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Soft Computing Approach To Recognition Of Human Face

ABHINESH KUMAR SAHU
MTech-CSE IV Semester(Multimedia)
Kalinga University, Naya Raipur(C.G)

Under the Guidance of

Asst Prof. Mr. DEEPESH DEWANGAN
Department of Computer Science & Engineering
KALINGA UNIVERSITY,NAYA RAIPUR(C.G)

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Abstract— In recent years face recognition has received substantial attention from both research communities and the market, but still remained very challenging in real applications. A lot of face recognition algorithms, along with their modifications, have been developed during the past decades. Face recognition systems are commonly trained with a database of face images, becoming "familiar" with the given faces. Many reported methods rely heavily on training database size and representativeness. But collecting training images covering, for instance, a wide range of viewpoints, different expressions and illumination conditions is difficult and costly. Moreover, there may be only one face image per person at low image resolution or quality.

A number of typical algorithms are presented, being categorized into appearance based and model-based schemes. Hidden Markov Models (HMMs) are a class of statistical models used to characterize the observable properties of a signal. HMMs consist of two interrelated processes: (i) an underlying, unobservable Markov chain with a finite number of states governed by a state transition probability matrix and an initial state probability distribution, and (ii) a set of observations, defined by the observation density functions associated with each state. we begin by describing the generalized architecture of an automatic face recognition (AFR) system. Then the role of each functional block within this architecture is discussed. A detailed description of the methods we used to solve the role of each block is given with particular emphasis on how our HMM functions.

Keywords— Image Processing, Face recognition, Hidden Markov Models,Neural Network.

Introduction

Hidden Markov Models (HMMs) are a class of statistical models used to characterize the observable properties of a signal. HMMs consist of two interrelated processes:

1. an underlying, unobservable Markov chain with a finite number of states governed by a state transition probability matrix and an initial state probability distribution, and
2. a set of observations, defined by the observation density functions associated with each state.

In this chapter we begin by describing the generalized architecture of an automatic face recognition (AFR) system. Then the role of each functional block within this architecture is discussed. A detailed description of the methods we used to solve the role of each block is given with particular emphasis on how our HMM functions. A core element of this chapter is the practical realization of our face recognition algorithm, derived from EHMM techniques. Experimental results are provided illustrating optimal data and model configurations. This background information should prove helpful to other researchers who wish to explore the potential of HMM based approaches to 2D face and object recognition.

1.1 Face recognition systems

In this section we outline the basic architecture of a face recognition system based on Gonzalez's image analysis system [Gonzalez & Woods 1992] and Costache's face recognition system [Costache 2007]. At a top-level this is represented by the functional blocks shown in Figure 1.1

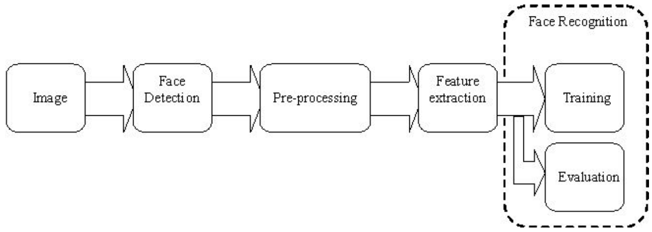

Figure 1.1 Automatic Face Recognition System

1.1.1 **Face detection and cropping block**: this is the first stage of any face recognition system and the key difference between a semi-automatic and a fully automatic face recognizer. In order to make the recognition system fully automatic, the detection and extraction of faces from an image should also be automatic. Face detection also represents a very important step before face recognition, because the accuracy of the recognition process is a direct function of the accuracy of the detection process[2].

1.1.2 **Feature extraction block(FEB)**: in this step the features used in the recognition phase are computed. These features vary depending on the automatic face recognition system used. For example, the first and most simplistic features used in face recognition were the geometrical relations and distances between important points in a face, and the recognition 'algorithm' matched these distances, the most widely used features in face recognition are KL or eigen faces, and the standard recognition 'algorithm' uses either the Euclidian or Mahalanobis distance to match features[3].

1.1.3 **Face recognition block**: this consists of 2 separate stages: a *training process*, where the algorithm is fed samples of the subjects to be learned and a distinct model for each subject is determined; and an *evaluation process* where a model of a newly acquired test subject is compared against all exisiting models in the database and the most closely corresponding model is determined. If these are sufficiently close a recognition event is triggered.

1.2 Face detection and cropping

face detection is one of the most important steps in a face recognition system and differentiates between semi-automatic and fully automatic face recognizer. The goal of an automatic face detector is to search for human faces in a still image and, if found, to accurately return their locations. In order to make the detection fully automatic the system has to work without input from the user. Many attempts to solve the problem of face detection exist in the literature beginning with the basic approach of and culminating with the method of Comprehensive surveys of face detection techniques can be found[4].

Face detection methods were classified by [Yang *et. al.* 2002] into four principle categories:

1. knowledge-based,
2. feature invariant,
3. template matching and
4. appearance-based methods.

The main disadvantage presented by the majority of these methods is the time required to detect all the faces in an image. State-of-the-art face detection methods provide real-time solutions. The best known of these methods, and the gold standard for face detection was originally proposed. The original algorithm was, according to its authors, 15 times faster than any previous approach. The algorithm has been well proved in recent years as being one of the fastest and most accurate face detection algorithms reported and is presently the gold standard against which other face detection techniques are benchmarked. For these reasons we adopted it to implement our face detection subsystem.

