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# Image verification using Gabor filter bank with Hidden markov model

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**Abstract**: This dissertation relates to the design, implementation and evaluation of identification of Facial images. Face identification system is a mechanism of identifying various faces against some stored pattern faces. It takes input an image of a human being face and searches for a match in the stored face images. If there is match, the user can see the result as face identified or not identified. Outsider cannot generate any type of modification in the stored image records. The vendor of the system has authentication to renew the storage records.This system is based on Gabor features extraction using Gabor filter bank. Gabor-based face representation has achieved enormous success in face recognition. In particular, the use of HMM (Hidden Markov Models) in various forms is investigated as a recognition tool various for matching the input face image to the template images.Current face identification techniques are very dependent on issues like background noise, lighting and position of key features (i.e. eyes, lips etc). In this dissertation the system developed uses the hidden Markov model (HMM) in various forms is investigated as a recognition tool and critically evaluated

**Keywords**: HMM(Hidden Markov Model),DRT(Discrete Random Transform)

## I. INTRODUCTION

A face recognition system is accepted to identify faces present in images automatically. It can operate in two modes (1) face verification and (2) face identification. Face verification involves a one to one match that compares a query face image against a template face image whose identity s being claimed. Face identification involves one too many matches that compares a query face images against all the templates images in the database to determine the identity of the query face.

The performance of face recognition system has improved significantly where illumination, expression, occlusion and so on vary considerably. Face recognition is a visual pattern recognition problem. The faces as a object subject to vary illumination, pose, expression and so on is to be identified based on its two dimensional image. A face recognition system generally consists of four modules detection, alignment, feature extraction and matching.

In this dissertation for Face recognition I have used two methods: (1) Gabor filter and (2) hidden Markov model (HMM). A hidden Markov model (HMM) is a statistical Markov model in which the system being modeled to be Markov process with unobserved (hidden) states. In a hidden Markov model, the states are not directly visible, but output, dependent on the state, is visible. In this dissertation hidden Markov model is used to match a test facial image with an appropriate reference image and Gabor filter is commenced on convolving a face image with a series of Gabor filter to extract the sequence of Gabor features from facial image. Discrete Radon transform (DRT) is generated to remove a series of feature vectors from an image.

## II. DESIGN OF SYSTEM

For the purpose of feature extraction Gabor filter technique is developed in this dissertation. The volume of the image processing and feature extraction involves the computation of the discrete Radon transform (DRT) of all images [8]. The projections of each image at different angles are obtained by calculating its DRT. The DRT is very similar to the Hough transform (Kaewkongka et al. (1999)). All of these projections constitute a feature vector in an observation sequence after some further image processing (normalization).

Modeling with HMM tends to be quite flexible. In this system to model a specific facial image two different techniques have been used. Each facial image is modeled by an observation sequence that represents the person most representative training image as in the case of the DTW-based system. It acts as a pattern for the image. While each facial image is modeled by an HMM of which the states are organized in a ring in the case of the HMM-based system.

For the purpose of matching the distance between a test image and a model for the claimed image is obtained. The DTW-based system matches the similarity between the observation images of the claimed facial image, by first aligning these observation sequences. This alignment is

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important to achieve rotation invariance and is discussed in more detail in further chapter.

