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Doubly truncated Multivariate Gaussian mixture model for Face images

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Abstract *:* In this paper, we introduce a face recognition algorithm based on doubly truncated multivariate Gaussian mixture model with DCT. The truncation on the feature vector has a significant influence in improving the recognition rate of the system using EM algorithm with K-means or hierarchical clustering, the model parameters are estimated. The EM algorithm requires the updated equations of the model parameters, which are derived for the doubly truncated multivariate Gaussian mixture model. A face recognition system is developed under Bayesian frame using maximum likelihood. The efficiency of the developed face recognition system is studied by conducting experimentation with two face image databases, namely, Jawaharlal Nehru Technological University Kakinada (JNTUK) and Yale. The performance of these algorithms are evaluated by computing the recognition rates, false acceptance rate, false rejection rate, true positive rate and half error rate. From the ROC curves, it is observed the developed models perform better. A comparative study of the developed face recognition systems with that of the face recognition systems based on Gaussian mixture models reveal that the proposed algorithms perform better. The effect of the number of DCT coefficients on the recognition rate is also studied. The influence of the size of the database on the recognition rate of the systems is also investigated. In this paper, we reduce the complexity with the help of Dimensionality reduction in feature vector.

Key words : Face recognition system, EM algorithm, Doubly truncated multivariate Gaussian mixture model, DCT coefficients.

INTRODUCTION

A face recognition system involves confirming or denying the identity claimed by a person. In contrast, a face recognition system attempts to establish the identity of a given person out of a closed pool of N people. Both modes are generally grouped under the generic face recognition term. Recognition and identification of face share the same preprocessing and feature extraction steps and a large part of the classifier design. However, both models target distinct applications. In recognition model, people are supposed to cooperate with the system (the claimant wants to be accepted) [23].

The decision to accept or reject a claim depends on a score (distance measure, Multi Layer Perceptrons (MLP) output or Likelihood ratio) which could be either above (accept) or under the problem of face recognition has been addressed by different researchers using various approaches. Thus, the performance of face recognition systems has steadily improved over the last few years. For a comparison of different approaches see [14].

The face recognition methods can be classified into two categories namely, threshold based methods and holistic methods [5]. In feature based approach the face recognition system is basically dependent on the detection and characterization of the individual facial features. The facial features generally include eyes, nose, mouth, etc. Feature based approaches are more useful in developing the automatic system for face recognition system. Hazim [12], they proposed a technique for localizing a face in a clustered image. Other approaches have been used for hierarchical clustering to fine searches. It is established that discrete cosine transformation can serve well in feature extraction for face classification compared to the Karhunen-Loeve Transform (KLT) approaches [23]. With this motivation, in this Chapter Discrete Cosine Transformation (DCT) for data comprehension and feature vector extraction for face recognition is considered.

Ahmed et al., [1] has pioneered the DCT applications in Signal processing. Later Wang et al., [22] has introduced four different transformations of DCT namely, DCT I, DCT II, DCT III and DCT IV. Among these four, DCT II is the one first suggested by Ahmed et al., [1] and this procedure is simple to compute. Once the feature vector has been extracted it is important to describe a probability model to characterize the feature vector of the face recognition system. In face recognition systems it is customary to considered Gaussian mixture model (GMM) [3,4,7,8,12].

However, the GMM model can characterize the feature vector accurately when it is meso kurtic and having infinite range. But in many practical cases, the feature vector represented by DCT coefficients may not be meso kurtic and having finite range. It is observed that these DCT coefficients are asymmetrically distributed. Hence to have a accurate recognition of faces it is needed to assume that the DCT coefficients [feature vector] follow a finite doubly truncated multivariate Gaussian mixture model.

No serious work has been reported in literature regarding face recognition with doubly truncated multivariate GMM. So, we propose a generative model for face recognition based on doubly truncated multivariate GMM. This model also includes GMM as a limiting case when the truncation points tend to infinite. The doubly truncated multivariate Gaussian mixture model is capable of portraying several probability distributions like asymmetric / symmetric / platy-kurtic / lepto-kurtic distributions [15, 21].