1.3 Pre-processing techniques

Automatic face detection is influenced by a number of key factors facial *orientation* or *pose*: the appearance of the face varies due to relative camera-face pose, between full frontal images and side-profile images; *in-situ occlusions* such as facial hair (e.g. beard, moustache), eye-glasses and make-up; facial *expressions* can significantly influence the appearance of a face image; *over lapping occlusions* where faces are partially occluded by other faces present in the picture or by objects such as hats, or fans; *conditions of image acquisition* where the quality of the picture, camera characteristics and in particular the *illumination conditions* can strongly influence the appearance of a face.

1.3.1 COLOR TO GRAYSCALE CONVERSION

In most face recognition applications the images are single or multiple views of 2D intensity data, and many databases built for face recognition applications are available as grayscale images. From the four databases used in our experiments, 3 contained grayscale images (BioID, Achermann, UMIST) and one contained RGB images. Practical images will, naturally, be acquired in color as modern image acquisition systems are practically all color and so we need to convert from color to grayscale, or intensity images of the selected face regions. In practice the intensity data may be available from the imaging system – many camera system employ YCC data internally and the Y component can be utilized directly. In other cases we may need to perform an explicit conversion of RGB data. Here a set of red, green and blue integer values characterize an image pixel[5]. The effective luminance, Y of each pixel is calculated with the following formula .

$Y = 0.3 \times Red + 0.59 \times Green + 0.11 \times Blue$………equation 1.3

1.3.2 IMAGE RESIZING

For a HMM-based face recognition system having a consistently sized face region is particularly important because the HMM requires regional analysis of the face with a scanning window of fixed size. A straightforward approach is to resize all determined face regions to a common size. To facilitate more efficient computation we seek the smallest sized face region possible without impacting the overall system recognition rate. Some empirical data will be presented later to illustrate how different factors, including the size of normalized face regions, affect recognition rate [6].

1.3.3 ILLUMINATION NORMALIZATION

One of the most important factors that impudence the recognition rate of a system is illumination variation. In was shown in that variations in illumination can be more relevant than variations between individual characteristics. Such variations can induce an AFR system to decide that two different individuals with the same illumination characteristics are more similar than two instances of the same individual taken in different lighting conditions.

Thus normalizing illumination conditions across detected face regions is crucial to obtaining accurate, reliable and repeatable results from an AFR. One approach suitable for face models which combine both facial geometry and facial texture such as active appearance models (AAM) is described by. However as HMM techniques do not explicitly rely on facial geometry or textures it is not possible to integrate the illumination normalization within the structure of the model itself. Instead we must rely on a discrete illumination normalization process. Fortunately most AFR systems employ a similar profiteering stage and we can draw on a wide range of techniques from the literature.

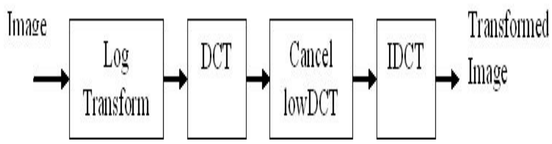

Figure 1.2 Block scheme of logDCT algorithm

Algorithms used for performing the normalization vary from a simple histogram equalization (HE) to more complex techniques such as albino maps [Smith & Hancock 2005] and contrast limited adaptive histogram equalization (CLAHE).

These algorithms perform well when the variations in illumination are small but there is no commonly adopted method for illumination normalization in images which performs well for every type of illumination. Some tests have been conducted to determine the robustness of face recognition algorithms to changes in lighting . Also, numerous illumination normalization techniques have been developed. Some of the more widely used of these -*histogram equalization*, *histogram specification* and *logarithm transformation* - have been compared in with more recently proposed methods, *gamma intensity* correction and *self-quotient image*. The results are interesting: both HE and logarithmic transform improved recognition rates over face regions that were not normalized, compared favorably to the other techniques [7].

1.4 Feature extraction

Feature extraction for both 1D and 2D HMMs was originally described [8] . His method was subsequently adopted in the majority of HMM-based face recognition papers. This feature extraction technique is based on scanning the image with a fixed-size window from left-to-right and top-to-bottom. A window of dimensions $h \times w$ pixels begins scanning each extracted face region from the left top corner sub-dividing the image into a set number of $h \times w$ sized blocks.

On each of these blocks a transformation is applied to extract the characterizing features which represent the observation vector for that particular region. Then the scanning window moves towards right with a step-size of n pixels allowing an overlap of o pixels, where o = w − n. Again features are extracted from the new block. The process continues until the scanning window reaches the right margin of the image. When the scanning window reaches the right margin for the first row of scanned blocks, it moves back to the left margin and down with m pixels allowing an overlap of v pixels vertically. The horizontal scanning process is resumed and a second row of blocks results, and from each of these blocks an observation vector is extracted.

1.5 Face recognition

In the earlier sections of this chapter we have described the main pre-filtering blocks for our AFR system. We nest focus on the actual HMM itself and the various operational processes required to implement the training and recognition phases of our AFR.

1.5.1 background to hidden markov models in face recognition

After their introduction in the late 60's by and the more detailed description in the late 80's HMMs have been widely used in speech recognition applications. In this field of application very high recognition rates are obtained due to the septic capacity of HMM to cope with variations in the timing and duration human speech patterns. HMMs have also been used successfully in other applications such as OCR and handwriting recognition. Thus it was no surprise that researchers began to consider their use for problems such as face recognition where adaptability of HMMs might offer solutions to some of the underlying problems of accurately recognizing a 2D face region.

