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# HIDDEN MARKOV MODELS (HMM) BASED FACE RECOGNITION

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***Abstract: Successive techniques for face acknowledgment depend on the investigation of nearby facial elements in a consecutive way, regularly with a raster check. In any case, the appropriation of discriminative data is not unifom over the facial surface. Case in point, the eyes and the mouth are more enlightening than the cheek. We propose an augmentation to the consecutive approach, where we consider neighborhood highlight saliency, and supplant the raster filter with a guided sweep that emulates the scanpath of the human eye. The particular consideration instrument that aides the human eye works by coarsely identifying notable areas, and coordinating more assets (the fovea) at fascinating then again instructive parts. We reenact this thought by utilizing a computationally shoddy saliency plan, in view of Gabor wavelet channels. Concealed Markov models are utilized for characterization, and the perceptions, i.e. highlights acquired with the reproduction of the scanpath, are demonstrated with Gaussian dispersions at every condition of the model. We demonstrate that by going by vital areas in the first place, our technique can achieve high precision with much shorter element arrangements. We look at a few elements in perception arrangements, among which DCT coefficients result in the most noteworthy precision. Various run of the mill calculations are exhibited, being sorted into appearance based and show based plans. Shrouded Markov Models (HMMs) are a class of measurable models used to describe the discernible properties of a sign. Well comprise of two interrelated procedures: (i) a fundamental, inconspicuous Markov chain with a limited number of states represented by a state move likelihood framework and an underlying state likelihood dissemination, and (ii) an arrangement of perceptions, characterized by the perception thickness capacities connected with every state. we start by portraying the summed up design of a programmed face acknowledgment (AFR) framework. At that point the part of each useful square inside this engineering is talked about. An itemized depiction of the techniques we used to fathom the part of every piece is given with specific accentuation on how our HMM capacities.***

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

## I. INTRODUCTION

A hidden Markov model (HMM) is one in which you observe a sequence of emissions, but do not know the sequence of states the model went through to generate the emissions. Analyses of hidden Markov models seek to recover the sequence of states from the observed data[1,7,10].

As an example, consider a Markov model with two states and six possible emissions. The model uses:

- A red die, having six sides, labeled 1 through 6.
- A green die, having twelve sides, five of which are labeled 2 through 6, while the remaining seven sides are labeled 1.
- A weighted red coin, for which the probability of heads is .9 and the probability of tails is .1.
- A weighted green coin, for which the probability of heads is .95 and the probability of tails is .05.

The model creates a sequence of numbers from the set {1, 2, 3, 4, 5, 6} with the following rules:

- Begin by rolling the red die and writing down the number that comes up, which is the emission.
- Toss the red coin and do one of the following:
  - If the result is heads, roll the red die and write down the result.
  - If the result is tails, roll the green die and write down the result.
- At each subsequent step, you flip the coin that has the same color as the die you rolled in the previous step. If the coin comes up heads, roll the same die as in the previous step. If the coin comes up tails, switch to the other die.

The state diagram for this model has two states, red and green, as shown in the following figure.

Hidden Markov Models (HMMs) are a class of statistical models used to characterize[2,3,5] the observable properties of a signal. HMMs consist of two interrelated processes:

- 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
- 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

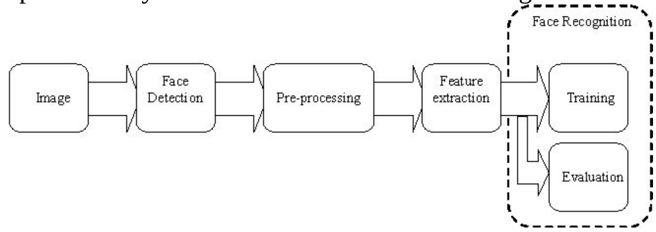


Figure 1.1 Automatic Face Recognition System

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:

- knowledge-based,
- feature invariant,
- template matching and
- 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[4].

*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].

## II. REVIEW OF LITERATURE

HMM, as described in the previous section, is applied to I-D observation sequence, hence called I-D HMM. Samaria [8] has applied 1-D HMM to the problem of face recognition. Clearly, the problem had to be reformulated in order to fit the 2-D image in a 1-Dobservation sequence such that the 1-D HMM can handle it. The 1-D sequence of observations consists of the luminance of vertically successive strips that scan the image from top to bottom or blocks that scan from left to right and top to bottom. The overlap between consecutive strips is permitted up to one pixel less than the strip width. 85% accuracy has been reported using 5-state top-to-bottom 1-D HMM with strip width of 10 pixels[12,15]. The HMM feature vector consists of the DCT coefficients that correspond to DC and lower frequency bands, exploiting the fact that the lower frequency bands are the most significant ands for normal images. Only the lower 3x13 coefficients out of the 10x92 DCT coefficients are considered for each strip to form 39-dimensional HMM feature vector. The main contribution in [7] is the complexity reduction due to the partial spectral processing. A similar accuracy of 85% has been achieved but with lower complexity.

