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Robust Feature Extraction using Embedded Hidden Markov Model for Face Identification and Verification

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Abstract

Robustness is one of the key issues in face identification and verification because of variations in image due to lightning, pose; environmental effect etc. & feature extraction is one of the methods to gather information of the facial image but it is not enough to understand the whole effect of the identification. Extraction of features robustly for face recognition under larger position movement is quite a challenging one. In this paper we propose a algorithm using rectangular features of facial recover with the help of byproducts of an embedded HMMs (Hidden Markov Models) which converts and monitor face image to a state sequence. As HMMs has ability to segment images into features at stable position, and several HMMs are instructed for individual face to robustly extract their features under large position movements. Extracted features are used for each individual and appearances models rely on subspace are designed for face verification and identification. Our analysis results with experiments demonstrate that proposed technique will help to extract facial feature efficiently and improve the performance in face identification and verification under great position movement scenario.

Keywords: Robustness, HMM, Feature Extraction, Face Identification, Face Verification.

INTRODUCTION

In recent year, massive experiments have been investigated for face recognition and received great attention from industrial and research communities [1]. Increasing demand in personal security raises in today's modern era [2]. The biometric market is growing each year and this trend is set to continue because of increasing need for border's security, in buildings, airport etc. [3]. Various approaches like iris scan, PIN and password, scan fingerprint, modern approaches to password such as dynamic password, graphical password have been implemented for verification system. However, certain drawbacks do exist while using them which cover inefficiency of hardware to provide good enough samples or inefficiency of algorithm to identity patterns under certain scenario. The tradeoff between drawbacks and benefits can be judged depending on the security, cost and other application's limitations.

Moreover, many current user security systems, once the user identity has been verified at login, system resources are made available for whole session until user exit the system. This might be useful for low-security conditions but can lead to session hacking in which attackers tracks a post authenticated session [4]. Recent research findings have shown that passwords and PINs are no longer very secure, owing to the increasing system users [5]. Continuous verification is of great importance due to the fact that a logged station is still vulnerable to encroachment and unauthorized access. So, keystroke dynamics are very helpful in such scenario. Therefore, one of the approaches can be the usage of a combination of modalities in place of single modality verification approach. Such approach will cover up the deficiencies of biometric model with the other, which might lead to a reduction in certain breaches of each modality and offer a better performance.

Human recognition by distinctive facial features supported by an image database is still an appropriate subject of study. For example, what happen if an individual's haircut is changed? Is make-up determining factor in the process of identification? Would it significantly distort facial features? For all these reasons, the study of different parts of face still requires investigation in order to improve identification level. Lip contour is one of the great attentions [6] [7].

HIDDEN MARKOV MODEL

Hidden Markov model is a form of finite state tool however, different from finite state because of its not deterministic nature [8]. A normal HMM emits a deterministic symbol in a given state. Further, it then deterministically transitions to some other state. HMMs do neither deterministically; rather they both emit and transition using a probabilistic model. To characterize an HMM completely following mention elements are required.

$P =$ Number of states of model

$Q =$ Number of distinct observations states

$R =$ Length of observation sequence i.e. number of observed symbols 1, 2… N.

$W =$ The discrete set of possible observation symbols $\{w_1, w_2, \dots w_m\}$.

$\Pi = \{\Pi_i\} = P(i_1 = 1)$ the probability of being in state i at initial time $t = 1$.

$L = \{l_{ij}\}$ where $l_{ij} = P(i_{t+1} = j \text{ I } i_t = 1)$ the probability of starting in state j at time $t + 1$ given that present state i at time t.

$M = \{m_j(k), m_j(k) = P(w_k at\ t \text{ I } \mathrm{i}_\mathrm{t} = j)$ the probability of observing the symbol w_k given that present state is j at time t.

O_t denotes the observations symbol observed at instant t.

$\lambda = (L, M, \pi)$ will be treated as compact notation of HMMs..

EMBEDDED HMM

Embedded HMM consist of a set of super state along with a set of embedded state [9]. Super state may be used to model 2-D data along one direction, with the embedded HMM modeling the data along other direction. The elements of embedded HMM are:

$A =$ The number of super states, $S =$ supers states; $S = \{S_i\}$ $1 \leq I \leq N$.