Note that the application of HMM techniques to the face recognition problem implies the use of an inherently 1D method of pattern matching to solve an inherently 2D problem. So why did researchers think this might work? Well, as the most significant facial features of a frontal face image occur in a natural order, from top to bottom, and this sequence is immutable, even if the face is moderately rotated. The first attempts to use HMMs for face recognition and detection were made, who used a left-to-right HMM and divided the face in a fixed succession of regions (observation states) such as eyes, nose, & mouth. This early work by Samaria was essentially 1D in scope and the first attempt to implement a more appropriate 2D models was*Pseudo 2D HMM*, introduced [9] for character recognition, subsequently adapted by [Samaria 1994] for the face recognition problem.

1.6 Training Hidden markov Model

To train the model we will use the **esthmm** program. This program needs to know the number of symbols in the alphabet of the HMM (that is, symbols that can be emitted); you can obtain this by typing % wc -l example0.key

In this case the number of symbols is 13. The number of states is something you can choose. Recall that for a HMM-based part-of-speech model like this one, each state corresponds to a part of speech (i.e. a syntactic category like noun, verb, etc.), so the number of states to choose corresponds to the number of parts of speech you believe are represented in the corpus. In this case, let's use 6 states. We run the **esthmm** program as follows:

```
% esthmm 6 13 example0.seq > example0.hmm
```

This creates file example0.hmm, which contains the trained model. Depending on the computer you're running this on, this might take a minute.

If you'd like, look at file example0.hmm -- it's not the easiest thing in the world to read, but you can see how the model is represented there. At the top are specified the number of states and the number of symbols (M=13 symbols, N=6 states). Then you have the complete A matrix, i.e. the 6-by-6 transition probability matrix. Next you have the 6-by-13 emission probability matrix, B. Finally you have the pi vector, giving initial probabilities for the 6 states[10].

II REVIEW OF LITERATURE

As an effective method, the hidden Markov model (HMM) has been widely used in pattern recognition. On applying the HMM to face recognition, the performance heavily depends on the selection of model parameters. Aiming at the problem of model selection, a selective ensemble of multi HMMs based face recognition algorithm is proposed. Experimental results illustrate that compared with the traditional HMM based face recognition algorithm the proposed method cannot only obtain better and more stable recognition performance, but also achieve higher generalization ability. We were studied more than 25 research papers and articles for associated with our project. Here some few important work related to our research are-

2. 1 A Face Recognition System by Embedded Hidden Markov Model & Discrimin- ating Set Approach

In recent years, a large number of methods have been investigated for automatic face recognition[11]. Face recognition has attracted attention from the research and industrial communities with a view to achieve a "handsfree" computer controlled systems for access control, security and surveillance. As a baby one of our earliest stimuli is that of human faces. We rapidly learn to identify, characterize and eventually distinguish those who are near and dear to us. This skill stays with us throughout our lives. As humans, face recognition is an ability we accept as commonplace. It is only when we attempt to duplicate this skill in a computing system that we begin to realize the complexity of the underlying problem. Understandably, there are a multitude of differing approaches to solving this complex problem. And while much progress has-been made many challenges remain.

2.1.1 The proposed face recognition algorithm based on e-hmm and discriminating set

A good machine learning or pattern classification system should have a strong generalization ability, which means the ability to recognize or process the unknown things using the obtained knowledge and techniques. Therefore, generalization ability is always the ultimate problem concerned about in machine learning. Assembly learning is a new machine learning technique developed in last decades, where results of many algorithms are jointly used to solve a problem. The assembly learning cannot only improve the classification or recognition accuracy, but also obviously improve the generalization ability of the learning system. So it is regarded as one of the fourth fundamental research topics in recent years.

In figure 2.1, M1, M2,….,Mn are models of faces with different parameters, denoted as M = (O; λ), where

$O = (o1, o2,……, oT/P \times L, \Delta x \times \Delta y, N2D\text{–}DCT)$

is the feature information of the model; $\lambda = (\Pi, A, \Lambda / Ns, Ni, K)$ is the structure information of the model. Therefore, model M is determined by the above six groups of parameters.

Based on the idea of discriminating set, a multiple EHMMs based face recognition algorithm is proposed in this paper, which solves the model selection problem HMM to some extent. The experimental result shows that this algorithm achieves higher recognition rate and stronger generalization ability. That is to say, this algorithm has a stronger ability to deal with new data. Of course, the assembly of multiple HMMs will lead to high computational complexity. Fortunately, the new algorithm is parallel virtually, which can be used to improve the efficiency by parallel computing.

2.2 LDA based face recognition by using hidden markov model in current trends.

Hidden Markov model (HMM) is a promising method that works well for images with variations in lighting, facial expression, and orientation. Face recognition draws attention as a complex task due to noticeable changes produced on appearance by illumination, facial expression, size, orientation and other external factors.

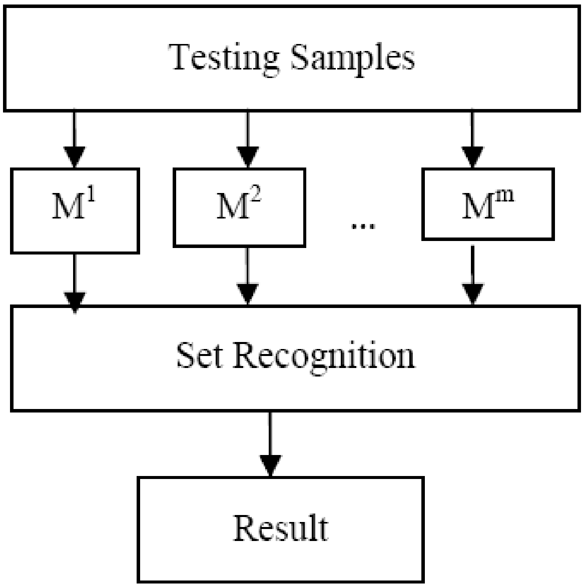

Figure 2.1 Proposed face recognition algorithm based on EHMM and discriminating set approach recognition algorithm

