

FACIAL EXPRESSION RECOGNITION USING MULTISTAGE HIDDEN MARKOV MODEL

¹MAYUR RAHUL, ²NARENDRA KOHLI, ³RASHI AGARWAL

¹research Scholar, Aktu, Lucknow, India

³assistant Professor, Uiet, Csjmu, Kanpur, India

²professor, Hbtu, Kanpur, India

Email: ¹mayurrahul209@gmail.com, ²kohli.hbti@gmail.com, ³dr.rashiagarwal@gmail.com

ABSTRACT

Facial Expression Recognition is an application used for biometric software that can be used to identify special expressions in a digital image by comparing and analysing the different patterns. These software are popularly used for the purpose of security and are commonly used in other applications such as home security, human-computer interface, credit card verification, surveillance systems, medicines etc.. Recognizing faces becomes very difficult when there is a change occurs in facial expressions. In this paper two layer extension of HMM is used to recognized continuous effective facial expressions. Gabor wavelet technique is used for feature extraction. Two layered extension of HMM consists of bottom layer which represents the atomic expression made by eyes, nose and lips. Further upper layer represents the combination of these atomic expressions such as smile, fear etc. In HMM, Baum-Welch method is used for parameter estimation. Viterbi Method and Forward Procedure are used for calculating the optimal state sequence and probability of the observed sequence respectively. This proposed system consists of three level of classification. Output of the first level is used for the training purposes for the second level and further this level is used for the third level for testing. Six basic facial expressions are recognised i.e. anger, disgust, fear, joy, sadness and surprise. Experimental result shows that Proposed System performs better than normal HMM and has the overall accuracy of 85% using JAFFE database.

Keywords: *JAFFE, Gabor Wavelets Transform, PCA, Local Binary Patterns, SVM, Faps, Cohn-Kanade Database, Markov Process, Static Modelling*

1. INTRODUCTION

An efficient human-computer interaction is very useful in the present scenario for the automatic recognition of facial expression[20]. The facial expression recognition is the process by which the facial expression made by the user can be recognised by the receiver. Extractions of emotions from the face are the region surroundings eyes, mouth and nose. These facial regions are tracked to generate suitable activities. The changes, location and place of the faces are very useful in recognising facial expressions. In order to recognise all facial expressions, the human face and its movement need to be sensed. This can be done by sensing device attached to the user. Devices can be magnetic field suits, gloves, cameras and computer vision methods. Each sensor has different characteristics for example they can differ in accuracy, resolution, latency,

range, comfort. Each require different techniques and approach. Our objective is to develop a robust system which is capable of recognize facial expressions and has good efficiency.

Human faces are non-rigid objects which are differ in size, shape, colour etc. and can be easily detected by human beings. The recognition of facial expression is the process of identifying facial gestures regardless of their illumination, scales, orientation, poses etc. Facial expressions recognition can be easily applicable in human-computer interface, credit card verification, security in offices, criminal identification, surveillance systems, medicines etc. They can also be used in information retrieval techniques such as query refinement database indexing, content based image retrieval, similarity based retrieval etc. The facial expression can be categorised in two categories: transient and permanent. Eye,

eyebrows, cheeks and facial hair are permanent features and region surrounding the mouth and eye are called transient features. Difference of appearance due to different identity is called face detection and change of appearance due to different movement is called facial expression recognition.

The HMM is the best method for facial expression recognition. On comparing HMM with human being, it is found to be similar. Hidden state of the HMM is the mental state of human being and facial expression is the observations. Rest of the paper is organized as follows. Paper has seven sections. Basics of HMM has been discussed in section 2, Basics of Gabor filter is explained in section 3, Related works have been explained in section 4, Proposed system have been discussed in section 5, Experiments and Results are in section 6 and finally conclusion and future works in section 7.

2. BASICS OF HMM:

Markov Models are graphical models used to deal with time series data[19]. This model is applicable for data analysis in which there is a dependability of current states of the system to its previous states (figure 1). For examples, in spoken sentence the present pronounced word is depending on the previous pronounced word. Further in other example bowler bowls the ball in cricket game, ball first hit the ground then hit the bat or pad. Markov process effectively handles such situations.