$\Pi = \{\pi, i\}$, the initial super state distribution, where π is the probabilities in super state $'i'$ at time zero.

$L = \{l, ij\}$ super state transition probability matrix where l, ij is the probability of transitioning from super state i to j.

$\Lambda =$ super state and the ith super state containing several embedded state defined as $\Lambda = \{\pi_i, L_i, M_i, 1 \leq i \leq A_s\}$ where $\Pi_i = \{\pi_{ik}, 1 \leq k \leq A_i\}$ is the initial distribution of embedded state in ith super state, l_i is the transition matrix of embedded state.

$M_i =$ state probability matrix of ith state and $M_i = \{m_k^i(O_{x,y})\}$ where m_k is distribution of observation vector in the kth embedded state and the ith super state. M_i is a finite mixture of the form:

$$m_k^i(O_{xy}) = \sum_{j=1}^{k} C_{jk}^i\, A\,(O_{xy}, \mu_{jk}^i, \Sigma_{jk}^i)\,, i \leq k \leq A^i \quad (1)$$

Where k denotes the number of mixture components described by Gaussian probability distributions function$A\,(O_{xy}, \mu_{jk}^i, \Sigma_{jk}^i)$, with mean μ_{jk}^i. The training algorithm based on classical Viterbi approach [10] [11] [12].

FEATURE BASED FACE RECOGNITION

The distance between an unknown people with a given image $'J'$ and person P the average distance between the features of $'j'$ and corresponding features of person $'P'$. Each feature $'F'$ can be obtained with the help of K-mean algorithm; sub images I_{FK} using center points of facial segmented by different HMMs as well as height $'h'$ and width $'w'$ of each feature obtained in training phase. Now, computing L2 distance, $D(J_{FK}, L_{FP})$, from J_{FK} to projection on the sub-space L_{FP} of feature for people P. In this approach a PCA subspace is taught for each feature and follows this as individual PCA.

Training set encompasses face images taken from various pose and each HMM is responsible for certain position with limited changes and each feature for distance $D(J_{FK}, L_{FP})$ will be particularly small for one HMM. So, observed segment for each image with the state sequence of HMM with least average distance is analyzed. The distance between a given face $'J'$ with people P can be evaluated as per equation (2), where N is the number of feature for $'P'$.

$$D(J, P) = \min_{l} \frac{1}{N} \sum_F D(J_{FK}, L_{FP}) \quad (2)$$

This distance metric $D(J, P)$, the job of face recognition can be determined easily. For face identification task the true identity is the people $'P'$ with least distance$D(J, P)$. For face verification, the threshold set on distance $D(J, P)$ with minimum recognition error rate.

FACE IDENTIFICATION AND VERIFICATION

Face identification is a matching process (one-to-many or many-to-one) that compares the asked face image against the entire template image stored in a database to identify the identity of the asked face. The identification of the test image is achieved by locating the image in the stored database and has maximum similarity with the test image. The identification process involved a closed test i.e. sensor must include an observation of an individual that is aware to be in the stored database. The normalized (test subject's) are matched to the other feature in the database of the system closed score is taken for each comparison. These closed scores are then ranked numerically in the descending order and the percentage of times that the maximum closed score is the right match for all individual known as top match score in testing.

If found any of the top 's' similarity score against the test subject, it is taken as a correct match in terms of cumulative match. The time of percentage of 's' similarity score is the correct pattern for all individuals and is referred to as the 'Cumulative Match Score'. The Cumulative Match Score curve is the position 'n' versus percentage of correct identification where 'n' indicates the number of top similarity scores acknowledged. Ex: "Who AM I".

Face verification is one-to-one matching process that compares a asked image against a template image whose identity is being verified. To, evaluate the performance of verification, the verification rate i.e. the rate at which legitimate users are provided access facility versus accept rat i.e. rate at which imposters are provided access facility is plotted is known as Region of Convergence (ROC). A efficient verification system should maintain these two rates depend upon operational requirements [13]. The identity of a face image is transferred by some other non-visual means and must be assured using face images which is equivalent to the known/unknown tasks with $N = 1$ i.e. there is only the reference face where, N is the known faces verifies a face against a stored image database.