To process images using HMM, the temporal or space sequences are to be considered. In simple terms HMM can be defined as set of finite states with associated probability distributions. Only the outcome is visible to the external user not the states and hence the name Hidden Markov Model. The paper deals with various techniques and methodologies used for resolving the problem .We discuss about appearance based, feature based, model based and hybrid methods for face identification. Conventional techniques such as Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA),

Independent Component Analysis (ICA) and feature based Elastic Bunch Graph Matching (EBGM) and 2D and 3D face models are well known for face detection and recognition. Face detection and recognition has emerged as an active area of research in fields such as security system, videoconferencing and identification. As security deserves prime concern in today's networked world, face recognition can be used as a preliminary step of personal identity verification, facial expression extraction, gender classification, advanced human and computer interaction. It is a form of biometric method utilizing unique physical or behavioral characteristics [11]. Face recognition is considered to be a complex task due to enormous changes produced on face by illumination, facial expression, size, orientation, accessories on face and aging effects. The difficulty level increases when two persons have similar faces. Usually, face recognition systems accomplish the task through face image based methods uses predefined standard face patterns where as feature based techniques concentrate on extracted features such as distance between eyes, skin colour, eye socket depth etc.

The report encloses various approaches and techniques to solve face identification problem. Appearance based methods namely Principal component analysis (PCA), Linear Discriminant Analysis (LDA), Independent Component Analysis (ICA) are gaining attention as efficient techniques for face recognition. Most of the conventional methods are feature based or appearance based and in many cases uses a combination of both (hybrid methods). Different decision making systems are utilized for implementing the recognition systems. Artificial neural networks play a remarkable role in resolving many of the related issues in face recognition because of the inherent properties of neural networks. The feed forward architecture of neural networks after proper training can function as powerful tool for face classification.

A major challenge faced by any face recognition system is its ability to identify images, which may be tampered or undetectable due to various reasons. Pre-processing and normalization of images becomes inevitable in the context of face identification. Varying lighting conditions or face expressions reduces the recognition rate resulting in poor performance of the system. In order to avoid these difficulties different image enhancement methods can be employed. The report gives a brief overview of some of the widely used methods. Model based approaches are equally significant as statistical methods in resolving the face identification problem. Accuracy and similarity to realistic face images are added features of model based systems. The use of face models and the transition from 2D to 3D face models have greatly improved the performance of face recognition systems. The introduction of 3D morph able models is a remarkable step in 3D face recognition over the last few decades.

2.3 A New Fast and Efficient HMM-Based Face Recognition System Using a 7-State HMM Along With SVD Coefficients

Face recognition is the recognizing a special face from a set of different faces. Face has a significant role in human beings communications where, each person along with his/her feelings mainly is distinguished by his/her face image. One can easily find out that one of the main problems in machine-human being interactions is the face recognition problem. A human face is a complex object with features varying over time. So a robust face recognition system must operate under a variety of conditions. Face recognition has been undoubtedly one of the major topics in the image processing and pattern recognition in the last decade due to the new interests in, security, smart environments, video indexing and access control. Existing and future applications of face recognition are many [13]. We divide these applications into two main categories of governmental and commercial uses. Rapid progression through customs by using face as a live passport in immigration, comparison of surveillance images against an image database of known terrorists and other unwanted people in security/counterterrorism, and Verifying identity of people found unconscious, dead or individuals refusing to identify themselves in hospital are examples of governmental uses.

2.3.1 Hidden Markov Models

HMMs are usually used to model one dimensional data but in the recent years, they have been used in vision: texture segmentation, face finding , object recognition and face recognition . For a deep study on HMMs the reader may refer to . Every HMM is associated with non-observable (hidden) states and an observable sequence generated by the hidden states individually. The elements of a HMM are as below:

- N= S is the number of states in the model, where S={s1,s2,...,sN} is the set of all possible states. The state of the model at time t is given by qt S
- M= V is the number of the different observation symbols, where V={v1,v2,...,vM} is the set of all possible observation symbols vi (also called the code book of the model). The observation symbol at time t is given by to V .

As the reader is expected to know, observation vector is another concept that frequently is used in the HMM models.

A fast and efficient system was presented. Images of each face were converted to a sequence of blocks. Each block was featured by a few number of its SVD parameters. Each class has been associated to hidden Markov model as its classifier. The evaluations and comparisons were performed on the two well known face image data bases; ORL and YALE. In both data base, approximately having a recognition rate of 100%, the system was very fast. This was achieved by resizing the images to smaller size and using a small number of features describing blocks.

2.4 Conformation-Based Hidden Markov Models: Application to Human Face Identification

The traditional HMM model represents a powerful machine learning formalism for observation sequence prediction. This Bayesian framework has been applied in several research areas with success. However, its broad spectrum of implementation still remains scarce[14]. The main reason behind this limitation is explained by the fact that HMMs are unable to: 1) account for long-range dependencies which unfold structural1 information, and 2) intrinsically unravel the shape2 formed by the symbols of the visible observation (VO) sequence. Because the traditional HMM modelling is based on the hidden state conditional independence assumption of the visible observations, therefore, HMMs make no use of structure. The fact that the HMM state transition graph is not embedded in a Euclidean vector space, therefore HMMs make no use of shape information. This lack of structure inherent to standard HMMs represents a major challenge to the machine learning and pattern recognition community. It has drastically limited the shape recognition task of complex objects.