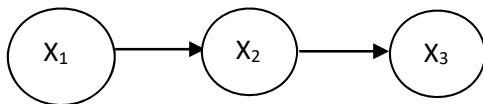


Figure 1: A Markov Model For 3 Observations Variables

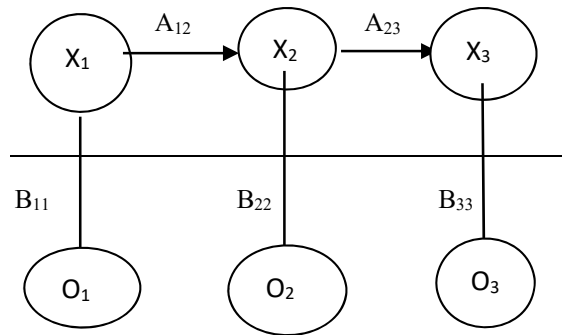
When an observation variable is dependent only on previous observation variable in a markov model is called first order markov chain. The joint probability distribution is given by

$$p(X_1, X_2, \dots, X_N) = p(X_1) \prod p(X_N | X_{N-1}) \tag{1}$$

where $p(X_1, X_2, \dots, X_N)$ is the joint probability distribution of states X_1, X_2, \dots, X_N and $p(X_1)$ is the probability of state X_1 and $p(X_N | X_{N-1})$ is the probability of state X_N given state X_{N-1} .

A Hidden Markov Model is a statistical model which is used to model a markov process with some hidden states. This model is widely used in speech and gesture recognition. Hidden markov model is a set of observable states are measured and these variables are assumed to be depend on the states of a markov process which are hidden to the observer (Figure 2). Hidden states are states above the dashed lines.

States



Observations

Figure 2: A Hidden Markov Model For Three Variables

$$p(X_{t+1} = j | X_t = i) = a_{ij} \tag{2}$$

where $p(X_{t+1} = j | X_t = i) = a_{ij}$ is the conditional probability of the state X_{t+1} given the state X_t and a_{ij} is the i th row, j th column entry of the transition matrix $A = (a_{ij})$.

$$p(O_t = k | X_t = l) = b_{lk} \tag{3}$$

where $p(O_t = k | X_t = l) = b_{lk}$ is the conditional probability of the observation variable O_t given the state X_t and b_{lk} is the l th row, k th column entry of the emission matrix $B = (b_{lk})$.

An HMM is defined by A, B and Π . The HMM is denoted by $\hat{\theta} = (A, B, \Pi)$ (4)

(a)HMM in Weather Prediction:

Predictions of event have been done using probability [19]. Predictions are mostly temporal i.e. when predicting the probability of happening A ; we can't consider the events that take place before A . In real world, when airplane is tracking, the probability distribution of plane's position at time t is depends on plane's position at time $t-dt$. This situation requires some more strong models to describe changes with respect to time.

Prediction is also used in the weather forecast because weather is always depends on previous state. This type of predictions are easily handle by HMM.

Let us consider a problem with two annual weather “Rainy” and “Sunny”. Suppose the probability of a Rainy year followed by another Rainy year is 0.6 and the probability that a Sunny year is followed by a Sunny year is 0.7. This information can be summarized as follows:

$$\begin{matrix}
 & R & S & & \\
 R & & & & \\
 S & & & &
 \end{matrix}
 \begin{matrix}
 & & & & \\
 & & 0.6 & & \\
 & 0.3 & & 0.7 & \\
 & & & &
 \end{matrix}
 \begin{matrix}
 & & & & \\
 & & & & 0.4 \\
 & & & &
 \end{matrix}
 \quad (5)$$

Where R is “Rainy” and S is “Sunny”

Also suppose that the current research indicates that the size of tree and weather dependent to each other. We consider three different sizes of the tree with respect to weather. The probabilistic relationship of weather and tree sizes is given by

$$\begin{matrix}
 & S & M & L & & \\
 R & & & & & \\
 S & & & & &
 \end{matrix}
 \begin{matrix}
 & & & & & \\
 & & 0.5 & & 0.4 & \\
 & 0.1 & & 0.2 & & 0.7 \\
 & & & & &
 \end{matrix}
 \begin{matrix}
 & & & & & \\
 & & & & & 0.1 \\
 & & & & &
 \end{matrix}
 \quad (6)$$

For the given system , the state is the annual weather either R and S. The transition from one state to another is a markov process. Next state depends on the current state. The actual states are “hidden” because we can’t directly calculate the weather in the past .