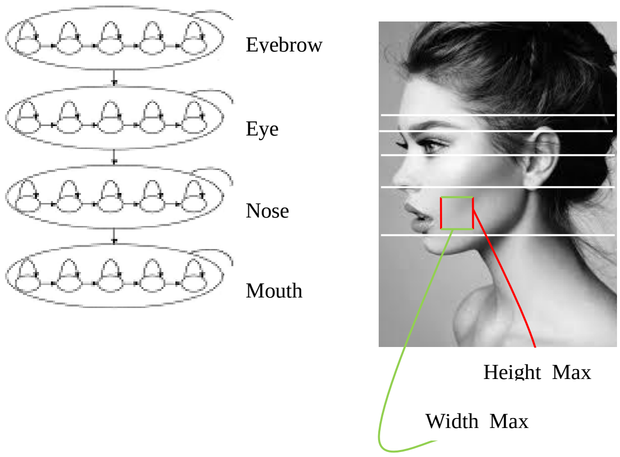
The approach that we are proposed based on the Hidden Markov Models (HMM) for the face identification and verification. The 'states' for a frontal face of the Markov model includes mouth, nose, eyes, forehead and hair. The frontal face 'states' always occur in the same order from bottom to top, even if the faces undergo small rotations in the plane perpendicular to the image, and/or small rotations in the image plane.

So, each of these facial regions will be assigned to a state, in a left to right one-dimensional continuous HMM which may be generalized, to give the appearance of a two-dimensional structure, by permitting each state in a one-dimensional HMM to be a HMM. In such a way, HMM contains a set of super states, including a set of embedded states. These super states now may be used to model two-dimensional data along one direction, while the embedded HMM model the data on the other direction. The embedded HMM-based approach add advantages by providing ability to tackle variations in scale, which is a serious issues for any face recognition and detection system and its computational accuracy compared to all other approaches.

FEATURE EXTRACTION IN POSITION VARIATION

Face recognition methods follow embedded HMMs to observed image $'I'$ with probabilistic estimate, $P(I \text{ I } \lambda)$. In this paper the by-product of embedded HMM by segmenting an observed image into regions using state transitions via Viterbi algorithm **[3][4]** is used to extract the features of face. A 2D-DCT coefficients are used to represent observation vectors with sampling windows which overlapped in both directions to have efficient model neighborhood relation is established. As embedded HMM has capability to tackle amount of variations arise by position variation but not accurately able to manage observations having large position variations. In such a situation, we follow K-mean algorithm to gather face image of individual person into K-cluster based on their positions and within each cluster, HMM is properly trained to accurately report for observed images as their positions variations is limited. For every person in database we teach K-HMM where each HMM take responsibility for decrypting face images having limited position changes.

Each trained HMM now able to segment each trained image into facial image based on decryption state sequence. Figure 1. shows the decomposition of face image into four super states and corresponding embedded states in that place.



(a) (b)

Figure 1: Embedded HMM structure (a) and decrypted state of an image with maximum height and width of a sub image of one feature (b).

Some of the decrypted states match visually important features like noses and eyes where as other facial parts e.g. cheeks. Pixels in the same region are evaluated with the same embedded state as well as their super state and these regions are considered to be as a facial feature. In experiments, we have thirty features results of using thirty states in the embedded HMM. To take out sub-images of each feature for individual person we first evaluate center point with maximum height and maximum width of corresponding facial regions decrypted by training HMMs. Sub images of each face features are extracted based on average height (h) and width (w) and its center points.

For this we perform principle components analysis (PCA) on the extracted sub images to get approximated PCA sub space $'L'$. Feature can be designed by $\{w, h, H, L\}$ where $H = \{h_1, h_2 \ldots\ldots, h_k\}$ is a set of HMMs responsible for segmenting images at different position.

EXPERIMENTS AND RESULTS

The proposed approach is verified using data set which contains image of 52 people acquired at different pose from left to right direction. These images are cropped manually and normalized to 64 × 64 pixels as shown in Figure 2.