In mixture models the number of components has significant influence on the performance of face recognition system. The number of components is determined by K-means algorithms. The model parameters are estimated by E.M. algorithm. The face recognition system is developed based on maximum likelihood functions of the face image. The efficiency of the proposed system is

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studied by conducting experimentation with the face data bases namely, Yale database and Jawaharlal Nehru Technological University Kakinada (JNTUK) database. The performance measures like false acceptance rate false rejection rate and percentage of correct recognition rate, etc., are computed. A comparative study of the developed algorithm with that of GMM is also carried. The effect of the number of DCT coefficients in the feature vector extraction is also studied. With this dimensionality reduction in feature vector will reduce complexity and also takes less execution time.

FEATURE VECTOR EXTRACTION USING DCT COEFFICIENTS

For developing the face recognition model, the important consideration is deriving the features of each individual face image. Several techniques are adopted to extract the feature vector associated with each individual face [7]. Among the transformations used for feature vector extraction, the 2D DCT is used as it is simple and more efficient in characterizing the face of the individual. This method has been recognized as worldwide standard [JPEG] for image compression [2] In transform coding systems the mean square reconstruction error of DCT is relatively less with respect to other compression methods. Even though it is a lossy compression technique it has good compression ratio, information packing ability and reconstruction capability. Compared to other input independent transforms it has advantages of packing the most useful information into the fewest coefficients and minimizing the block like appearance called blocking artifice that results when boundaries between sub images become visible.

The reason for preferring DCT over KLT, which is known to be the optimal transform in terms of compactness of representation, is mainly because of its data independent bases. For data representation, one has to align training face images properly; otherwise the basis images can have noisy appearance. Although alignment can be done for the entire face with respect to some facial landmarks such as the centers of the eyes, it is almost impossible to align local parts of the face as successful as the entire face image. Suitable landmarks for each part of the face cannot be easily found. Hence, noisy basis images from the KLT on a training set of local parts are inevitable. Moreover, since DCT closely approximates KLT in the sense of information packing, it is a very suitable alternative for compact data representation. DCT is a well-known signal analysis tool used in compression standards due to its compact representation power. Although KLT is known to be the optimal transform in terms of information packing, its data dependent nature makes it unfeasible for use in some practical tasks. Furthermore DCT closely approximates the compact representation ability of the KLT, which makes it a very useful tool for signal representation both in terms of information packing and in terms of computational complexity due to its data independent nature [13].

These characteristics attracted in proposing the DCT coefficients as feature vector for face recognition system. The DCT is an orthogonal transform and consist of phase shifted cosine functions. The DCT can be used to transform an image from spatial domain to frequency domain. For obtaining the feature vector associated with each individual face we assume that it consists of (N_P x N_P) blocks. In each block the 2D DCT coefficients are computed using the method given by [7]. The DCT coefficients are calculated using the formula:

$$C(v,u) = \alpha(v)\alpha(u) \sum_{y=0}^{Np-1} \sum_{x=0}^{Np-1} f(y,x)\, \beta(y,x,v,u) \quad (1)$$

for v, u = 1, 2, ... Np

$$\text{where } \alpha(v) = \begin{cases} \sqrt{\frac{1}{Np}} & \text{for } v = 1 \\ \sqrt{\frac{2}{Np}} & \text{for } v = 2, 3, \ldots Np \end{cases}$$

$$and\ \beta(y,x,v,u) = \cos\left(\frac{(2y+1)v\pi}{2Np}\right)\cos\left(\frac{(2x+1)\pi u}{2Np}\right)$$

These coefficients are ordered according to a zig-zag pattern (consisting of 15 coefficients) reflecting the amount of information stored as given by [10]. After comprehensing the DCT coefficients we get the feature vector of the each individual face as $\vec{x}_i = [\ c_1\, c_2 \ldots c_K\ ]^T$ consisting of N_P x 15 coefficients.