We can’t calculate the states in the past but we can observe the size of the trees from eq. (2) tree growth provides us some information regarding the weather. This system is called Hidden Markov Model because states are hidden in this system.

State transition matrix

$$A = \begin{matrix} & R & S \\ R & & \\ S & & \end{matrix}
 \begin{matrix} & & \\ & 0.6 & \\ 0.3 & & 0.7 \end{matrix}
 \quad (7)$$

And the observation matrix

$$B = \begin{matrix} & S & M & L \\ R & & & \\ S & & & \end{matrix}
 \begin{matrix} & & & \\ & & 0.5 & \\ & 0.1 & & 0.2 & \\ & & & & 0.4 \end{matrix}
 \begin{matrix} & & & \\ & & & \\ & & & 0.1 \end{matrix}
 \quad (8)$$

In this example suppose that initial state is denoted by π

$$\pi = [\quad 0.7 \quad \quad \quad \quad 0.3] \quad (9)$$

Let us consider four year period from the distant past. We observe the series of the tree growth S,M,S,L and suppose that S=0,M=1 and L=2 then $O=(0,1,0,2)$

$$t=4, n=2, m=3$$

$$Q=\{R,S\} \quad V=\{0,1,0,2\}$$

Consider a sequence of length four $X=(X_0,X_1,X_2,X_3)$

With corresponding observations $O=(O_0,O_1,O_2,O_3)$

Then π_{X_0} is the probability of starting in state X_0 . $b_{X_0}(O_0)$ is the probability of observing O_0 . And $a_{X_0X_1}$ is the probability of transiting from X_0 to X_1 . Then the probability of state sequence is

$$P(X,O) = \pi_{X_0} \cdot b_{X_0}(O_0) \cdot a_{X_0X_1} \cdot b_{X_1}(O_1) \cdot a_{X_1X_2} \cdot b_{X_2}(O_2) \cdot a_{X_2X_3} \cdot b_{X_3}(O_3) \quad (11)$$

Consider the observation sequence $O=(0,1,0,2)$
We can compute

$$P(RRSS) = 0.7 \times 0.5 \times 0.6 \times 0.4 \times 0.4 \times 0.1 \times 0.7 \times 0.7 = 0.0016464$$

$P(RRSS)$ is the prediction of RRSS(Rainy, Rainy, Sunny, Sunny)

Hidden Markov Model is a useful tool for the time-series data modelling[19]. It is used in almost every speech recognition systems, in computational molecular biology, in data compression and in various applications of artificial intelligence and pattern recognition. Recently HMM is also used in computer vision applications such as image sequence modelling and object tracking. Some applications of HMM are:

Patient Monitoring: This is very useful in patient monitoring. Symptoms of patients are observations. These observations decide the current health status of the patients and decide the treatments.

Radar Tracking: This is also useful in predicting the future observations. The past positions of the plane are our observations. We want to predict the position of the radar so that radar will never lose it.

Hindsight Problem: Suppose we want to observe a truck crash at time $t=30$. We want to know the status of the car at time $t=10$ to see the mistake made by the driver. This is called Hindsight Problem.

3. BASICS OF GABOR FILTERS:

In Image Processing, a Gabor filter named after Dennis Gabor, is a linear filter used for edge detection [21]. Frequency and orientation of Gabor filter are best for texture representation and discrimination. Image analysis with Gabor filters with different orientations and frequencies are very helpful for extracting important features from an image. 2-D Gabor filters are given in discrete domain by:

$$X = -((i^2 + j^2) / 2\sigma^2) \quad (12)$$

$$TC[i,j] = B e^{X} \cos(2\pi f(i \cos\theta + j \sin\theta)) \quad (13)$$

$$TD[i,j] = C e^{X} \sin(2\pi f(i \cos\theta + j \sin\theta)) \quad (14)$$

Where B and C are normalizing factors to be determined, f is the frequency, θ is the orientation and σ is the size of the image being analysed. Gabor filters are widely used in feature extraction in texture analysis and segmentation.