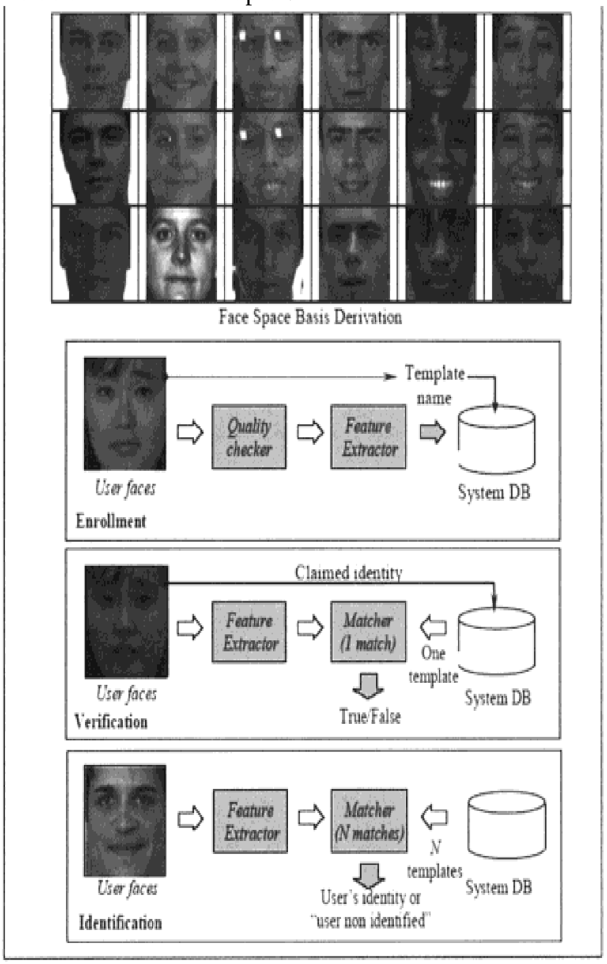


Fig :a schematic representation of face recognition method

## III. HIDDEN MARKOV MODEL(HMM)

In a regular Markov model, the state is directly visible to the observer, and therefore the state transition probabilities are the only parameters. In a *hidden* Markov model, the state is not directly visible, but output, dependent on the state, is visible. Each state has a probability distribution over the possible output tokens. Therefore the sequence of tokens generated by an HMM gives some information about the sequence of states. Note that the adjective 'hidden' refers to the state sequence through which the model passes, not to the parameters of the model; even if the model parameters are known exactly, the model is still 'hidden'[25].

Hidden Markov models are especially known for their application in temporal pattern recognition such as speech, handwriting, gesture recognition, part-of-speech tagging, musicalscore following, partialdischarges and bioinf ormatics. A hidden Markov model can be considered a generalization of a mixture model where the hidden variables (or latent variables), which control the mixture component to be selected for each observation, are related through a Markov process rather than independent of each other.

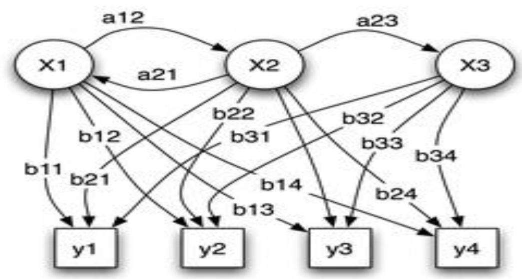


Figure : Probabilistic parameters of a hidden Markov model Where x states, y -possible observation. a - state transition probabilities, b - output probabilities

## IV. VITERBI ALGORITHM

The Viterbi algorithm is a dynamic programming algorithm for finding the most likely sequence of hidden states – called the Viterbi path – that results in a sequence of observed events, especially in the context of Markov information sources, and more generally, hidden Markov models. The forward algorithm is a closely related algorithm for computing the probability of a sequence of observed events. These algorithms belong to the realm of information theory.

The algorithm makes a number of assumptions.

- First, both the observed events and hidden events must be in a sequence. This sequence often corresponds to time.
- Second, these two sequences need to be aligned, and an instance of an observed event needs to correspond to exactly one instance of a hidden event.
- Third, computing the most likely hidden sequence up to a certain point $t$ must depend only on the observed event at point $t$, and the most likely sequence at point $t - 1$.

These assumptions are all satisfied in a first-order hidden Markov model.

The terms "Viterbi path" and "Viterbi algorithm" are also applied to related dynamic programming algorithms that discover the single most likely explanation for an observation. **For example**, in statistical parsing a dynamic programming algorithm can be used to discover the single most likely context-free derivation (parse) of a string, which is sometimes called the "Viterbi parse".

## V. PROPOSED ALGORITHM

IN THIS DISSERTATION I HAVE MERGED TWO TECHNIQUE/ ALGORITHM:

- Gabor filters.

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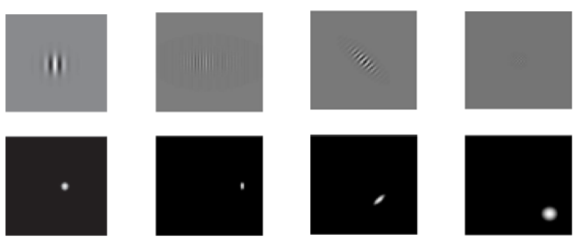
- Hidden Markov model.

## VI. GABOR FILTER

A Gabor filter is a linear filter whose impulse response is defined by a harmonic function multiplied by a Gaussian function. Gabor filters are among the most popular tools for facial feature extraction. Their use in automatic face recognition system is motivated by two major factors: their computational properties and their biological relevance. Formally, a 2D Gabor filter in the spatial domain is defined by the following expression:

$_{\theta\lambda(f,\varphi,\mu,\rho)(}x,y)=f^2/\Pi\beta\eta e^{-(a2x1+b2y1)}ei^{2\Phi fx1}$ ……………..(1)



where $x_1$= xcosΦ +ysinΦ, $y_1$= -xsinΦ + ycosΦ, f (cycles/pixel) is the central frequency of the sinusoidal plane wave, Φ is the anticlockwise rotation of the Gaussian and the plane wave, a is the sharpness of the Gaussian along the major axis parallel to the wave, and b is the sharpness of the Gaussian minor axis perpendicular to the wave. β = f /a and η = f /b are defined such that the ratio between frequency and sharpness is constant. Figure 3.1 shows four Gabor filters with different parameters in both spatial domain and frequency domain.

