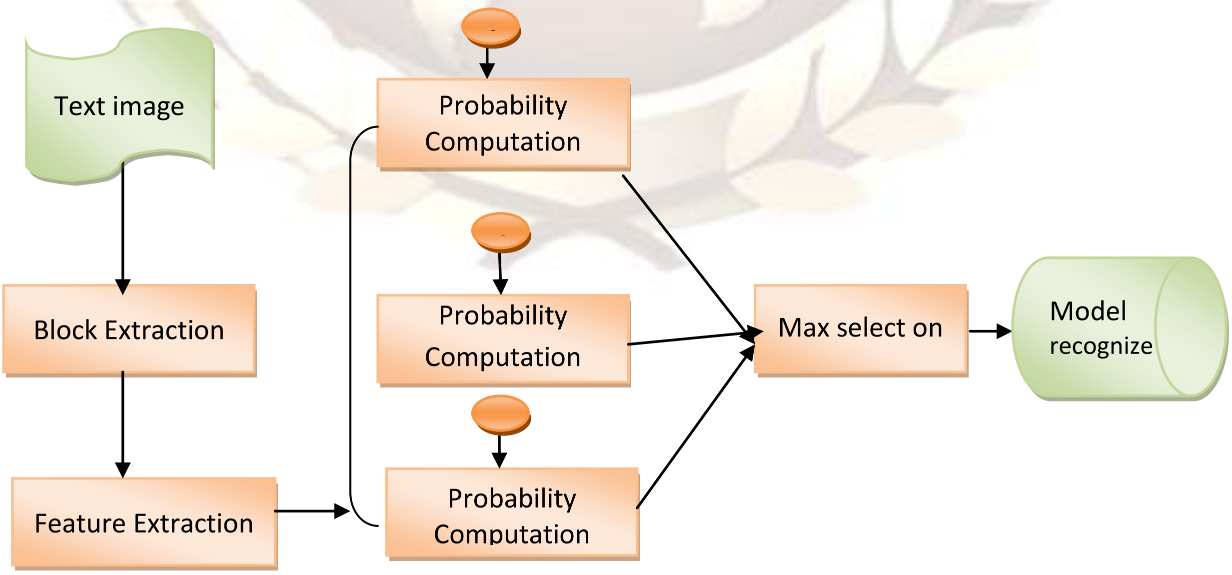

Fig 1: HMM Face Recognition system architecture.

In the first step, a sequence of sub-images of fixed dimensionality is obtained by inspecting the face image. In the basic approach, that sequence is acquired by using a raster scan, i.e. by sliding a fixed sized window with a predefined overlap over the face image. The raster scan has some advantages, e.g. it is simple and exhaustive, but it also presents several problems I seek a better scanning strategy, free of these specifications. Our approach is the recognition using selective attention based scanning. The advantage of employing a saliency-based scheme is twofold: first, Salient parts of the image can be concentrated, gaining robustness with respect to registration; second, since the patches are extracted in decreasing order of importance, a decision can be taken to stop the analysis.

Face recognition using HMMs typically involves the solution of different problems:

Coding: A sequence of features is extracted from each face image. The ability of the system to discriminate among different faces strongly depends on the nature of extracted features, and their success in coping with the experimental conditions.

Learning: The learning problem is solved by training a statistical classifier. Depending on the classification strategy chosen, it could be realized in different ways:

1. Training one HMM for each class, subsequently using the standard Bayesian scheme for classification when a novel sequence is given, the posterior probabilities are calculated under each model, and the sequence is assigned to the class whose model shows the highest posterior probability.
2. Training one HMM for each sequence: This scheme trains more models per class, provided that there is more than one training sample available per class. However, the amount of data used in training each model is smaller. This type of modeling approach can be said to compute distances between sequences, the classification in this case becomes a nearest neighbor rule in this likelihood sense.
3. Mixed classification: There exist models that explore tradeoff between the two approaches. One can train one HMM for each sequence and for each class, making the classification scheme more complex, but also more powerful. Such a mixed approach is based on a dissimilarity-based representation.

Once the sequence is extracted, the second step consists of computing features in each gathered sub-image. Statistical features, based on image moments or gradients, examined for this purpose local neural network experts were employed to evaluate the sub-image, producing a class-posterior probability vector for each spot in the sequence that was used as the observation feature in the subsequent Markov model. This method provides a good level of range for the classification module, yet it is costly to maintain a large number of neural network experts. A more straightforward approach is to compute a few coefficients based on compression transformations. The HMM recognition system architecture is as shown in below figure:

Test Image: All images are cropped to consist of mostly facial data with very limited background, make data base ideal for face classification experiments.

Block Extraction: Divide the image into sub blocks and extract the feature of each block.