4. RELATED WORKS:

Human shows their emotions in many ways. The most common way of displaying emotions is facial expressions. Lots of research has been done in recognizing facial expressions.

Studies on Facial Expressions and Physiognomy was introduced in the 4th century BC. Physiognomy is the science of assessment of the person's character and personality with the help of their outer appearances of the faces [23]. But over the years, the interest in Physiognomy becomes low and the study of facial expressions has become more popular and active topic. The studies on facial expressions that have formed the foundations of today's research can be found in 17th century.

A description on the various expressions and head movements was given in 1649 by John et. al. in his popular book "Pathomyotomia". Another more popular work was done by Le Brun, the French academician and painter. In 1867, he gave a lecture at the royal academy of painting and produced as a book in 1734 [24]. His book was referred by actors and artists in order to achieve "The perfect imitation of genuine facial expressions".

In the 19th century, Charles Darwin works has a great influence to the modern day science of automatic facial expressions and the means of the expressions in both animals and humans [25]. He was also able to group various kinds of expressions into similar categories.

After Darwin, this research has introduced by Ekman and Freisan [1] in the field of psychology. Cohen et. al. used this model to construct the automatic methods for recognising facial expressions in image and videos [2].

Hidden Markov Model was also used to recognise facial expressions [3]. Further Cohen et. al. proposed a multilevel HMM to recognise emotions and further optimize it for better accuracy as compared to emotion specific HMM [2]. Pardas et. al. [2002] used the automatic extraction of MPEG-4 Facial Animation Parameters (FAP) and also proved that the FAPs provide the necessary information required to extract the emotions [4]. FAPs were extracted using an improved active contour algorithm and motion estimation. They used the HMM classifier. They also used the Cohn-kanade database for recognition. Their recognition rate was 98% for joy, surprise and anger and 95% for joy surprise and sad. The average recognition rate was 84%.

Aleksic et. al. [2006] showed their performance improvement using MS-HMM [5]. They also used PCA to reduce dimensionality before giving it to HMM. They used MPEG-4 FAPs, outer lip (group 8) and eyebrow (group 4) followed by PCA to reduce dimensionality. They used HMM and MS-HMM as classifiers. They used Cohn-kanade databases with 284 recordings of 90 subjects. Their recognition rate using HMM was 88.73% and using MS-HMM was 93.66%.

Shang et. al. [2009] proposed an effective nonparametric output probability estimation

method to increase the accuracy using HMM [6]. They worked on CMI database and get the accuracy of 95.83% as compared to non-parametric HMMs. Jiang [2011] proposed a method based on code-HMM and KNN further applied some discrimination rules [7]. Their proposed method achieves better accuracy to some extent. Suk et. al. proposed a real-time temporal video segmenting approach for automatic facial expression recognition[8]. They used SVM as a classifier and get the accuracy of 70.6%.

Wu et. al.[2015] incorporated a multi-instance learning problem using CK+ and UNBC-McMaster shoulder pain database[9]. They combine both multi-instance learning and HMM to recognize facial expression and outperforms state-of-the-arts. Sikka et. al.[2015]proposed a model based similarity framework and combine SVM and HMM[10]. They worked on CK+ and OULU-CASIA databases and get the accuracy of 93.89%. Ramkumar et. al. incorporated the Active Appearance Model(AAM) to identify the face and extracted its features[11]. They used both KNN and HMM to recognize facial expression and get the better results. Senthil et. al. proposed a method for recognizing facial expression using HMM[12].