DOUBLY TRUNCATED MULTIVARIATE GAUSSIAN MIXTURE FACE RECOGNITION MODEL

In this section we briefly discuss the probability distribution (model) used for characterizing the feature vector of the face recognition system. After extracting the feature vector of each individual face it can be modeled by a suitable probability distribution such that the characteristics of the feature vector should match the statistical theoretical characteristics of the distribution. Since each face is a collection of several components like mouth, eyes, nose, etc, the feature vector characterizing the face is to follow a M-component mixture distribution. In each component the feature vector is having finite range it can be assumed to follow a doubly truncated Gaussian distribution. This in turn implies that the feature vector of each individual face can be characterized by a M-component doubly truncated multivariate Gaussian mixture model. The joint probability density function of the feature vector associated with each individual face is

$$h((\vec{x}|\lambda)) = \sum_{i=1}^{M} \alpha_i\, d_i(\vec{x}) \quad (2)$$

where, $d_i(\vec{x})$ is the probability density function of the ith component feature vector which is of the form doubly truncated Gaussian distribution [21], [12].

$$d_i(\vec{x}) = \left(\frac{1}{(B-A)(2\pi)^{\frac{D}{2}}|\Sigma_i|^{\frac{1}{2}}}\right) * exp\left\{-\frac{1}{2}(\vec{x_i} - \vec{\mu_i})'\, \Sigma_i^{-1}(\vec{x_i} - \vec{\mu_i})\right\} \quad (3)$$

where, $\vec{x}$ is a D dimensional random vector ($\vec{x_t} = (x_1\, x_2 \ldots x_t)$) is the feature vector, $\vec{\mu_i}$ is the ith component feature mean vector, Σ_i is the ith component of co-variance matrix,

$A = \int_{-\infty}^{x_L} \ldots \int_{-\infty}^{x_L} d_i(\vec{x_t})\vec{d}x_t$ and

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$B = \int_{-\infty}^{x_M} \dots \int_{-\infty}^{x_M} d_i\,(\overrightarrow{x_t})\vec{d}x_t$.

The mean vector of the component feature is

$$E(X_i) = \mu_i + {\sigma_i}^2 \left[\frac{f(x_L) - f(x_M)}{\emptyset(x_L) - \emptyset(x_M)} \right] \quad (4)$$

where, $\emptyset(x_L)$ and $\emptyset(x_M)$ are the standard normal areas and x_L , x_M are the lower and upper truncated points of the feature vectors. $d_i(\vec{x}), i = 1 \dots . M$ are the component densities and $\alpha_i(\vec{x}), i = 1 \dots . M$ are the mixture weights, with mean vector. The mixture weights satisfy the constraints $\sum_{i=1}^{M} \alpha_i = 1$

The variance of each feature vector of DCT coefficients under logarithm domain is Σ with diagonal elements as

$$V_i(X) = \left[1 + \frac{\left(\frac{x_L-\mu_i}{\sigma_i}\right) x_L - \left(\frac{x_M-\mu_i}{\sigma_i}\right) x_M}{B-A} \right] {\sigma_i}^2 \quad (5)$$

The DTGMM is parameterized by the mean vector, Co-variance matrix and mixture weights from all components densities. The parameters are collectively represented by the parameter. Set $\lambda_i = \{\alpha_i\,,\, \mu_i\,,\, \Sigma_i\,\}\; i = 1,2, \dots M$. For face recognition each image is represented by its model parameters.

The doubly truncated multivariate Gaussian mixture model can represent different forms depending on the choice of the co-variance matrix for all Gaussian component(Grand co-variance) or a single co-variance matrix shared by all face models(global covariance) used in DTGMM. The covariance matrix can also be full or diagonal. Here, we used diagonal covariance matrix for our face model. This choice is based on the works given by [9] and initial experimental results indicating better identification performance and hence Σ can be represented as

$$\Sigma_i == \begin{bmatrix} V_{i1} & 0 & 0 & 0 \\ 0 & V_{i2} & 0 & 0 \\ - & - & - & - \\ - & - & - & - \\ 0 & 0 & 0 & V_{iD} \end{bmatrix} \quad (6)$$

This simplifies the computational complexities. The doubly truncated multivariate Gaussian mixture model includes the GMM model as a particular case when the truncation points tend to infinite.

ESTIMATION OF THE MODEL PARAMETERS

For developing the face recognition model it is needed to estimate the parameters of the face model. For estimating the parameters in the model we consider the EM algorithm which maximizes the likelihood function of the model for a sequence of i training vectors $(\overrightarrow{x_t} = (x_1\, x_2 \dots x_t))$.

The likelihood function of the sample observations is

$$L(\vec{x}\,;\,\lambda_j) = \prod_{i=1}^{T} h(\vec{x}\,;\,\lambda_j) \quad (7)$$

where, $h(\vec{x}\,;\,\lambda_j)$ is given in equation (2).