Feature Extraction: The extraction of features concerns the passing on of object data in a specific format and size to some model, mainly for the purpose of recognizing the object.

The following features were investigated and specifically used to train the HMMs used in the face classification experiments:

1. Pixel intensity values.
2. Discrete cosine transforms coefficients
3 DCT-mod2 coefficients

Pixel intensity values are the raw data representing an image. In grey format they typically vary in value from 0 to 255. DCT coefficients are obtained by applying the two dimensional DCT to blocks of a given image. The DCT-mod 2 coefficients are extended DCT based features.

Probability Computation:

A Hidden Markov Model $\wedge$ is defined as a set of N emitting states as well as an initial and end of line state, so we end up with N+2 states. The expression S_t =I will indicate the occurrence of state I at time t. The time indices run from t=1 to t=T, where T is the length of the observation sequence X=[x_1, x_2,…x_T] to be matched to HMM. The states are coupled by transition a_{ij} denotes state transition probability with the subscripts indicating the two states involved and a_{ij} refers to the self loop probability. The first null state has a transition probability of 1 and no self loop probability. Each emitting state has an associated probability density function described as f_i $(x|s_t,\wedge)$.A single left to right HMM can now be described as $\wedge$ ={a, f}.The possible solution to this problem is to enumerate all possible sequences of states $S^{T+1}{}_0$ and determine the value of $f(X^T1,S^{T+1}{}_0|\wedge)$.

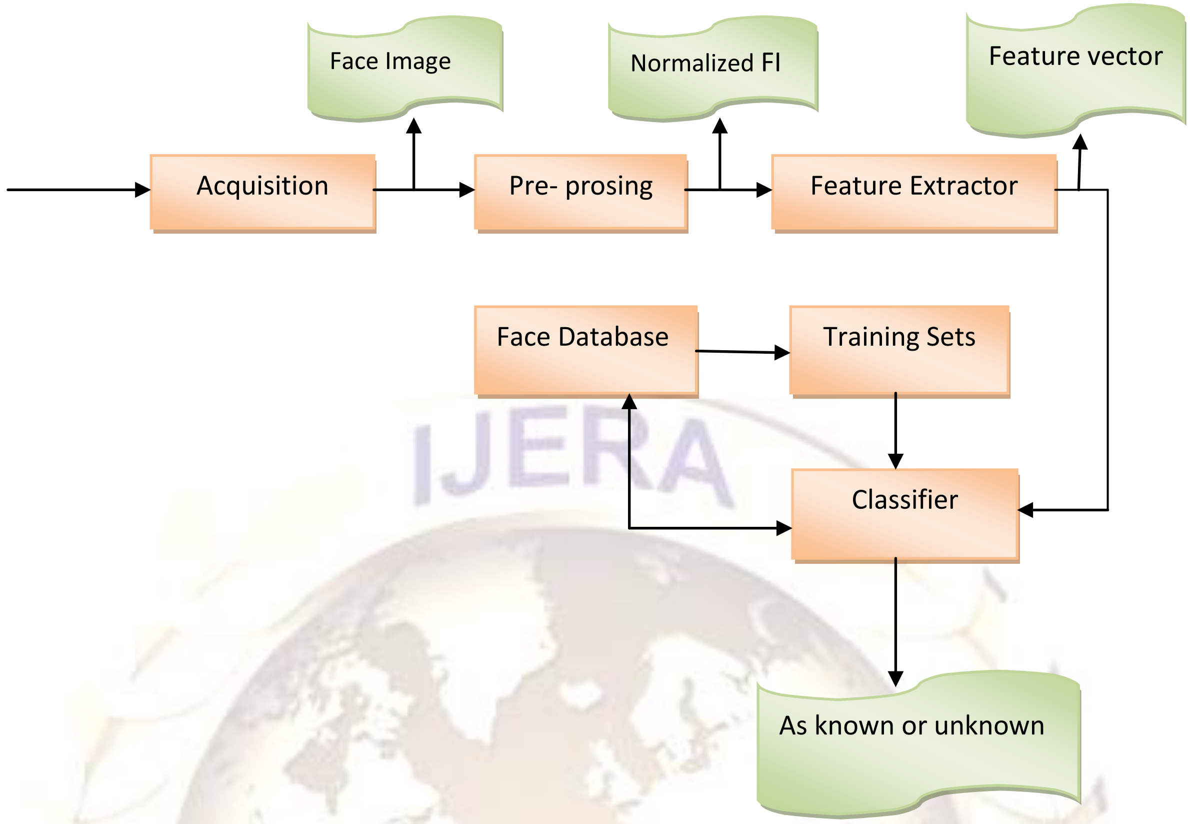

Fig 2: How pattern reorganization is classified.