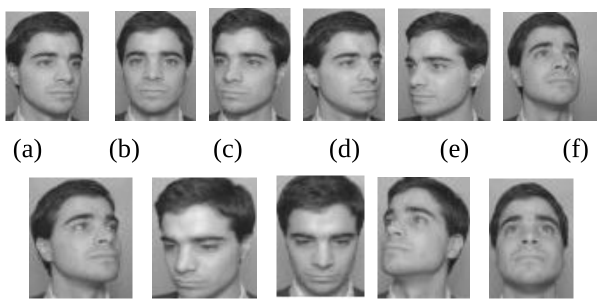


Figure 2: Normalized and cropped image of similar face with different pose.

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For each person, five images i.e. a, d, f, i and k are used for training and rest are used for testing. There are total four embedded and four super states are present in each embedded HMM. Image blocks of size 4 × 4 for each observations denoted by first five 2-D discrete cosine transform coefficients. Observations window overlap four pixels with each other in both vertical and horizontal directions. For large position changes, we train two embedded HMMs for each face and images are clustered using K-mean algorithm. The approach that tech multiple embedded HMMs for individual person for recognition is denoted by Extraction (a) (Embedded HMMs extraction). K-mean algorithm doesn't cluster images according to their position or pose accurately but manually arrange trained images to monitor whether better results can be achieved with ground truth clustering denoted by Extraction (b) (Embedded HMMs extraction) . in experiments, the training samples of each person are clustered, into sets according to their position. The baseline algorithm for experimental comparison is based on Eigen face approach [14]. So, constructing single PCA of all persons we experiment with individual PCA subspace for each person's image known as Individual Eigen face. For comparison, we evaluate embedded HMM with the stored database set. For feature based face recognition, twelve facial feaure resulting from four embedded and four super state for each super state are extracted in experiments of extraction (Fig. a & b).

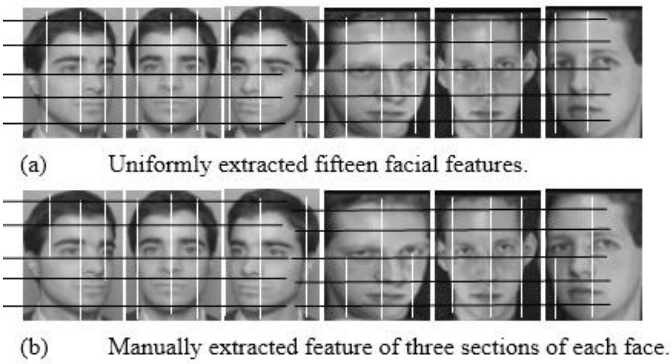

Figure 3: Facial feature extraction.

For uniform extraction, twenty five facial features are uniformly extracted from images as shown in Figure 3(a). For manual extraction we manually crop five facial features like eyes, nose, forehead, lip and cheek and check for each image to minimize the localization error as shown in Figure 3(b).

All feature based approaches we follow the distance metric. The image size for Eigen face is 8 × 8 and each sub image of facial features are evaluate to 3 × 3 pixels for experiments. Here we perform two recognition task for face i.e. identification and verification. The experiments results of face identification and verification is shown in Table I.

Table I: Identification and Verification

Approaches	Identification	Verification	
	Accuracy rate (%)	Error (%)	Hit (%)
Individual Eigen	94.12	75.65	4.65
Eigen	82.54	55.74	9.45
Uniform Extraction	93.33	74.06	7.43
Embedded HMM	99.89	3.39	30.34
Manual extraction	99.98	82.56	3.56
Extraction (a)	98.56	85.09	3.54
Extraction (b)	99.88	95.11	2.56

We conclude that accuracy is considerably improved by the use of multiple spaces in individual Eigen face and Extraction (a) and extraction (b) methods with the corresponding distance metrics. The proposed algorithm where the features are extracted automatically has almost the same identification rate with the one in which features are extracted manually. Verification results are shown in same Table I with hit rate when false rate of alarm is 1% and the error rate when false rate is equal to false alarm rate. So, our proposed algorithm performs efficiently compared to other approach by large margin.

Characteristics curve of above mentioned methods are shown in Figure 4.