Xufen et. al. incorporated some modification in HMM to get better recognition rate[13]. Xiaorong et. al. proposed a framework for partially occluded face recognition using HMM and get the better result to some extent[14]. Punitha et. al. proposed a real-time facial expression recognition framework and get the better results as compared to existing framework[15]. Pagariya et. al. also proposed a system using Multilevel HMM for recognizing facial expression from the video[16].Islam et. al. incorporated both PCA and HMM for appearance and shape based facial expression recognition framework[17]. Singh et. al. introduced a 3 state HMM for recognising faces under various poses[18].

5. PROPOSED SYSTEM:

There are some model which are capable of describing temporal processes, HMMs have been used in speech recognition (Rabiner,1989;Morgan and Bourland,1995). Gaussian Mixtures Model is often used to calculate the state densities and it is also used in training task to estimate the parameters of the mixture models. Different image databases required different feature extraction techniques and classifiers. It is not easy to

conclude which feature extraction techniques and classifiers best suit the situation. HMM has not been used in facial expression in our knowledge so far. In this paper, Multistage HMM has been introduced for classifying six basic facial expressions: anger, sad, happy, disgust, joy and surprise. Previous studies also proved that even human beings have so much difficulty in differentiating between these facial expressions. Our proposed framework overcomes this difficulty to some extent. Gabor wavelet is used for feature extraction and Multistage HMM is used as a classifier. Baum-Welch method is used for parameter estimation. Viterbi Method and Forward Procedure are used for calculating the optimal state sequence and probability of the observed sequence respectively. The proposed framework is shown in figure 3.

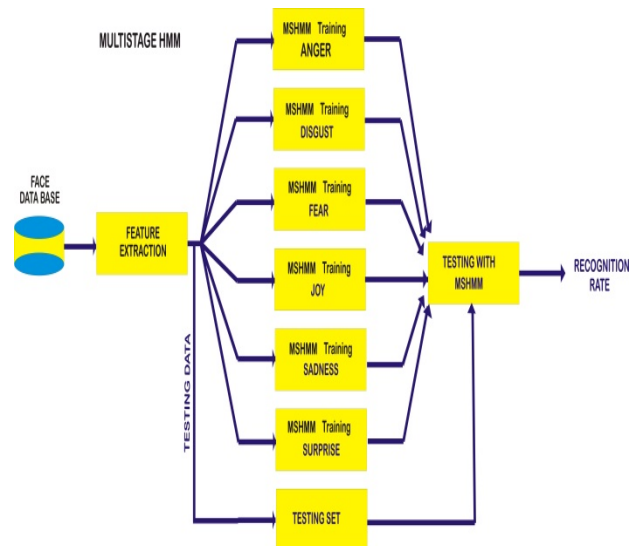


Figure 3: Block Diagram For Facial Expression Recognition Using Multistage HMM

(a)Baum-Welch method for parameter estimation: The Baum-Welch algorithm is used to find the unknown parameters of a hidden Markov model (HMM)[22]. It makes use of the forward-backward algorithm and is named for Leonard E. Baum and Lloyd R. Welch. The Baum-Welch is based on the EM algorithm to find maximum likelihood estimates of the parameters used in the HMM. From the equation 4, we can describe the hidden markov chain as

$$\partial = (A, B, J)$$

Where A is the transition matrix and B is the emission matrix. The Baum-welch method is used

to find the local maxima $\hat{\delta}^* = \arg \max_{\delta} P(B|\hat{\delta})$. This parameter $\hat{\delta}$ that maximise the probability of observations.

Algorithm

Take A,B and JI with some initial values. They can also be taken using prior information to speed up the process and to get the desired maxima.

Forward Procedure

Let $\alpha_i(t) = P(Y_1=y_1, \dots, Y_t=y_t, X_t=i|\hat{\delta})$ (15)

The probability of y_1, y_2, \dots, y_t in state i at time t can be recursively solved by:

$$1. \alpha_i(1) = J_i b_i \quad (y_1) \quad (16)$$

$$2. \alpha_i(t+1) = b_i(t+1) \sum_{j=1}^N \alpha_j(t) a_{ji} \quad (17)$$

Backward Procedure

Let $\beta_i(t) = P(Y_t=y_{t+1}, \dots, Y_T=y_T, X_t=i|\hat{\delta})$ is the probability of the sequence y_{t+1}, \dots, y_T for the state i at the given time t . We can calculate $\beta_i(t)$ by the given equation

$$1. \beta_i(T) = 1 \quad (18)$$

$$2. \beta_i(T) = \sum_{j=1}^N \beta_j(t+1) a_{ij} b_j(y_{t+1}) \quad (19)$$

we can calculate the temporary variables using Baye’s theorem.