The likelihood function contains the number of components M which can be determined from the K-means algorithm or Hierarchical clustering algorithm. The K-means algorithm or Hierarchical clustering algorithm requires the initial number of components which can be taken by plotting the histogram of the face image using MATLAB code and counting the number of peaks. Once M-is assigned the EM algorithm can be applied for refining the parameters. The updated equations of the parameters of the model are

$$\alpha_k{}^{l+1} = \frac{1}{T} \sum_{i=1}^{T} h(i|\overrightarrow{x_t}\,,\lambda_j) \quad (8)$$

$$\mu_k{}^{l+1} = \frac{\sum_{i=1}^{T} \overrightarrow{x_t}\, h(i|\overrightarrow{x_t}\,,\lambda_j) + \sum_{i=1}^{T} \frac{f(\overrightarrow{x_M}) - f(\overrightarrow{x_L})}{B-A} \;\; \sigma_k{}^2\; h(i|\overrightarrow{x_t}\,,\lambda_j)}{\sum_{i=1}^{T} h(i|\overrightarrow{x_t}\,,\lambda_j)} \quad (9)$$

$$\sigma_k{}^{l+1} = \frac{\sum_{i=1}^{T} h(i|\overrightarrow{x_t}\,,\lambda_j)(\overrightarrow{x_t} - \mu_i{}^{l+1})}{c\,\sum_{i=1}^{T} h(i|\overrightarrow{x_t}\,,\lambda_j)} \quad (10)$$

where,

$$c = \frac{1}{B-A}(1 + \mu_k{}^{l+1})\left[\left(f(\overrightarrow{x_M}) - f(\overrightarrow{x_L})\right) + \left(x_M f(\overrightarrow{x_M}) - x_L f(\overrightarrow{x_L})\right)\right]$$

$$f(x_M) = \int_{-\infty}^{x_M} d_i\,(\overrightarrow{x_t})\vec{d}x_t\;,$$

$$f(x_L) = \int_{-\infty}^{x_L} d_i\,(\overrightarrow{x_t})\vec{d}x_t \quad \text{and}$$

$$h(i|\overrightarrow{x_t}\,,\lambda_j) = \frac{\alpha_i\, d_i(\overrightarrow{x_t})}{\sum_{i=1}^{k} \alpha_i\, d_i(\overrightarrow{x_t})} \quad (11)$$

INITIALIZATION OF MODEL PARAMETERS

To utilize the EM algorithm we have to initialize the parameters $\{\alpha_i\,,\, \mu_i\,,\, \sigma_i\,\}, i = \{1 \dots . M\}$. X_M and X_L are estimated with the maximum and the minimum values of each feature respectively. The initial values of α_i can be taken as $\alpha_i = \frac{1}{M}$. The initial estimates of α_i , μ_i *and* σ_i of the i[th] component are obtained by using the method given by [6].

FACE RECOGNITION SYSTEM

Face Recognition means recognizing the person from a group of H persons. The Fig 1 describes the face recognition algorithm under study.

Let us considered our face recognition system has to detect the correct face with our existing database. Here, we are given with a face image and a claim that this face belongs to a particular person C to classify the face a set of feature vectors $X = \{x_i\}_{i=1}^{T}$ is extracted using the computational methodology of feature vector extraction is discussed in section 2.

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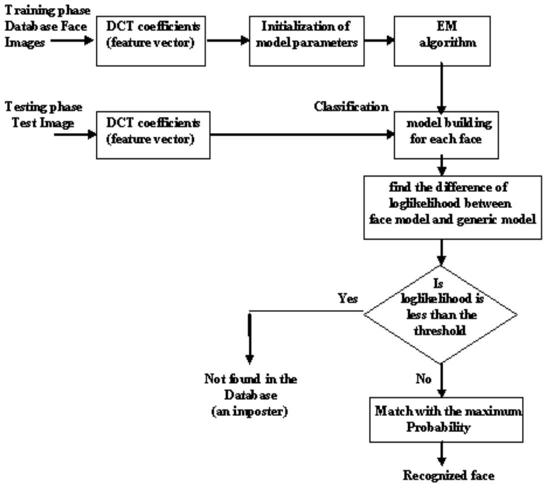