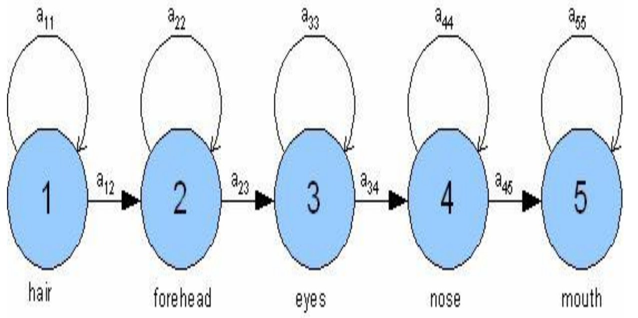


Figure 2.1 1-D HMM

The 2-D PHMM is a recent variation of the original HMM designed to deal with the 2-D signal. It has been introduced to many applications including the optical character recognition [19,21,23], color image retrieval [10], and face recognition [8]. The 2-D PHMM is composed of an I-D HMM whose states are called super states. Each of these super states contains a 1-D HMM arranged in the transverse dimension, left-to-right in this case. This way, the 2-D PHMM deals with one dimension at a time. The image is divided into blocks instead of strips. The blocks are arranged in one 1-D sequence before being fed to the 2-D PHMM that is equivalent to an I-D HMM. The equivalent 1-D HMM is either unrestricted or restricted. In the restricted equivalent 1-D HMM, an extra state, called end-of-line state, is inserted between each two consecutive sub-chains to ensure that no row is shared between two super states.

## III. PROBLEM IDENTIFICATION

*3.1 Problem Identification*

Hidden Markov Models have been successfully used for speech recognition where data is essentially one dimensional. Extension to a fully connected two dimensional HMM has been shown to be computationally very complex [SI. In [11], Kuo and Agazzi have used a pseudo two dimensional HMM for Character recognition that was shown to perform reasonably fast for binary images. In this paper we investigate the recognition performance of a one dimensional HMM for gray scale face images. For frontal face images, the significant facial regions (hair, forehead, eyes, nose, and mouth) come in a natural order from top to bottom, even if the images are taken under small rotations in the image plane and/or rotations in the plane perpendicular to the imageplane. Each of these facial regions is assigned to a state in a left to right 1D continuous HMM. The state structure of the face model and the non-zero transition probabilities aij are shown in Figure 2.1.

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[27].

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[30].

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[22,28].

## IV. PROPOSED METHODOLOGY

Face Recognition is a term that incorporates a few sub-issues. There was a push to attempt to gauge the significance of certain natural elements (mouth, eyes, and cheeks) and geometric measures (between-eye separation, width-length proportion). These days is still an important issue, generally in light of the fact that disposing of certain facial elements or parts of a face can prompt a superior execution.

As such, it's vital to choose which facial components add to a decent acknowledgment and which ones are no superior to anything included commotion. Be that as it may, the presentation of theoretical numerical apparatuses like Eigen appearances made another way to deal with face acknowledgment. It was conceivable to register the likenesses between appearances blocking those human-applicable components. This new perspective empowered another deliberation level, deserting the human-centric methodology.

There are still some human-pertinent components that are being considered. For instance, skin shading is an essential component for face identification. The area of certain components like mouth or eyes is likewise used to perform standardization before the element extraction step. To entirety up, an architect can apply to the calculations the information that brain science, neurology or basic perception give. Then again, it's crucial to perform reflections and assault the issue from an immaculate numerical or computational purpose 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

*4.2 Face detection*

Face location is characterized as the procedure of removing appearances from scenes. In this way, the framework emphatically distinguishes a specific picture area as a face. This technique has numerous applications like face following, posture estimation or pressure. The following stride - highlight extraction-includes getting important facial components from the information. These elements could be sure face locales, varieties, points or measures, which can be human important (e.g. eyes separating) or not. This stage has different applications like facial component following or feeling acknowledgment. At long last, the framework recognizes the face[14,18]. In a distinguishing proof errand, the framework would report a personality from a database. This stage includes an examination technique, an order calculation and a precision measure. This stage utilizes strategies regular to numerous different zones which likewise do some arrangement procedure - sound designing, information mining et al[24,13]. These stages can be combined, or new ones could be included. Accordingly, we could discover various building ways to deal with a face acknowledgment issue. Face location and acknowledgment could be performed in coupled, or continue to a look investigation before normalizing the face. 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[25,21]. Then, some tracking algorithms may be needed - see Figure 4.2.

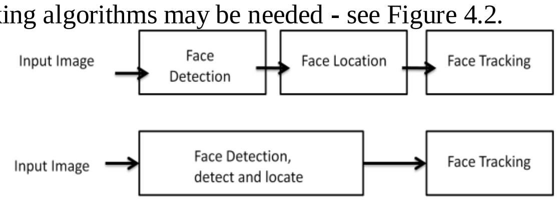


Figure 4.2 Face Detection Process

*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[15]. 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 $q_t$ , $1\leq t \leq T$ , where $T$ is the length of the observation sequence.

