Face Recognition Algorithm Based on Doubly Truncated Gaussian Mixture Model Using Hierarchical Clustering Algorithm

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Abstract

A robust and efficient face recognition system was developed and evaluated. The each individual face is characterized by 2D-DCT coefficients which follows a finite mixture of doubly truncated Gaussian distribution. In modelling the features vector of the face the number of components (in the mixture model) are determined by hierarchical clustering. The model parameters are estimated using EM algorithm. The face recognition algorithm is developed by maximum likelihood under Baysian frame. The method was tested on two available face databases namely JNTUK and yale. The recognition rates computed for different methods of face recognition have revealed that the proposed method performs very well when compared to the other approaches. It is also observed that the proposed system require less number of DCT coefficients in each block and serve well even with large and small databases. The hybridization of hierarchical clustering with model based approach has significantly improved the recognition rate of the system even with the simple features like DCT.

Keywords: *Face recognition system, doubly truncated Gaussian mixture model, Hierarchical clustering algorithm, DCT coefficients.*

1. Introduction

With the rapid development of IT industry, information security has received substantial attention from both researcher communities and the market. Therefore expeditious and effective automatic identity authentication techniques are in need. Physiological and behavior characteristics such as face, fingerprint, iris, gait and handwriting are utilized as features of identity distinguishing, because they have self-stability and individual differences. Among the existing biological identification techniques, face recognition has become the most popular method because of its friendly interface and understanding ability[29].

Research on face recognition began in 1960s. There are two main methods in early period, one is based on geometrical local feature and another based on holistic template. The comparison study of the two methods by R. Brunelli[3] indicates that the first method is fast and small memory required with a lower recognition rate, while the second one is slow and large memory required with a higher recognition rate. In recent years a lot of new methods are presented, for example, the K-L transform based method [15, 24], the elastic bunch graph matching based method [13], neural network based method [16], Hausdorff distance based method[26], Gaussian mixture models (GMMs) [4] and the hidden Markov model (HMM)[20] based method.

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 share the same preprocessing and feature extraction steps and a large part of the classifier design. However, both modes target distinct applications. In recognition model, people are supposed to cooperate with the system (the claimant wants to be accepted). The main applications are access control systems, such as computer or mobile devices log-in, building gate control, digital multimedia access. On the other hand, in identification mode, people are generally not concerned by the system and often even do not want to be identified. Potential applications include video surveillance (public places, restricted areas) and information retrieval (police databases, video or photo album annotation/identification)[21,22].

The decision to accept or reject a claim depends on a score (distance measure, 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

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improved over the last few years. For a comparison of different approaches see [14].

The face recognition methods can be classifieds into two categories namely threshold based methods and holistics methods[7]. 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 includes eyes, noses, mouth, etc. Feature based approaches are more useful in developing the automatic system for face recognition system. Govinda raju et al [11] proposed a technique for localising 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 KLT approaches [30]. With this motivation in this paper we considered the discrete cosine transformation for data comprehension and feature vector extraction for face recognition.

Ahmed et al [2] has pioneered the DCT applications in Signal processing. Later wang [27] has introduced four different transformations of DCT namely, DCT I, DCT II, DCT III and DCT IV. Among these four, DCT II were the one first suggested by ahmed et at [2] and this procedure is simple in computation. Once the feature vector has been extracted it is important to escribe a probability model to characterized the feature vector of the face recognition system. It is customary to considered Gaussian mixture model [4,5,6,9].

However, the GMM model can characterize the feature vector accurately only when it is miso kurtic and having infinite range. But in many practical cases, the feature vector represented by DCT coefficients may not be miso kurtic And having finite range. It is observed that these DCT coefficients are asymmetrically distributed. Hence to have a close approximation to characterise the DCT coefficients representing the face is needed to assume that the DCT coefficients [feature vector] follows a finite doubly truncated Gaussian mixture model. In mixed models the number of components (the classes of facial features) has significant influence on estimating the model parameters (developing the initial estimates). Compared to the most non hierarchical segmentation algorithms such as k-means algorithm, hierarchical clustering algorithm preserves the spatial neighbouring information among the segmentation regions. The main disadvantage of k-means algorithm is it does not necessarily find most optimal configuration corresponding to the global objective function and it is sensitive to the initial random selected segments. To overcome these disadvantages hierarchical segmentation algorithm is considered for determining the number of components in the mixture model and to refine the initial estimates of the model parameters. In hierarchical clustering the database in divided into various groups by multi brands tree structure[19].