(b)Viterbi Method for state sequence

The Viterbi algorithm is the dynamic programming algorithm used to calculate the most likely sequence of the hidden state in Hidden Markov Model[22]. This algorithm is very popular in speech recognition, speech synthesis and bioinformatics. Most likely sequence can be solved using max-sum algorithm, which is also known as Viterbi algorithm in the context of HMM(see figure 2).

Input

- The state space $S = \{s_1, s_2, \dots, s_N\}$
- The observation space $O = \{o_1, o_2, \dots, o_N\}$

- Transition matrix of size $N.N$ such that A_{ij} stores the transition probability of transiting from state s_i to s_j state.
- Emission matrix of size $N.K$ such that B_{ij} stores the probability of observing o_j from state s_i .
- An array of initial probabilities J of size N such that J_i stores the probability of state s_i at time $t=1$.
- Sequence of observations Y_1, Y_2, \dots, Y_T

Output

The most likely hidden state sequence

$$X = \{x_1, x_2, \dots, x_T\}$$

Algorithm

function VITERBI(O,S, JI,A,T,B) : X

for each state s from 1 to N do

$$Viterbi[s,1] \leftarrow J_s * B_{s,o1}$$

$$Backpointer[s,1] \leftarrow 0$$

for each time step from 2 to T do

for each state s from 1 to N do

$$Viterbi[s,t] \leftarrow \max_{k=1}^N (Viterbi[k,t-1] * A_{k,s} * B_{s,o_t})$$

$$Backpointer[s,t] \leftarrow \operatorname{argmax}_{k=1}^N (Viterbi[k,t-1] * A_{k,s} * B_{s,o_t})$$

End for

End for

$$Z_T \leftarrow \operatorname{argmax}_{S=1}^N (Viterbi[S,T])$$

$$X_T \leftarrow S_{Z_T}$$

for $i \leftarrow T, T-1, \dots, 2$ do

$$Z_{i-1} \leftarrow \operatorname{Backpointer}[Z,i]$$

$$X_{i-1} \leftarrow S_{Z_{i-1}}$$

End for

Return X

End function

(c) **Forward Procedure for observation probabilities**

The Forward procedure is used to calculate the probabilities of the observed sequence [22]. This is very efficient method to obtain such probabilities (see figure 2). This procedure will produce most likely state sequence rather than state at each time step (also known as filtering).

$P(x_t|y_{1:t})$ can be calculated using this procedure, where x_t is the hidden state and $y_{1:t}$ is the sequence of observations.

Algorithm

The objective of this procedure is to calculate the joint probability $p(x_t, y_{1:t})$. Marginalizing over all state sequence $x_{1:t-1}$ to calculate $p(x_t, y_{1:t})$. Forward procedure will perform the calculation recursively with the help of conditional independence rule of HMM.

To show the recursion, let

$$R_t(x_t) = p(x_t, y_{1:t}) = \sum_{x_{t-1}} p(x_t, x_{t-1}, y_{1:t}) \quad (20)$$

Applying chain to expand the above equation

$$R_t(x_t) = \sum_{x_{t-1}} p(y_t|x_t, x_{t-1}, y_{1:t-1}) p(x_t|x_{t-1}, y_{1:t-1}) p(x_{t-1}, y_{1:t-1}) \quad (21)$$

Since y_t is conditionally dependent on x_t and x_t is conditionally dependent on x_{t-1} , equation becomes

$$R_t(x_t) = p(y_t|x_t) \sum_{x_{t-1}} p(x_t|x_{t-1}) A_{t-1}(x_{t-1}) \quad (22)$$

We can easily calculate the $p(y_t|x_t)$ and $A_{t-1}(x_{t-1})$ by the figure 2.