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

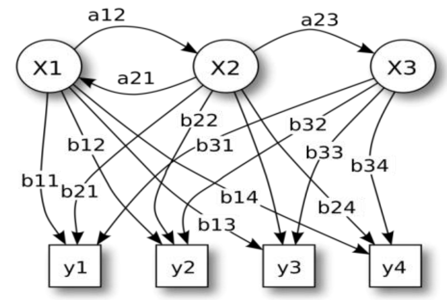


Figure 4.3 Training Of HMM Model

$a_{ij}$ = 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) = $\sum C_{tk} N(O;\mu_{tk},U_{tk})$, 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. $N(O;\mu_{tk},U_{tk})$ is a Gaussian pdf with the mean vector *ik* μ and the covariance matrix $U_{tk}$.

• π , the initial state distribution, i.e.,π ={ $\pi_i$ } , 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).

*4.4 Feature Extraction*

Each face image of width *W* and height *H* is divided into overlapping blocks of height *L* and width *W*. The number of blocks extracted from each face image equals the number of observation vectors T and is given by:

T= (H-L)/(L-P) + 1

The decision of parameters P and L can essentially influence the framework acknowledgment rate. A high measure of cover P altogether builds the acknowledgment rate since it permits the elements to be caught in a way that is free of the vertical position. The decision of parameter L is more sensitive. Utilizing a little L can convey lacking discriminant data to the perception vector, while expansive L expands the likelihood of cutting over the components. The utilization of the pixel values as perception vectors has two vital detriments: First, pixel values don't speak to powerful components, being extremely touchy to picture commotion and in addition picture turn, move or changes in light and second, the expansive measurement of the perception vector prompts high computational many-sided quality of the preparation and acknowledgment frameworks, and consequently expands the handling time required for acknowledgment. This can be a real issue for face acknowledgment over substantial databases or when the acknowledgment framework is utilized for ongoing applications. In this paper, the perception vectors comprise of an arrangement of 2D-DCT coefficients that are extricated from every piece. The DCT pressure properties for characteristic pictures make the utilization of this change an appropriate element extraction method for the face acknowledgment framework.

  

## V. EXPECTED RESULT

In the acknowledgment stage, an arrangement of 200 test pictures, not utilized as a part of the preparation, are considered to decide the acknowledgment exhibitions of the framework. In the wake of extricating the perception vectors as in the preparation stage, the likelihood of the perception vector given each HMM face model is figured.

Figure 5.1 Face recognition training set

The face acknowledgment framework has been tried on the Olivetti Research Ltd. database (400 pictures of 40 people, 10 face pictures for every person at the determination of 92 x 112 pixels). The database contains face pictures demonstrating distinctive outward appearances, haircuts, eye wear (glasses/no glasses), and head introductions. The framework accomplished an acknowledgment rate of 84% with L = 10 and P = 9. On the same database the acknowledgment rate of the eigen faces strategy is 73% and the acknowledgment rat of the Well based methodology displayed in below figure is 84% over a small amount of the same database.

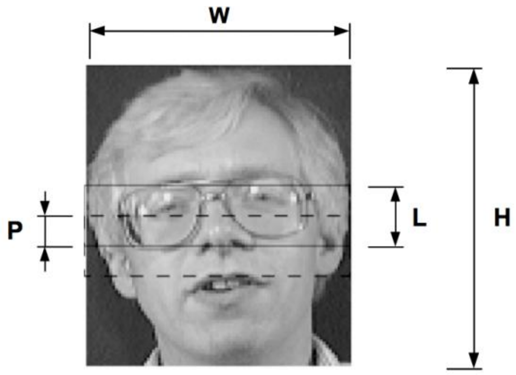


Figure 5.2 HMM for face recognition

## VI. CONCLUSION AND SCOPE OF FURTHER WORK

*6.1 Conclusion*

Because of the pressure properties of the DCT, the measure of the perception vector in the present methodology is lessened from Lx W (L = 10 and W = 92) to 39, while saving the same acknowledgment rate (The acknowledgment execution in [12] depended on a small amount of the database, while the examinations displayed here were led over all pictures of the same database). The utilization of a lower dimensional element vector (more than 23 times littler than the measure of the perception vector in the past technique) prompts a noteworthy lessening of the computational multifaceted nature of the strategy and thus to a critical diminishing of the face acknowledgment time. The HMM demonstrating of human confronts seems, by all accounts, to be an empowering technique for face acknowledgment under a more extensive scope of picture introductions and outward appearances. Future work will be coordinated on the investigation of pseudo 2D HMM for face picture acknowledgment, the consideration of state length in face displaying, and additionally other element extraction procedures. We propose to utilize HMM to perform picture based face acknowledgment. Amid the preparation procedure, the insights of preparing picture groupings of every subject, and their transient progression are found out by a HMM. Amid the acknowledgment procedure, the transient qualities of the test video succession are broke down after some time by the HMM relating to every subject. The probability scores gave by the HMMs are looked at, and the most noteworthy score gives the personality of the test picture succession. Besides, with unsupervised adapting, each HMM is adjusted with the test video grouping, which results in better displaying after some time. Taking into account broad examinations with different databases, we demonstrate that the proposed calculation gives preferable execution over utilizing larger part voting of picture based acknowledgment 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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