Various approaches are discussed by different researchers on the problem of face recognition. But, there is no serious work is done on face recognition with doubly truncated GMM. So, we propose a generative approach for face recognition, based on doubly truncated GMM. This model also includes GMM as a limiting case when the truncation points tends to infinite. The doubly truncated Gaussian mixture model is capable of portraying several probability distributions like asymmetric / symmetric / platy kurtic / lepty kurtic distributions [17,18].

The paper is structured as follows. Section 2 summarizes feature extraction, Section 3 summarizes doubly truncated Gaussian mixture face recognition model, Section 4 summarizes the estimation of model parameters using EM Algorithm, Section 5 deals with the initialization of model parameters and Section 6 and 7, the face recognition algorithm and experimental results are given respectively and finally, conclusions are presented in Section 8.

2. Feature Extraction

For developing the face recognition model, the important consideration is deriving the features of the each individual face image. Several techniques are adopted to extract the feature vector associated with each individual face [4]. Among the transformations used for feature vector extraction, the 2D Discrete Cosine Transform is simple and more efficient in characterizing the face of the individual. This method has been recognized as world wide standard [JPEG] for image compression [1]. 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. These characteristics attracted in proposing this approach. 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. Besides, it can be implemented using a fast algorithm which significantly reduces the computational complexity. It is calculated using the formula :

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

For $v, u = 1, 2, \ldots\ldots Np$

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

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

For obtaining the feature vector associated with the 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 [4]. The computation of 2D DCT coefficients for a face of (N_P x N_P) blocks is given in x_i.

These coefficients are ordered according to a zig-zag pattern (consisting of 15 coefficients) reflecting the amount of information stored as given in [10]. After comprehensing the DCT coefficients we get the feature vector of the each individual face as $x_i = [\,a_1\ a_2 \ldots a_M\,]^T$ consisting of N_P x 15 coefficients.

3. Doubly truncated 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 modelled 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 Gaussian mixture model. The joint probability density function of the feature vector associated with each individual face is

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

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 [18].

$$d_i(\vec{x}) = \left(\frac{1}{(B-A)(2\pi)^{\frac{D}{2}}|\Sigma_i|^{\frac{1}{2}}}\right) * \exp\left\{-\frac{1}{2}(\vec{x}_t - \vec{\mu}_i)' \Sigma_i^{-1}(\vec{x}_t - \vec{\mu}_i)\right\} \qquad (2)$$

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,

$A = \int_{-\infty}^{x_L} \ldots \int_{-\infty}^{x_L} d_i(\vec{x}_t)\, d\vec{x}_t$ and
$B = \int_{-\infty}^{x_M} \ldots \int_{-\infty}^{x_M} d_i(\vec{x}_t)\, d\vec{x}_t$.
The mean ith component feature is

$$E(X_i) = \mu_i + \sigma_i^2 \left[\frac{f(x_L) - f(x_M)}{\emptyset(x_L) \quad \emptyset(x_M)}\right] \qquad (3)$$

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. $d_i(\vec{x}), i = 1 \ldots M$ are the component densities and $\alpha_i(\vec{x}), i = 1 \ldots M$ 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 is Σ with diagonal elements as

$$V_i(X) = \left[1 + \frac{\left(\frac{x_L-\mu_i}{\sigma_i}\right)x_L - \left(\frac{x_M-\mu_i}{\sigma_i}\right)x_M}{B-A}\right]\sigma_i^2 \qquad (4)$$

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 $\lambda_i = \{\alpha_i, \mu_i, \Sigma_i\}\ i = 1, 2, \ldots M$. For face recognition each image is represented by it's 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 [19] and initial experimental results indicating better identification performance and hence Σ can be represented as

$$\Sigma_i == \begin{bmatrix} V_{i1} & 0 & 0 & 0 \\ 0 & V_{i2} & 0 & 0 \\ - & - & - & - \\ - & - & - & - \\ 0 & 0 & 0 & V_{iD} \end{bmatrix} \qquad (5)$$

This simplifies the computational complexities.

The doubly truncated multivariate Gaussian mixture model includes the GMM model as a particular case when the truncation points tends to infinite.

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4. Estimation of the model parameters using E.M. algorithm

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 $(\vec{x_i} = (x_1, x_2, \ldots, x_i))$.