2.4.1 Standard and embedded hidden markov models

To better understand the contribution of the COHMMs, we provide a summarized description of the traditional HMMs and the embedded HMM.

Traditional HMMs

A HMM is a doubly embedded stochastic process with an underlying stochastic process that is not observable (it is hidden), but can only be observed through another set of stochastic processes that produce the sequence of observations.

Elements of an HMM

We now introduce the elements of an HMM, and explain how

the model generates observation sequences. An HMM is characterized

by the following parameters:

• N, the number of hidden states q_i in the model;

• R, the number of distinct observation O_i per hidden state, i.e., the size of the discrete alphabet;

- The initial state distribution $\pi = \{\pi_i\}$
- the state transition probability matrix $A = \{a_{ij}\}$
- the emission (or state) probability matrix, $B=\{b_j(K)\}$

We have devised a novel machine learning paradigm that extends an HMM state-transition graph to account for local structures as well as their shapes. This projection of a discrete structure onto a Euclidean space is needed in several pattern recognition tasks. Long-range structural dependencies with their metric information can therefore be explored. The results obtained from the selected application demonstrate the significance of the COHMMs formalism. The COHMMs classifier has outperformed both the traditional and the embedded HMMs classifiers. This achievement has revealed the predominant role of the local structure shape information assigned to a time series (sequence of data). An evaluation of further experiments with: 1) an increase of the number of images used in the training set which allow for a more robust estimation of the COHMM parameters, 2) a more discriminative mechanism between block windows, 3) an optimal number of UNIFs selected in the -means clustering algorithm, and 4) a different shape representation technique, is underway. We believe that the embedment of shape properties within the HMM framework will leapfrog the mathematical modelling of spatial objects.

2.5 **Face Recognition**

A transform domain face recognition approach is presented. The DCT is coupled with the HMM to achieve a recognition rate of 100% on ORL face database of 40 subjects with 10 images per subject[15]. The recognition time for ORL database is little over 2Sec. 5 images of a subject are used to train HMM and remaining *5* are used for recognition test. The proposed method is tested on another face data base of 249 subjects w,ith 3 training images and 4 test images per subject. The recognition rate is 90%. A test of recognition is carried out at different resolutions with recognition rate varing from 100% to 95% depending on the resolution. Further, a simple scheme is proposed to incorporate rejection of images of new subjects. On ORL database 100% rejection occurs for the images of new subjects.

This paper presents two transform domain schemes for face recog - nition with the basic block being the HMM (Hidden Markov Model). The proposed method combines DCT (Discrete Cosine Transform) with HMM to exploit the best of the two. The face recognition has two steps - HMM training, and then the actual face recognition.

2.5.1 vector sequence generation

Since, the proposed method uses HMMs for face recognition the 2D face image data must be converted to 1D data without loosing significant information. The DCT based method is proposed to generate 1D vector sequence from the 2D images.

2.5.2. Subimage sequence generation

The square sampling window is slid over the entire face image in raster scan fashion from top left comer of the face image upto bottom right comer window is slid with predefined overlap. The grey levels captured by the sampling window form the subimage. Each of the face image generates a sub image sequence.

2.5.3 DCT based vector sequence

Since, the DCT transforms spatial information to decoupled frequency information in the form of DCT coefficients with excellent energy compaction, it is used to obtain transformed vector sequence from subimage sequence.

2.5.4 hmm for face recognition

HMM Training: Following steps give a procedure of ergodic HMM training.

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Step 1: Cluster all R training vector sequences, generated from R number of training face images of the subject to be recognized, i.e. *{Ow},* 1 *5 w 5* R, each of length *T,* in *N*

clusters using some clustering algorithm, say k-means clustering algorithm. Each cluster will represent a state of the training vector.

Step 2: Assign cluster number of the nearest cluster to each of the training vector. i.e. *t th* training vector will be assigned a number 2' if its distance, say Euclidean distance, is smaller than than its distance to any other cluster *j , j # i.*

Step 3: Calculate mean *{pa}* and covariance matrix {E,} for each state (cluster).

Step 4: Calculate *A* and Jl matrices using event counting.

Step 5: Calculate the *B* matrix of probability density for each of the training vector for each state. Here we assume that *b, (ot)* is Gaussian. For 1 <= j <= *N*

Step 6: Now use the Viterbi algorithm to find the optimal state sequence *Q'* for each training sequence. Here, the state reassignment is done. A vector is assigned state *i* if *q; = i.*

Step 7: If there is any state reassignment, then repeat Steps 3 to 6; else STOP and the HMM is trained for the given training sequences.

DCT-HMM method is experimented on ORL database has 40 subject with 10 different images. *5* poses of the subject are used to train the HMM, and remaining 5 poses are used for recognition (see 1. The sampling window of 16 x 16 75% overlap is used to generate 1D transformed vector sequences. Significant first 10 DCT coefficients are used to ***form*** vector from DCT transformed subimage. The recognition rate ***of*** 100% is obtained. Average recognition time of little over 2Sec. is obtained on Pentium 200Mhz machine. When the recognition test was carried on with full database of 249 subjects (3 training poses and 4 test poses i.e. 249 x **4**) a recognition rate of 90% is obtained. Sample training posesand test poses are in Fig. 2. For the SPA" (in house) database the recognition rate is 95% with 20 randomly chosen subjects. To substantiate the above findings, eigen face based method is implemented. The recognition rate for ORL face database is 88% and for SPA" face database is 77.5% . Comparative results, as reported by the respective authors for OFU face database are reposted. Also, an investigation is made into the recognition at different resolution using ORL face database. The images are converted to different resolution using the pyramid algorithm proposed.