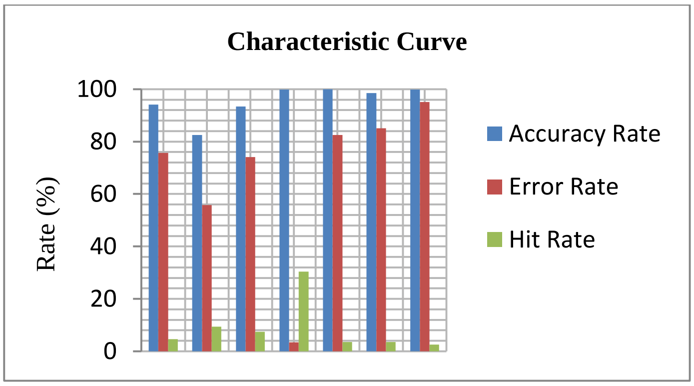

Figure 4: Characteristic curve in verification tests

From verification and identification experiments, the approach using manually cropped features yields good results than holistic Eigen face, Individual Eigen face and feature based method with feature uniformly extracted. The identification is done on a close set with no imposter refusal. Since, the identification is quite simpler and have smaller error rate in identification compared to verification task. It is clear in the embedded HMM approach which has better performance in identification experiments but poor results in verifications tests. Unexpectedly the proposed method Extraction- a) whose features are extracted automatically and manually cropped facial features performs better in the verification experiments. The proposed method make full use of the embedded HMMs and users are segmented consistently with the training face images through trained HMMs and this helps to localized errors of extracted features and make it small. On the other hand for any pretender localization errors of features in a test images will be larger. So, HMMs are trained for each legitimate person in the database. The localization error is large when computing the distance of test image to a person where as the localization error for both pretender and legitimate user are same in the method with manually cropped features. Each HMM in this approach is tuned for each person and handles any impostors and hence provide good results in verification. When images are manually clustered as per their pose without error, the propose method i.e. (Extraction-b) achieve good results. So, more elaborated clustering algorithms other than K-mean may be implemented to improve further (Extraction-a) method. Some of the extracted facial is shown in Figure 5 where the first column indicates decoded states using proposed method. The extracted features shown in second and third row obtained in test phase for a legitimate user in test phase.

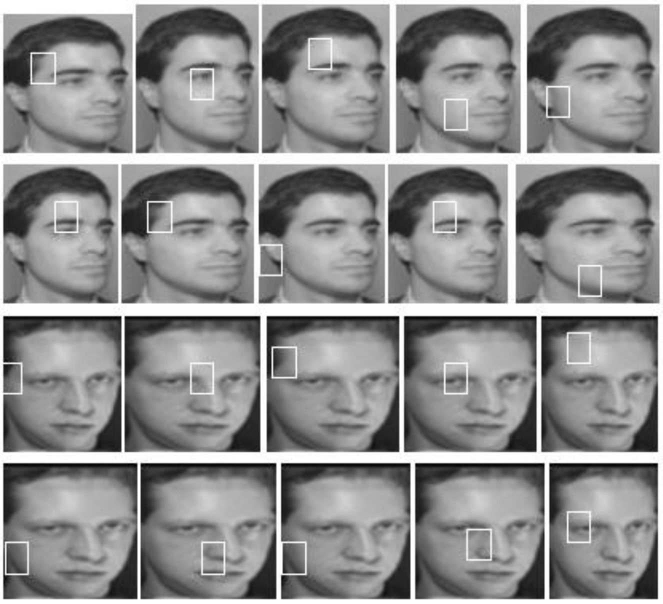

Figure 4: Results obtained using proposed approach.

CONCLUSION & FUTURE SCOPE

Robust facial feature extraction for face identification and verification has been proposed that utilizes the decoded states from an embedded HMM to extract features under large position changes. We also highlighted the advantages of our algorithm by extracting features for identification and verification tests with small localization error for legitimate and pretender users. The proposed approach extracts rectangular features via embedded HMM without using shape information.

Future scope of this paper include some information of shape for feature extraction and extend the person specific extraction approach so, it can robustly extract feature of any image.

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