The likelihood function of the sample observations is

$$L(\vec{x}, \lambda_l) = \prod_{t=1}^{T} h(\vec{x}, \lambda_l) \qquad (6)$$

where, $h(\vec{x}, \lambda_l)$ is given in equation (1).

Using the Expectation Maximization algorithm the updated equations of the model parameters are:

$$\alpha_k^{\,l+1} = \frac{1}{T}\sum_{t=1}^{T} h(i|x_t^{l}, \lambda_l) \qquad (7)$$

$$\mu_k^{\,l+1} = \frac{\sum_{t=1}^{T}\vec{x_t}\, h(i|\vec{x_t},\lambda_l) + \sum_{t=1}^{T}\frac{f(x_M)-f(x_L)}{B-A}\,\sigma_k^{2}\, h(i|\vec{x_t},\lambda_l)}{\sum_{t=1}^{T} h(i|\vec{x_t},\lambda_l)} \qquad (8)$$

$$\sigma_k^{\,l+1} = \frac{\sum_{t=1}^{T} h(i|\vec{x_t},\lambda_l)(\vec{x_t}^{2}-\mu_k^{(l+1)2})}{c\sum_{t=1}^{T} h(i|\vec{x_t},\lambda_l)} \qquad (9)$$

where,

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

,

$$f(x_M) = \int_{-\infty}^{x_M} d_i(\overline{x_t})\, d\vec{x}_t \quad , \quad f(x_L) = \int_{-\infty}^{x_L} d_i(\overline{x_t})\, d\vec{x}_t$$

and

$$h(i|\vec{x_t}, \lambda_l) = \frac{\alpha_i\, d_i(\overline{x_t})}{\sum_{i=1}^{M}\alpha_i\, d_i(\overline{x_t})} \qquad (10)$$

5. Initialization of model parameters using hierarchical clustering algorithm

One problem in using EM algorithm in face recognition is that of model parameter initialization. Wu[28], and sailaja et al[19] have utilized the hierarchical clustering algorithm for obtaining the initialization of model parameters.

The efficiency of the EM algorithm in estimating the parameters is heavily dependent on the number of components of face data (M) and the initial estimates of the model parameters μ_{ij}, σ_{ij} and α_i (i = 1,2,…,M ; j=1,2,…,D). The truncation points X_L and X_M are obtained as Minimum and maximum values of the DCT coefficients of the whole face. Usually in EM algorithm, the mixing parameter α_i and the distribution parameters μ_{ij}, σ_{ij} are given with some initials values. A commonly used method in initialization is by drawing a random sample in the entire face data. This method can be performed well when the sample size is large, but the computation is heavily increased. When the sample size is small it is likely that some small regions may not be sampled. The initial value of the α_i can be taken as α_i =1/M, where, M is obtained from the hierarchical clustering algorithm. After obtaining the final value of M , we obtain the initial estimates of σ_{ij}, μ_{ij} for i^{th} component using the method of moments given by A.C. Cohen [8]. After getting the initial estimates, the final refined estimates of the model parameters are obtained through EM Algorithm

To utilize the EM algorithm we have to initialize the parameters $\{\alpha_i, \mu_i, \sigma_i\}, i = \{1 \ldots M\}$. 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 $\alpha_i = \frac{1}{M}$. The initial estimates of x_i, μ_i and σ_i of the i^{th} component is obtained using the method given by A.C.Cohen[8].

6. Face recognition system

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

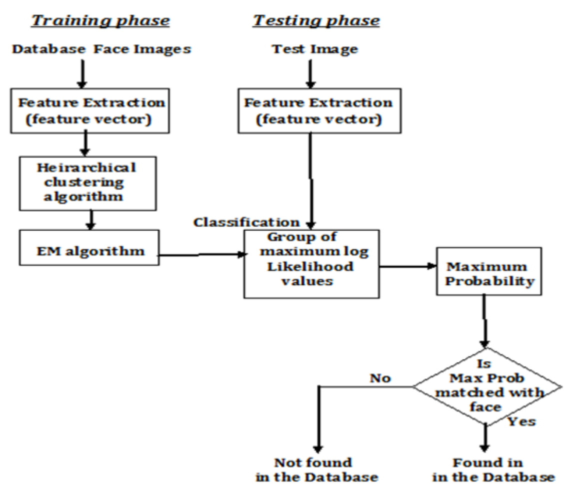

Figure-1 : flow chart for Face recognition algorithm

The feature vectors are obtained by using the procedure discussed in section 2. By using H\hierarchical clustering algorithm we divide the DCT coefficients of each face into M groups. We take initially