(i) (ii) (iii) (iv)

Figure : Gabor filter in spatial domain ($1^{st}$row) and different frequency domain ($2^{nd}$ row)

Let $I_r(x_1, y_1)$ denote a gray-scale face image definite on a grid of dimension c × d and let $_{\theta\lambda(f,\varphi,\mu,\rho)(}x,y)$ signify a Gabor filter determined by the parameters f and Φ. ∗ denotes the convolution operator in equation (1).Then filtering operation of image with the Gabor filter is:

$_{\theta\lambda(f,\varphi,\mu,\rho)(}x,y) = I_r\,(x_1, y_1){*}\,_{\theta\lambda(f,\varphi,\mu,\rho)(}x,y)$ ......................(2)

Orthogonality is one of the key elements for many pattern representations. Gabor filters do not represent orthogonal filters and hence the information encoded in the filter responses is therefore likely to be unnecessary. To overcome this problem we propose to orthogonalize the commonly adopted filter bank (featuring filters of 5 scales and 8 orientations). It is interesting to see that most of the selected Gabor features are located around the important facial features such as eyebrows, eyes, noses, and chins, which indicates that these regions are more robust against the variance of expression and illumination. This result is agreeable with the fact when the person's face expression changes, the eye and eyebrow regions remain relatively constant.

## VII. RESULT

Gabor filters for feature extraction and DRT to extract the series of feature vectors are used in this dissertation. The scheming of Gabor filter is free to the difference in size of the face image used; the size is limited to the matrix dimension 8 x 5. The features are extracted during the convolution of the face image through the filter; the size of characteristic matrix depends on the image size dissimilarity. Without considering the Gabor filter the DRT is performs directly to the image, the size of feature vector depends on the image size. For different values of observations, position and feature length, it is obvious that the presentation of the scheme will differ. Number of observations have been used in this dissertation i.e. the feature length = 512, number of states = 64, with 4 image faces of dimension 138 * 140. The time elapsed on computing the DRT is 60.6560seconds. If the number of states increases from 64 to 128 computation time also increases to 91.5620 seconds. On increasing equally the features length (to 1024) with no. of states (to 128) the computation time increases to 146.8310seconds. On increasing the face storage file to 69 faces of size 18*27, with feature length = 512 and no. of states = 64 computation time increases to 32.6560 seconds.

To model study sequences HMM is used. Every state in the HMM used in this dissertation is characterized by a PDF for which simply the mean vector is expected, variations among an test image study series and the model HMM is based on an Euclidean distance measure D(x^ (w)) test, Tw) assume a threshold of t=0.16 is chosen, equation 2.16 of chapter 2 implies that all test pattern for which

D(x^ (w)) test, Tw) = 1.16 micro w are discarded the extra pattern accepted.

The computational difficulty of the HMM based scheme is usually increased as no. of observations, states and feature length increases. When only one forward link is permitted in the HMM the finest result are attained.

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## VIII. CONCLUSION

In this dissertation, study in Hidden Markov Model facial image verification system is done. Investigation of HMM as a facial recognition tool is used and HMMs topologies are also used as a face classifier against available database. The feature extraction method is based on the GABOR features extraction and the calculation is done with help the DRT. For detection a set face image is used in the training of HMM. The images in the training set represent frontal faces of different people. The uniform segmentation is replaced by Viterbi segmentation. Face detection of test image that contains more than one face is done by looking within each rectangular window in the test image extracting the observation vectors, and computing the probability of data inside each window given the face model.

## REFERENCES

1. Auckenthaler, R., Carey, M., and Lloyd-Thomas, H. (2000). Score Normalisation for Text-Independent Speaker Verification Systems, Digital Signal Processing, vol. 10, and pp.42-54.
2. Barua, S. (1992). Neural Networks and their Applications to Computer Security. Proceedings of the SPIE - International Society for Optical Engineering, pp. 735-742
3. Bastos, L.C., Bortolozzi, F., Sabourin, R., and Kaestner, C. (1997). Mathematical Modelation of Handwritten Signatures by Conics. Revista da Sociedade Paranaese de Matem´atica, vol. 18, pp. 135-146.
4. Beylkin, Gregory, (1987) Discrete Randon Transform. IEEE.
5. Bhuiyan, Al-Amin,(2007) On Face Recognition using Gabor Filters. IEEE.
6. Bracewell, R.N. (1995). Two-Dimensional Imaging. Prentice Hall.
7. Cardot, H., Revenu, M., Victorri, B., and Revillet, M.J. (1994). A Static Signature Verification System Based on a Cooperative Neural Network Architecture. International Journal on Pattern Recognition and Artificial Intelligence, vol. 8, no. 3, pp. 679-692.
8. Chapman, Stephen J., (2008). Matlab Programming for Engineers. New Delhi.
9. Coetzer, J., Herbst, B.M., and Du Preez, J.A. (2004). Offline Signature Verification Using the Discrete Radon Transform and a Hidden Markov Model. Eurasip Journal on Applied Signal Processing - Special Issue on Biometric Signal Processing, Bourland
10. Deller, J.R., Proakis, J.G. and Hansen, J.H. (1999). Discrete-Time Processing of Speech Signals IEEE.