2.6 **Using Hidden Markov Models and Wavelets for face recognition**

Face recognition is undoubtedly an interesting research area, growing in importance in recent years, due to its applicability as a biometric system in commercial and security applications[16]. These systems could be used to prevent unauthorized access or fraudulent use of ATMs, cellular phones, smart cards, desktop PCs, workstations, and computer networks. The appealing characteristic of a face recognition system is that, differently from fingerprint or iris biometric systems, it represents a not invasive control tool. To the best of our knowledge, the best results obtained on standard database were proposed, using Hidden Markov Model-based approaches, obtaining an almost perfect classification accuracy. More in detail, a pseudo 2D HMM was used for classifying faces: face images are described using the DCT (Discrete Cosine Transform) coefficients, computed on a set of partially overlapped Sub-images.

2.6.1 The DCT-HMM approach

In this section, the method proposed is detailed. In this approach, HMMs were used in a standard manner: one model is trained for each class, using standard Baum Welch algorithm, and the subsequent classification was performed using standard Maximum Likelihood classification rule, *i.e.* , assigning an unknown item to the class whose model shows the highest likelihood. In this paper, differently than , where the model selection issue was disregarded, the model size is carefully estimated, using the technique proposed. This technique is able to deal with drawbacks of standard general purpose methods, like those based on the *Bayesian inference criterion* (BIC), *i.e.*, computational requirements, and sensitivity to initialization of the training procedure. The basic idea is to perform a "decreasing" learning, starting each training session from a "nearly good" situation, derived from the result of the previous training session by pruning the "least probable" state of the model. As shown in the experimental session, this permits the improvement of the method performances presented

2.6.2 The Wavelet coding

The wavelet transform is a methodology emerged in the last years, useful in many applications, especially in the field of image compression. Wavelet-based coding provides substantial improvements in picture quality at higher compression ratios, with respect to standard DCT transform. Over the past few years, a variety of wavelet-based schemes for image compression have been developed and implemented. Because of the many advantages, the compression technologies used in the upcoming JPEG-2000 standard are all based on the wavelet technology.

In this paper, a new approach for face recognition has been proposed, based on HMMs and wavelet coding. A model selection procedure has been applied to the HMMs in order to automatically find the best model for the data. The effectiveness of HMMs in tackling the face recognition problem has been proved by the interesting results obtained using both "naive" and accurate features. This method, compared to the DCT approach, reported similar results, confirming the HMM suitability to deal with the new JPEG2000 image compression standard. The obtained results outperform all results presented in the literature on the ORL database, reaching a perfect classification accuracy.

2.7 Analysis and Design of Principal Component Analysis and Hidden Markov Model for face recognition

Automatic verification and identification of a person from a digital image or video frame from a video source is done by facial recognition system[17]. Here, in this work the facial features are selected and compare these features with the data base collected. Facial recognition system is similar to other biometrics such as fingerprinting, iris recognition and many others. Some facial recognition algorithms extract some features of the face and matches with the features of the image that are stored in the data base. There are many recognition algorithms which include PCA using Eigen faces, linear discriminate analysis, elastic bunch, Hidden Markov Model and many others. In this paper,it exploits principal component analysis (PCA) algorithm with Hidden Markov model.

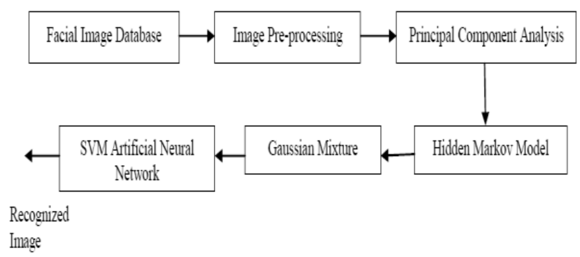

Figure 2.2 Block diagram of proposed work for identification of facial organs

Fig.2.2 shows the overall block diagram of proposed method. It consists of following blocks facial image database, image pre-processing, principal component analysis (PCA), Hidden Markov model (HMM), Gaussian Mixture model (GMM) and Artificial Neural Network (ANN). The facial images from different sources such as videos and still images are collected and stored in the database. The preliminary step for face detection is the Image Pre-processing. The image is to be matched with the image stored in the database after pre-processing test. The pre-processing module consists of Smoothing and Sharpening, Contrast Enhancement.

2.7.1 Gaussian Mixture Model (GMM)

At a given hidden variable time m (t) the hidden variable m depends only on the hidden variable (t-1) this is called Markov property. Hidden Markov property has two parameters namely transition probability and emission probability. GMM is the sum of densities of Gaussian components. Since, the expression in the human face will be changing according to the situation detecting or understanding it is difficult. Therefore, Gaussian mixture model is

Used to find out invariant face recognition. This method is used to characterize human faces and find out variations in the faces with different mixture components. These mixture components learn from the trained data present in the mixture model. GMM is a powerful algorithm and ability to smoothen arbitrarily shaped densities. Gaussian mixture distribution function consists of one or more multivariate Gaussian distribution components.

The implementation is done using Matlab 2012A. A Graphical User Interface is created. The face image is collected from different sources. This image is to analyze by selected through the GUI. The selected image is smoothened and sharpened using wiener filter, and then applied to the histogram equalizer to increase the contrast of the image. From the experimental results by this method the performance factors are improved FRR to 99.8%, FAR 0.672% and the accuracy to 96%. In this work, proposed four algorithms for various parts of face recognition and analyzed simulated for performance improvement from the existing 50 images obtained from data base. GUI for the identification of face detection of facial organs. GUI for the identification of eyes detection. shows GUI for the identification of nose detection.