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$\alpha_i = \frac{1}{M}, i = 1, 2, \ldots M$ and find means (μ_i) and variances (V_i) of each feature for each group. Using the EM algorithm the refined estimates of the model parameters $\{\alpha_i, \mu_i \text{ and } \sigma_i\}$ for i^{th} component of each face Image are obtained. For the given a claim of a person C's identity and a set of feature vectors X, supporting the claim, the log likelihood of the claimant is calculated using

$$L(X|\lambda_C) = \frac{1}{T}\sum_{t=1}^{T} \log h(x_t|\lambda_C)$$

where, $h(x|\lambda)$ which is given in eq (1), and T is the number of samples (blocks).

Find the log likelihood value for all faces in the training group of samples, each represented by DTGMM's with parameters $(\lambda_1, \lambda_2, \ldots \lambda_H)$. The face which has the maximum posterior probability for a given, feature vector that the face is matched with the person, i.e., the k^{th} face for which log likelihood is maximum ($\hat{H} = \arg\max_{1 \le k \le H} \sum_{t=1}^{T} \log h_r(\overline{x_t}|\lambda_k)$) out of all faces.

7. Experimental results:

The performance of the developed algorithm is evaluated using two types of databases namely, JNTUK and yale face databases [21,12]. Sample of 20 persons images from JNTUK database is shown in figure.2.

figure 2: Sample images from JNTUK database

The whole dataset are divided into test and training datasets. The training faces were first processed by feature vector extraction explained in section2 to produce the transformed feature vector (DCT coefficients) for each face. The Hierarchical clustering algorithm is utilized for dividing the samples of the each image features into M components like face, chick, nose, forehead, etc. Using these M groups the model parameter's in each component are initially estimated with the method given by A.C.Cohen [8]. With these initial coefficients and the updated equations of the EM algorithm the model parameters of the doubly truncated multivariate Gaussian mixture model of each face is estimated. With the test dataset the face recognition algorithm is validated by computing the recognition rate with its confidence limits. Table.1 shows the recognition rate of the face recognition system using GMM and DTGMM.

Table.1: face recognition rates

Database	Recognition rate			
	GMM		DTGMM	
	k-means	Hierarchical	k-means	Hierarchical
JNTUK	89.5±1.5	90.5±1.3	96.17±1.3	97.19±0.9
yale	89.39±2.1	90.29±1.8	96.07±1.2	97.18±0.8

From Table.1, it is observed that the proposed algorithm identifies the 96.17% and 96.07% for JNTUK and yale faces correctly by using k-means algorithm and 97.19% and 97.18% for JNTUK and yale faces correctly by using hierarchical clustering algorithm. Where as, for the face recognition model using GMM has 89.5% recognition rate using k-means algorithm and 90.5% using hierarchical clustering algorithm for JNTUK database. Graph-1 describes the recognition rate for different sizes of datasets. It is observed that the recognition rate stabilized after the data size of 25 faces. i.e. the algorithm is consistent with small and large databases for face recognition.

From the Fig.4, we found that face recognition algorithm using hierarchical clustering algorithm based on doubly truncated Gaussian mixture model is giving better recognition rate compared to the Face recognition algorithm using k-means algorithm based on doubly truncated Gaussian mixture model.

Since the proposed face recognition system performance is linked with the number of DCT coefficients the optimal number of DCT coefficients required for effective recognition of the system is evaluated. For different number of DCT coefficients taken from the total of 64 coefficients of each block in say 5, 10,

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15, 20, 25, 30, 35 and 40 the recognition rates are of the system computed for both the proposed model and the model with GMM. Table.2 shows the computed recognition rates for both JNTUK and yale databases using the face recognition system based on DTGMM and GMM. Fig.3 shows the relationship between recognition rates and number of DCT coefficients.