This process is used recursively to obtain the required probability.

The above three procedures are easy to apply, efficient and relatively fast as compared to procedures used by Jiang et. al.[13]. This proposed system is robust to dynamic background, occlusions etc and gives better results when it is compared with the work of chan et. al.[6]. This two layered techniques is also very useful in recognition of atomic expressions such as expressions made by eyes only. Further this also

becomes suitable for all six basic facial expressions. Results shows that the accuracy of this proposed system is better than the results of cohen et. al.[2].



Figure 4(A) Original Image



Figure 4(B) Filtered Image Using Gabor Filter

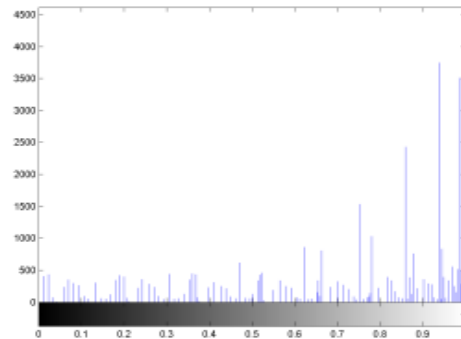


Figure 4(c) Corresponding Histogram

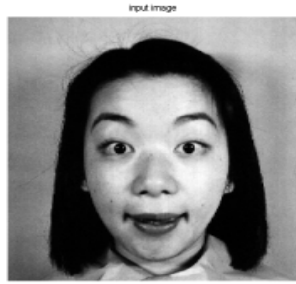


Figure 5(A) Original Image

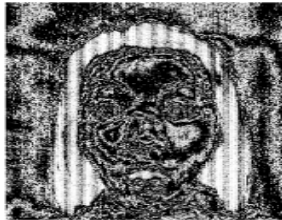


Figure 5(B) Filtered Image Using Gabor Filter

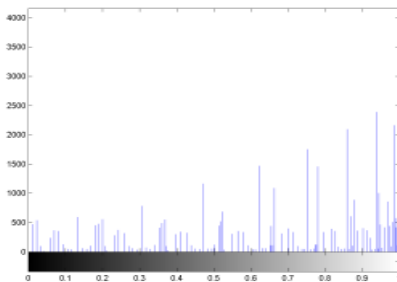


Figure 5(C) Corresponding Histogram

6. EXPERIMENTS AND RESULTS:

Following conditions have been observed during the experiments:

- (1) Facial image has been analysed from the frontal view only.
- (2) There is no movement in the head.
- (3) There is no conversation during image capturing.

- (4) Subjects are not wearing glasses during image capturing.

Hidden Markov Models are very popularly used in speech recognition and more recently in facial expression recognition where data is essentially in one dimensional over time. In this paper, we investigate the performance of the recognition of a one dimensional Hidden Markov Model for gray scale images. For the facial regions of the frontal face images comes in a order from top to bottom, even if the images undergo some rotations in the images plane and some rotations in the plane perpendicular to the image plane. Each of these facial images can be represented from left to right one dimensional Hidden Markov Model.

Feature extraction of each of these images is done by Gabor filter, which is most popular feature extraction technique. The performance of this technique found to be good among various face detection algorithms.

For facial expressions recognition, each set each set of facial expressions is used to train each facial expression HMM. The images in the training set represents the frontal faces of different people are kept under different illumination conditions.

After extracting the essential features from every image in the training set. These features are very helpful in training each of these HMMs. The HMM $\partial = (A, B, JI)$ is initialised by the following steps: The training data is uniformly segmented from top to bottom. The observation associated with each state of the HMM are used to obtain initial probabilities matrix B. The initial values for A and JI are set according to facial expressions. In the next iterations, the Viterbi segmentations is used. When the Viterbi segmentation is smaller than the threshold, Iteration stops and HMM is initialised. The final parameters are obtained using Baum-Welch procedure.

In testing of these facial expressions, given a set of images which contain one or more faces with a cluttered background. Facial expression recognition begins by looking the essential features in the test images and calculating the probability of essential features extracted by Gabor feature extraction method. This probability can be calculated using Viterbi algorithm.