III **PROBLEM IDENTIFICATION**

3.1 Problem Identification

The recognition of human faces, which are 3D deformable objects, from their 2D images poses many challenges. In face recognition research, the sources of variation in facial appearance can be categorized into two types, intrinsic or extrinsic. "Intrinsic variation takes place independently of any observer and is due purely to the physical nature of the face". In general, faces exhibit many degrees of intrinsic variability and the intrinsic sources of variation can be listed primarily as: Identity, Facial Expression, Speech, Sex, Age[21].

Extrinsic variations related to transformations resulting from changes in viewing angle, scene environment as well as changes in imaging processes. Extrinsic factors that affect the visual appearance of a face can be highlighted as:

a) Viewing geometry: Pose;

b) Illumination: Shading, color, shadow;

c) Imaging process: Resolution, focus, noise;

d) Occlusion.

The difference between images of a face depends on the lighting condition. Illumination conditions, e.g. control/uncontrolled, indoor/outdoor, and in particular self-shadowing change considerably the appearance of a face. The camera characteristics also affect the resulting image quality. Moreover, one of the most significant sources of variation is pose change. Pose changes usually appear when the face changes its position and orientation in three-dimensional (3D) space relative to the camera. However, a face can also undergo non-rigid motion when its 3D shape changes due to such factors as speech or facial expression. Some expression types can cause large deformations and appearance changes. In addition, partial occlusion and disguise are the source of challenges too. These sources of variations, both intrinsic and extrinsic, are not independent of each other.

Different face recognition systems may use different learning methods to develop 'biometric signatures' for all individuals. They can work with one or several types of input data, such as gray, colour or infrared. Systems may be presented with a single image, a collection of images, a 3D model or a video sequence. The data may be acquired under a controlled condition or different conditions of lighting, viewpoint and background. While face recognition systems vary depending on many factors, they share the same characteristic. They are usually trained with a database of face images.

3.2 Solution of the Problem

In order to implement our AFR system two different software programs were designed: one for the face detection and normalization processes and one to support the HMM based face recognition process. Many functions for face detection and recognition were based on a well known open source image processing library.

3.2.1 Face detection

For the detection and cropping of all faces in the test databases we employed a well-known face detection algorithm. In order to implement detection and cropping of all faces in all images in a single step, a tool was required to operate batch processes. This is implemented using Matlab or java program. Such an approach allows additional high-level filters and other image processing techniques, also implemented in Matlab or java program,, to be easily linked with the OpenCV based face detection process. Thus the speed and efficiency of the OpenCV routines are coupled with the flexibility to incorporate supplemental Matlab filters into our test and evaluation process.

3.2.2 Face recognition

The second step in implementing the face recognition system was to build a program that would perform the main face recognition processes. The face recognition implementation was done in the C language using Microsoft Visual Studio. The implementation consists of three main components:

1. Top-level component is the first component and has the purpose of (i) reading multiple images from the disc, (ii) saving the output of the training stage (which is represented by the models) and (iii) analyzing the output of the testing stage.

2. Mid-level component: the second component which processes (pre-processing: illumination normalization, resize, filtering etc) the faces, computes observation vectors, builds and stores HMM models and computes likelihoods between faces and models.

3. Low-level component is the third component which contains the basic routines of the HMM algorithm (feature extraction, segmentation, Viterbi, state probability distribution etc) and uses functions implemented in the OpenCV library.

3.2.3 Databases and training datasets

Each database provides some of our desired variations, high variations in illumination, some expression variations and slight pose variations, Ackermann presents some head rotations and slight illumination variations; UMIST covers a range of poses from frontal to semi-profile. A short description of each of these in database[22].

IV PROPOSED METHODOLOGY

Face Recognition is a term that includes several sub-problems. There was an effort to try to measure the importance of certain intuitive features (mouth, eyes, and cheeks) and geometric measures (between-eye distance, width-length ratio). Nowadays is still an relevant issue, mostly because discarding certain facial features or parts of a face can lead to a better performance.

In other words, it's crucial to decide which facial features contribute to a good recognition and which ones are no better than added noise. However, the introduction of abstract mathematical tools like Eigen faces created another approach to face recognition. It was possible to compute the similarities between faces obviating those human-relevant features. This new point of view enabled a new abstraction level, leaving the anthropocentric approach behind.

There are still some human-relevant features that are being taken into account. For example, skin color is an important feature for face detection. The location of certain features like mouth or eyes is also used to perform normalization prior to the feature extraction step. To sum up, a designer can apply to the algorithms the knowledge that psychology, neurology or simple observation provide. On the other hand, it's essential to perform abstractions and attack the problem from a pure mathematical or computational point of view[23].

4.1 A Simple face recognition system

The input of a face recognition system is always an image or video stream[22]. The output is an identification or verification of the subject or subjects that appear in the image or video.

Figure 4.1 Simple Face Recognition

Some approaches define a face recognition system as a three step process - see Figure 4.1. From this point of view, the Face Detection and Feature Extraction phases could run simultaneously.

Face detection is defined as the process of extracting faces from scenes. So, the system positively identifies a certain image region as a face. This procedure has many applications like face tracking, pose estimation or compression. The next step -feature extraction-involves obtaining relevant facial features from the data. These features could be certain face regions, variations, angles or measures, which can be human relevant (e.g. eyes spacing) or not. This phase has other applications like facial feature tracking or emotion recognition. Finally, the system does recognize the face.