Fig 1: Flow chart for face recognition algorithm using DCT coefficients

By assuming that the likelihood of the face belonging to person C is found with

$$L(X|\lambda_C) = \prod_{i=1}^{T} p(x_i|\lambda_C) \quad (12)$$

where

$$p(x_i|\lambda_C) = \sum_{i=1}^{K} \alpha_i \, b_i(x/\mu_i, \sigma_i) \quad (13)$$

and

$$\lambda = \{\alpha_i, \mu_i, \sigma_i\}_{i=1}^{K} \quad (14)$$

and $b(x; \mu_i, \Sigma_i)$ is a D-dimensional doubly truncated Gaussian density function. λ_C is the parameter set for person C, K is the number of components in the model and $\alpha_i$is the weight of ith component such that $\sum_{i=1}^{K} \alpha_i = 1$ and $\forall\, i: \alpha_i \geq 0$).

The universal background model is used to find the likelihood of the face belonging to an imposter. $L(X|\lambda_{generic})$ is the likelihood function of the claimant computed based on the parameter set $\lambda_{generic}$. The $\lambda_{generic}$ is computed by considering all faces in the dataset and obtaining the average values of the parameters.

The decision on the face belonging to the person C is found using

$$O(X) = \left| \log L(X|\lambda_C) - \log L(X|\lambda_{generic}) \right|.$$

The final decision for given face is then reached as follows. Given a threshold t for O(X) the face is classified as belonging to person C, when O(X) is greater than or equal to t. It is classified as belonging to an imposter, when O(X) is less than t.

For a given set of training vector λ_C for all faces in the data bases and $\lambda_{generic}$ are computed by using the updated equations for the model parameters discussed in section 4 and using the initial estimates of the model parameters obtained by using either K-means algorithm or hierarchical clustering algorithm.

EXPERIMENTAL RESULTS

The performance of the developed algorithm is evaluated using two types of databases namely Jawaharlal Nehru Technological University Kakinada (JNTUK) and Yale face databases [16],[17],[18],[19]. The JNTUK face database consisting of 120 face database and Yale database consists of 120 faces. Sample of 20 persons images from JNTUK database is shown in Fig 2.

Fig 2: Sample Images from JNTUK database

Using the method discussed in section 2, the feature vectors consisting of DCT coefficients under logarithm domain for each face image for both the databases are computed. For each image the sample of feature vectors are divided into K groups representing the different face features like neck, nose, ears, eyes, etc.

For initialization of the model parameters with K-means algorithm or Hierarchical clustering algorithm, a sample histogram of the face image is drawn and counted the number of peaks. After diving the observations into three categories by both the methods and assuming that the feature vector of the whole face image follows a three component finite doubly truncated multivariate Gaussian mixture model. The initial estimates of the model parameters α_i , $\vec{\mu_i}$, $\vec{\Sigma_i}$ are obtained by using the method discussed in section 5 with K-means algorithm or Hierarchical clustering algorithm.

With these initial estimates the refined estimates of the model parameters are obtained by using the updated equations of the EM algorithm and MATLAB code discussed in section 4. Substituting these estimates the joint probability density function of each face image is obtained for all faces in the database. By considering all the feature vectors of all faces in the database the generic model for any face is also obtained by using the initial estimates and the EM algorithm discussed in section 4 and 5 respectively. The parameters of the generic model are stored under the parametric set $\lambda_{generic}$. The individual face image model parameters are stored with the parametric set λ_i , i= 1,2,. ..N. N is the number of face images in the database.

Using the face recognition system discussed in section 6, the recognition rates of each database is computed for different threshold values of t in (0, 1). The false rejection rate, false acceptance rate and half total error rate for each threshold are computed using the formula's given by [7]

.

$$FAR = \frac{number\ of\ FA's}{number\ of\ imposeter\ face\ presentations}$$

$$FRR = \frac{number\ of\ FR's}{number\ of\ true\ face\ presentations}$$

where, FA indicates the false acceptance and FR indicates the false rejection

$$Half\ Total\ error\ rate = HTER = \frac{FAR+FRR}{2}$$

$$True\ positive\ rate = 1 - FRR$$

The HTER is a special case of Decision Cost function and is often known as equal error rate when the system is adjusted. Plotting the FAR and FRR for different threshold

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values, the ROC curves for both the databases are obtained are shown in Figs 3 and 4. From this ROC the optimal threshold value 't' for each database is obtained. These threshold values are used for effective implementations of the face recognition system. Table 1 shown the values of HTER and recognition rates of both face recognition systems.