First configuration 1D HMM:

For the face classification task usage of two basic configurations of hidden Markov model taken place. In the first case the face was modeled with a vertical HMM running along the rows of the image .With each state of the HMM representing a distinct facial region (i.e. eyes, mouth, chin etc.) the characteristic features of any person can be modeled.

Inside each state S use a Gaussian mixture model (GMM) as the probability density function fi (X|st, ˄) within the state. A Gaussian mixture model can be expressed as a weighted sum of k Gaussian distributions:

$$t(x) = \sum_{k=1}^{k} p\,(k) N_K(X) \quad \text{-------(1)}$$

Where $N_k(X)$ is a D dimensional Gaussian distribution with mean μ and covariance matrix.

$$\sum: N_k(X|\mu,\sum)= 1/((2\prod)^{D/2}\ |\sum|^{1/2}\ )\ \exp\ [-(1/2)(X-\mu)^T \sum{}^{-1}(X-\mu)] \quad \text{--------(2)}$$

Now the density functions, finalize our HMM by initializing it. This is done by uniformly segmenting the face under consideration along its rows and obtaining the mean vector and covariance matrix of each of these segments. Furthermore set all the transitional probabilities of HMM equal to a_{ij}=0.5, keeping that each state of the HMM these probabilities sum to 1.

Training the Face Model:

The process of classification on a database of faces can be summarized as follows:

First a database is partitioned into a training and a testing part with the training data used to train an HMM for each person in the database. This means for each person in the database an HMM trained on the training data. Each test face is then scored against all these models and it is classified to the model with the highest similarity measure. Each score represents the similarity between the test face image and the first paragraph under each heading or subheading should be flush left, and subsequent paragraphs should have train model.

Each individual in the data base is represented by a HMM face model. A set of images representing different instances of same image are used to train each HMM. In this, 2D- DCT coefficients obtained from each block are used to form the observation vectors. These observation vectors are efficiently used in the training of each HMM.

First, the HMM λ= {A, B, ∏} is initialized. The training data is uniformly segmented from top to bottom in N=5 states and the observation vectors associated with each state are used to obtain initial estimates of the observation probability matrix B. The initial values for A and ∏ are set given the left to right structure of the face model. Here iterations stops when model convergence achieved.

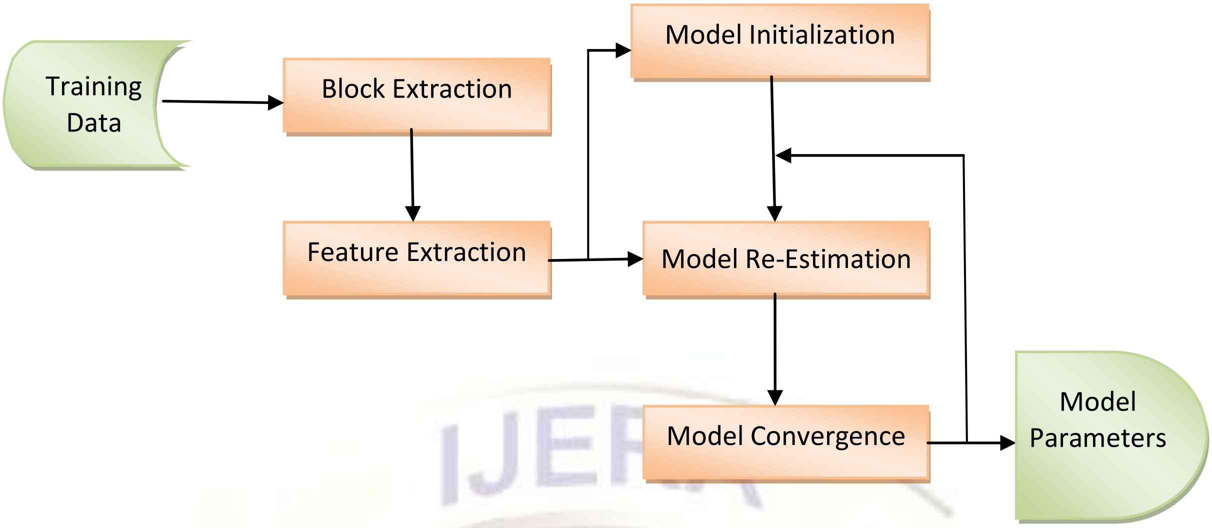

Fig 3:HMM training model

Testing Model of System

After learning process, each class (face) is associated to a HMM. For a K-class classification problem, we find K distinct HMM models. Each test image experiences the block extraction, feature extraction and quantization process as well. Indeed each test image like training images is represented by its own observation vector. Here for an incoming face image, we simply calculate the probability of the observation vector (current test image) given each HMM face model. A face image m is recognized as face d if:

$$P(O^{(m)} \mid \lambda_d) = \max NP(O^{(m)} \mid \lambda_n) \qquad ------ (3)$$

The proposed recognition system was tested on database, in order to decrease computational complexity (which affects on training and testing time) and memory consumption; we resized the mpeg format images of this database. Here the recognition rate of the system was calculated for different values of the number of symbols. The number of symbol is simply changed by changing the number of quantization levels. Obviously the three features used in the system have the best classification rates.