This proposed system has been tested in JAFFE databases.

JAFFE database has the 114 images from 13 subjects. They are 9 of anger, 21 of disgust, 13 of fear, 26 of joy, 24 of sadness and 21 of surprise. To train the HMM, we follow N fold cross validation rule. For example if there is k fold, then k-1 fold are used to train the HMM and remaining 1 fold is used to test HMM. There are 9 images of anger. These 9 images are divided into nine folds. We are using 8 images to train and 1 for test. Further final result is the mean of all the results.

The recognition results using Gabor Wavelet and Proposed System is shown in table 1. From the results we can see that using the Proposed System will improve the recognition rate.

Table 1: Confusion Matrix For FER Using Proposed System

	Ang er	Disgu st	Fe ar	Jo y	Sadn ess	Surpr ise	Reco gniti on Rate (%ag e)
Ang er	7	0	1	0	0	1	78%
Disg ust	0	19	0	0	1	1	91%
Fear	1	0	7	3	2	0	54%
Joy	0	0	0	26	0	0	100%
Sadn ess	2	0	0	0	22	0	92%
Surpr ise	0	0	0	2	0	19	91%

The Receiver Operation Characteristics (ROC) curve, is a graph used to represent the performance of the classifier (Figure 6). It is the plot of True Positive Rate against False Positive Rate. TPR is the proportion of positive samples identified as positive and FPR is the proportion of negative samples identified as positive. In the given graph, the 45 degree line is called "line of no-discrimination". The ROC curve above this line indicates that the classifier's rate of identifying positive samples as positive is greater than the rate of misclassifying negative samples. Our curve

indicates the goodness of our classifier to recognise Facial Expression Recognition.

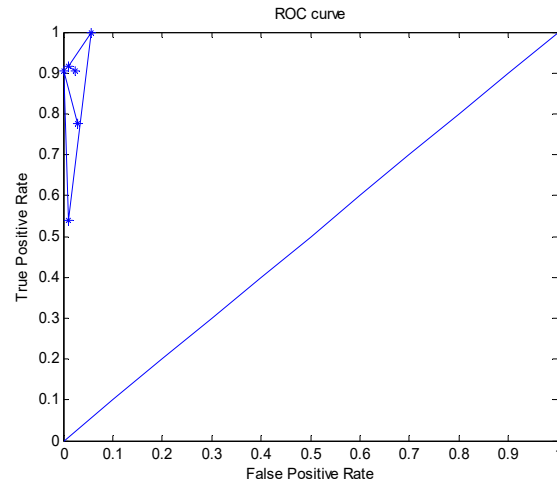


Figure 6: ROC Curve For The Given Confusion Matrix

7. CONCLUSION AND FUTURE WORKS:

This paper explains an HMM based approach for facial expression recognition and uses an efficient and reliable set of observations vectors based on the extraction of essential features by the Gabor filter method. A robust HMM based facial expression recognition is introduced in this paper. The accuracy of this proposed system with respect to variations in lightning conditions and its efficiency in complexity suggest that this method may be a very promising approach for facial expressions recognition. The HMM modelling of faces appears to be a challenging for facial expressions recognition under a wide range of image orientations and facial expressions.

It is not easy to conclude which feature extraction method and classifier is best for this situation, but still modification of HMM significantly improves accuracy for the recognition of six basic facial expressions. This paper introduced a first framework for Gabor Wavelet as a feature extraction method and modified HMM as a classifier for Facial Expression Recognition. HMM provides some modelling advantages over other feature based methods in Facial Expression Recognition. Due to generative nature of HMM, It is weak classifier as compared to other discriminative classifier such as SVM. Our proposed method makes HMM more powerful as a classifier with compared to other discriminative classifiers. We have also showed its strength using Confusion Matrix and Receiver Operating

Characteristics (ROC) curve and found the overall accuracy of 84%.

In the future, this modified HMM will be incorporated with other feature extraction methods such as partition based, moments invariants based and Zernike moments based methods and compare it with other state-of-the-art methods and try to improve the accuracy to some extent. This new technique should be very useful in facial expression recognition field.

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