Table 1: Face recognition Rates

Database	Recognition system	HTER	Recognition rate
JNTUK	GMM with K-means	5.58335	88.33±1.5
	GMM with hierarchical	4.75	90±1.3
	DTMGMM with K-means	3.7484	96.7±1.3
	DTMGMM with hierarchical	3.3333	97.5±0.9
Yale	GMM with K-means	6	87.5 ±2.1
	GMM with hierarchical	5.1667	89.1667±1.8
	DTMGMM with K-means	4.1667	95.83±1.2
	DTMGMM with hierarchical	3.749	96.934±0.8

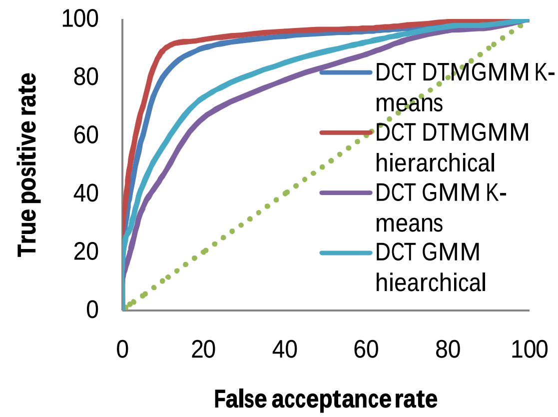

Fig 3: ROC curve for DTMGMM and GMM for JNTUK

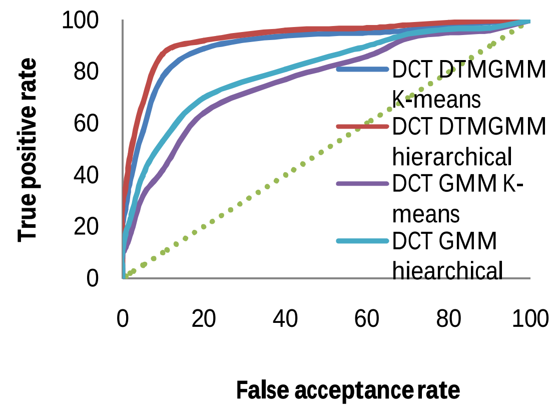

Fig 4: ROC curve for DTMGMM and GMM for Yale

Table 2: The values of HTER and recognition rate for different databases using DTMGMM

Total number of images	K-means algorithm				Hierarchical clustering algorithm			
	JNTUK		Yale		JNTUK		Yale	
	HTER	Recognition rate	HTER	Recognition rate	HTER	Recognition rate	HTER	Recognition rate
5	4.25	92.5	4.632	90.8333	3.75	93.3333	4.167	93
10	4.167	93.3333	4.167	92.5	3.832	94.1667	3.832	93.667
15	3.832	94.1667	4.25	93.3333	3.333	95	3.75	94.667
20	4.25	95	4.167	94.1667	4.25	95.8333	4.632	95.437
25	3.832	95.8333	4.25	94.8	4.167	96.6667	4.25	96.3
30	3.749	96.3	4.632	95.4	3.749	97	4.167	96.667
40	3.75	96.65	4.665	95.805	3.333	97.4964	4.167	96.891
50	3.788	96.6682	4.167	95.810	3.832	97.4974	4.25	96.897
60	4.167	96.6751	4.25	95.815	3.75	97.4981	3.749	96.903
80	4.167	96.6835	4.665	95.821	4.167	97.4991	3.832	96.915
100	3.75	96.6884	4.167	95.827	3.333	97.4996	3.75	96.925
110	4.25	96.6966	4.25	95.829	4.167	97.4998	3.749	96.93
120	3.749	96.7	4.167	95.83	3.333	97.5	3.749	96.934