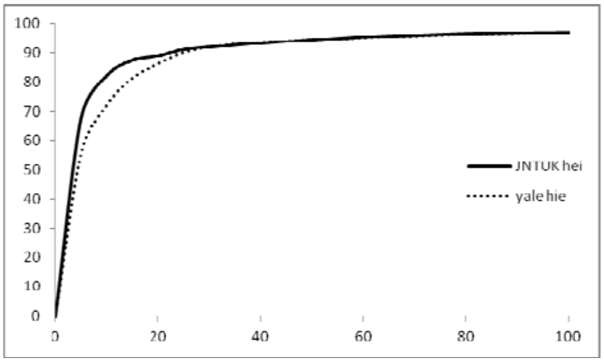

Fig 3: Recognition rate for different databases using hierarchical clustering algorithm

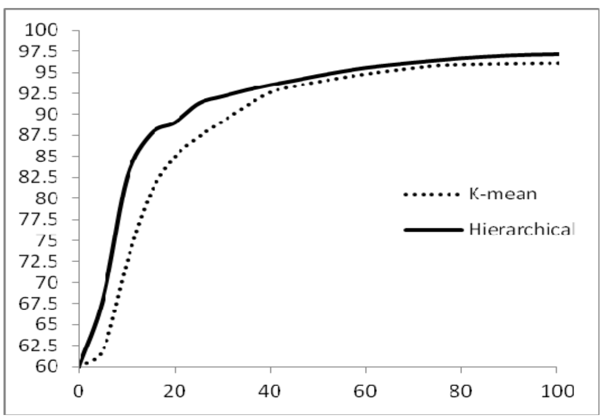

Fig. 4: Recognition rate for JNTUK database using K-means and hiearachical clustering algorithm

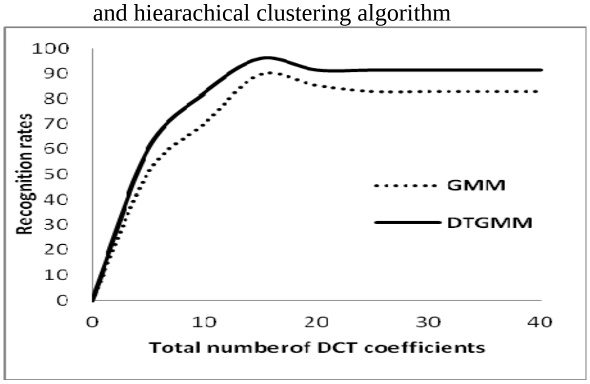

Fig. 5: Recognition rate versus total no of DCT coefficients on JNTUK database using GMM and DTGMM

Table.2: Recognition rate for different number of DCT coefficients

Number of DCT coefficients	Recognition rate			
	DTGMM k-means		DTGMM hierarchical	
	JNTUK	yale	JNTUK	yale
5	60.23±1.2	60.18±1.1	68.13±1.1	68.1±1.1
10	82.4±1.1	82.3±1.4	85.45±0.9	85.11±0.9
15	96.17±1.3	96.07±1.2	97.19±0.9	97.18±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 Table.2 and Graph.3, it is observed that for both JNTUK and yale databases the recognition rate stabilizes after 15 DCT coefficients for the face recognition system with DTGMM. Whereas, the recognition rate stabilizes after 20 DCT coefficients for the face recognition system with GMM. This indicates even with low dimension feature vector also will have high recognition rate with DTGMM model. This feature has a significant effect on execution time of the system.

From Graph.4, we observed that for the face recognition algorithm based on doubly truncated Gaussian mixture model using hierarchical clustering algorithm is giving higher recognition rate compared to the face recognition model based on doubly truncated Gaussian mixture model using k-means algorithm. In both face recognition algorithms (k-means algorithm) and hierarchical clustering algorithm with DTGMM, it is giving higher recognition rate compared to that of GMM.

8. Conclusion

In this paper a robust and accurate face recognition system is proposed and evaluated by using finite doubly truncated Gaussian mixture model and hierarchical clustering. This model also includes the GMM model as a limiting case. This method overcome the drawback associated with the GMM model in face recognition of being miso kurtic and having infinite range. Here each individual face is uniquely modelled with the DCT coefficients as facial features. The facial features are first segmented into different categories and for each category the pattern of the DCT coefficients are modelled through the doubly truncated Gaussian model. The model parameters are estimated by using the EM algorithm. The initialization of the parameter's is done through hierarchical clustering and the method of moments. By maximum likelihood under baysian frame the face

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recognition algorithm is developed. Using two databases namely, yale and JNTUK database, which is collected at Jawaharlal Nehru Technological University, Kakinada, the recognition rate of the proposed system is computed and compared with that of GMM and k-means. These studies reveal that the proposed model is having high recognition rate with small and large databases. The number of DCT coefficients for effective face recognition in this method is (15) less than that of face recognition with GMM. This method can be utilized at authentication and surveillances with more accuracy.

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