IV. While with PCA Based Face Recognition System

The various experiments are performed on the Face Recognition technique using ORL database. The ORL database consists of 40 Subjects (Classes) and each subject consists of 10 patters. Each of the Subjects like (S1, S2, ….. .S40) consists of 10 different patterns of which to classify. The experiments performed on Subjects S1 to S40. The System is tested for different training samples i.e. the system trains some faces from ORL database. The training of patters may be defined on user interest. For example of all the 40 classes and each 10 patterns present I can take 5 images for training and remaining 5 images for testing. And not a concern we can train the system with 3 images as training and remaining 7 images for testing. But the point to notes is that we got the recognition % with max values of 5 Training and 5 testing. The recognition percentage may vary according to the input with training and testing images. The probability of getting maximum recognition percentage is done with 5 training and 5 testing.

V. Comparative Analysis of HMM with PCA Face Recognition Results

PCA based Face Recognition Percentage for 5 Training & 5 Testing images are 82%.

The Recognition percentage using 5 Training & 5 testing images is resulted in between 90-95 % with approx value of 96.5%.

Table 1: Comparison of feature extraction methods

	Pixel intensities	DCT	DCT mod 2
Pre processing	none	No 2D DCTs	No 2D DCTs and ND2 linear operations
Dimensionality	large	small	small
Robustness	none	vary	most

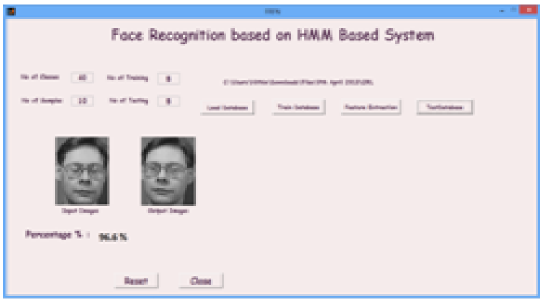

Fig 4: GUI Design of HMM model based System

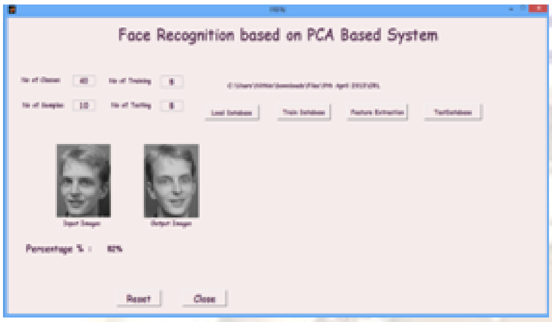

Fig 5: GUI Design of PCA Based System

Table 2: Comparative analysis of HMM with PCA Face recognition results.

<table>
<tr><th colspan="2">PCA based Face Recognition</th><th colspan="2">HMM based Face Recognition</th></tr>
<tr><td>7 Training & 3 Testing</td><td>91.6%</td><td rowspan="2">7 Training & 3 Testing</td><td rowspan="2">16.11%</td></tr>
<tr><td>6 Training & 4 Testing</td><td>88.75%</td></tr>
<tr><td>5 Training & 5 Testing</td><td>82.00%</td><td rowspan="2">6 Training & 4 Testing</td><td rowspan="2">28.02%</td></tr>
<tr><td>4 Training & 6 Testing</td><td>80.39%</td></tr>
<tr><td>3 Training & 7 Testing</td><td>74.64%</td><td>5 Training & 5 Testing</td><td>96.05%</td></tr>
<tr><td>2 Training & 8 Testing</td><td>72.83%</td><td>4 Training & 6 Testing</td><td>64.02%</td></tr>
<tr><td>1 Training & 9 Testing</td><td>61.66%</td><td>3 Training & 7 Testing</td><td>18.24%</td></tr>
</table>

VI. CONCLUSION

However in this Article shortcomings are more relevant point in the future of facial recognition systems. With continued research and development, in concert with the inevitable progress in processing power, camera resolution, networks, databases, and improved algorithms. The parameter values were investigated although more extensive testing of the various parameters with a larger set of images is required. From the limitations identified, improvements to the training data were made, and the performance of the modified system was compared to the original system's performance. The performance statistics show an improvement in the detection rate, but an accompanying increase in the number of false positives.

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