In an identification task, the system would report an identity from a database. This phase involves a comparison method, a classification algorithm and an accuracy measure. This phase uses methods common to many other areas which also do some classification process -sound engineering, data mining et al[24].

These phases can be merged, or new ones could be added. Therefore, we could find many different engineering approaches to a face recognition problem. Face detection and recognition could be performed in tandem, or proceed to an expression analysis before normalizing the face.

4.2 Face detection

Nowadays some applications of Face Recognition don't require face detection[23]. In some cases, face images stored in the data bases are already normalized. There is a standard image input format, so there is no need for a detection step. An example of this could be a criminal data base. There, the law enforcement agency stores faces of people with a criminal report. If there is new subject and the police has his or her passport photograph, face detection is not necessary. However, the conventional input image of computer vision systems is not that suitable. They can contain many items or faces. In these cases face detection is mandatory. It's also unavoidable if we want to develop an automated face tracking system.

Face detection must deal with several well known challenges. They are usually present in images captured in uncontrolled environments, such as surveillance video systems. These challenges can be attributed to some factors:

- **Pose variation**: The ideal scenario for face detection would be one in which only frontal images were involved. But, as stated, this is very unlikely in general uncontrolled conditions.
- **Feature occlusion**: The presence of elements like beards, glasses or hats introduces high variability. Faces can also be partially covered by objects or other faces.
- **Facial expression**: Facial features also vary greatly because of different facial gestures.
- **Imaging conditions:** Different cameras and ambiental conditions can affect the quality of an image, affecting the appearance of a face.

4.3 Face detection problem structure

Face Detection is a concept that includes many sub-problems[24]. Some systems detect and locate faces at the same time, others first perform a detection routine and then, if positive, they try to locate the face[25]. Then, some tracking algorithms may be needed - see Figure 4.2.

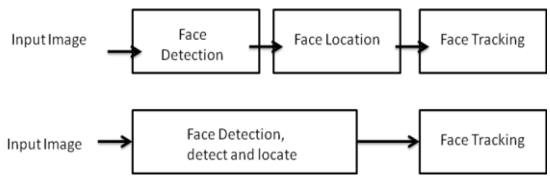

Figure 4.2 Face Detection Process

4.4 Hidden Markov Model for Face Recognition

A Hidden Markov Model is a statistical model used to characterize the statistical properties of a signal. An HMM consists of two stochastic processes: one is an unobservable Markov chain with a finite number of states, an initial state probability distribution and a state transition probability matrix; the other is a set of probability density functions associated with each state[25]. There are two types of HMM: discrete HMM and continuous HMM. The continuous HMM is characterized by the following:

• N, the number of states in the model. We denote the individual state as **S { S1,S2,S3,.....S$_N$ }** and the state at time t as q_t , $1 \le t \le T$, where T is the length of the observation sequence.

• **A**, the state transition probability matrix, i.e.,A={a_{ij}}, where

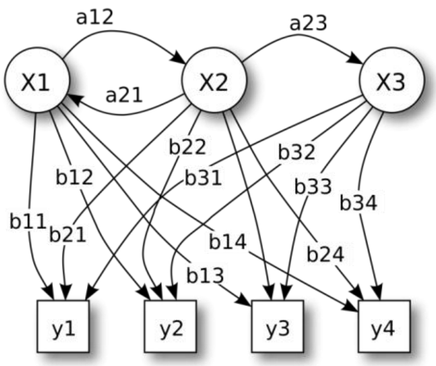

Figure 4.3 Training Of HMM Model

a_{ij} = P | q_t = S_j | q_{t-1}= S_i| 1<=i, j<= N

with the constraint

$\sum a_{ij} = 1$, 1<=i<=N

• **B**, the observation probability density functions (pdf), i.e., **B** ={ b_1**(O)**} ,

Where b_i (O) = $\sum C_{tk}$ N(O;μ_{tk},U_{tk}), 1<=i<=N

where C_{tk} is the mixture coefficient for *k*th mixture component in State *i*. *M* is the number of components in a Gaussian mixture model. N(O;μ_{tk},U_{tk}) is a Gaussian pdf with the mean vector *ik* **μ** and the covariance matrix U_{tk}.

• **π** , the initial state distribution, i.e.,**π** ={ **π**$_i$ } , where *P*[q_1= S_i] *i N i i* = = 1≤ ≤ 1 π **,** .

Using a shorthand notation, an HMM is defined as the triplet **λ** =(**A**,**B**, **π**).

V EXPECTED RESULT

There are a few reasons why the proposed algorithms work better than the baseline algorithm. The first is that HMM is able to learn both the dynamics and the temporal information. The second is that there is mismatching between the training and test sets, i.e., some of the test sequences show the new appearance that is barely seen in the training set. So the adaptive HMM enables the HMM to learn this new appearance in the test set and thus enhance the modelling.

VI CONCLUSION AND SCOPE OF FURTHER WORK

6.1 Conclusion

We propose to use HMM to perform image based face recognition. During the training process, the statistics of training image sequences of each subject, and their temporal dynamics are learned by an HMM. During the recognition process, the temporal characteristics of the test video sequence are analyzed over time by the HMM corresponding to each subject. The likelihood scores provided by the HMMs are compared, and the highest score provides the identity of the test image sequence. Furthermore, with unsupervised learning, each HMM is adapted with the test video sequence, which results in better modelling over time. Based on extensive experiments with various databases, we show that the proposed algorithm provides better performance than using majority voting of image-based recognition results.

6.2 Scope of Further Work

Every research has a scope to be work, Here the given research is for face recognition we can do it via video streaming. The new adaptive HMM method will be use for the our next research in future.

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