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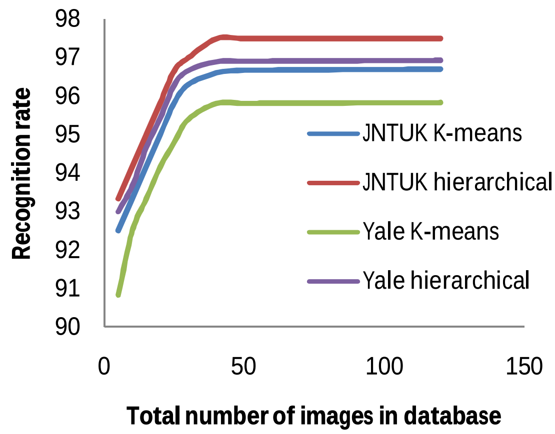

Fig 5: Recognition rate for different databases using DTMGMM

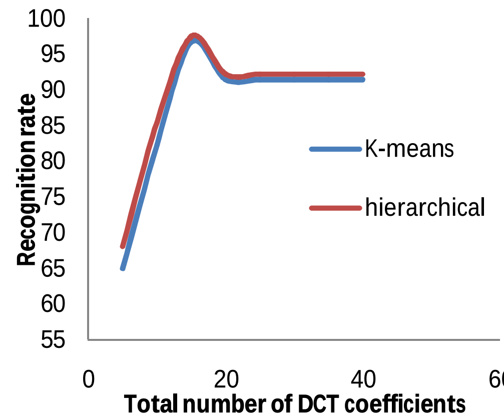

Fig 6: Recognition rate versus total no of DCT coefficients on JNTUK database

The efficiency of the developed system with respective to the size of the database is also studied by varying the no of face images from 5 to 120 available in JNTUK database. The HTER and recognition rates for different sizes of the databases from JNTUK database are computed and shown in Table2. Fig 5 shows the relationships between the number of faces in the database and the performance measures of the system.

From Table 2 and Fig 5, it is observed that the recognition rate increases when the number of face in the database increases. The recognition rate increases upto a size of 30 images and stabilize thereafter. This may be due to more number of observations available for training the recognition system and efficiency of estimating the model parameters increases with observations. However, the recognition rate is above 90% for all sizes and it stabilizes after a size of 30 faces. This indicates the face recognition system is suitable for small and large databases.

Table 3: Recognition rate for different number of DCT coefficients

Number of DCT coefficients	Recognition rate			
	DTMGMM with K-means		DTMGMM with hierarchical	
	JNTUK	Yale	JNTUK	Yale
5	65±1.2	64±1.1	68.13±1.1	68.1±1.1
10	82.4±1.1	82.3±1.4	85.5±0.9	85.1±0.9
15	96.7±1.3	95.±1.2	97.5±0.9	96.9±0.8
20	91.5±1.2	91.4±1.1	92.2±1.2	92.1±1.2
25	91.5±1.3	91.4±1.1	92.2±1.1	92.1±1.2
30	91.5±1.1	91.4±1.3	92.2±1.1	92.1±1.1
35	91.5±1.2	91.4±1.3	92.2±1.2	92.1±1.2
40	91.5±1.3	91.4±1.1	92.2±0.8	92.1±0.8

From Fig 8, it is observed that for both K-means and hierarchical clustering algorithms on JNTUK database, the recognition rate stabilizes after 15 DCT coefficients for the face recognition system with DTMGMM. This indicates even with low dimension feature vector also will have high recognition rate for the face recognition system with DTMGMM model. This dimensionality reduction feature has a significant effect on execution time of the system.

From the above discussions it is observed that the face recognition system with doubly truncated multivariate Gaussian mixture model and hierarchical clustering algorithm is more efficient compared to that of the systems based on doubly truncated multivariate Gaussian mixture model and GMM and with K-means algorithm.

CONCLUSIONS

Face recognition system based on doubly truncated multivariate Gaussian mixture model with DCT coefficients was developed and analyzed. The model parameters are estimated by deriving the updated equations of the Expectation-Maximization algorithm. The initialization of the model parameters is done by K-means or hierarchical clustering algorithms and method of moments. The face recognition algorithm is developed. The performance of the algorithm is studied with the experimentation on two databases (JNTUK and yale) and computing the performance measures. A comparative study of the present face recognition systems with that of the face recognition systems based on Gaussian mixture models reveal that the proposed algorithms perform better. The effect of the number of DCT coefficients on the recognition rate is also studied and found 15 DCT coefficients provide efficient results. The influence of size of the database on the recognition rate of the systems is investigated and found that the recognition rates get stabilizes of a large samples size 30.

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