Face Recognition in Frequency Domain

Chapter 5

Face Recognition in Frequency Domain

5.1 Background

Face recognition is neither a new problem nor the one that we can yet consider largely solved A plethora of paradigms, algorithms and systems have been proposed over the past three decades towards this problem (Chellappa et al 2003) One of these methodologies is frequency domain representation of face images which has twofold significance (1) effective characterization of a pattern of interest, or effective classification of different patterns, and (2) dimensionality reduction This exploration is based on the frequency space representation of facial images, which relies on a global transformation, (i e every pixel in the image contributes to each value of its spectrum) The frequency spectrum is a plot of energy against spatial frequencies, where spatial frequencies relate to the spatial relations of intensities in the image

---

* Some parts of the material in this chapter appeared in the following research papers

1 **Face Recognition Based on fractional Discrete Cosine Transform,** in IEEE International Conference on Recent Trends in Information Technology-ICRTIT-2011 pp 987-991, 2011

2 **Face Recognition based on Discriminative Fractional Discrete Cosine Transform** Proceedings of Indian International Conference on Artificial Intelligence-IICAI, Tumkur, India, December 16-18, pp 1914-1927, 2011

All face images possess high information redundancy and correlation which results in inefficiency in recognition Transformation of facial images in frequency domain can be used to reduce image information redundancy because only a subset of transformed coefficients are necessary to preserve most desired and important features required for recognition Data compression is essential for both biological and computer signal processing In fact, at the retinal level, only approximately 1 million signals (out of almost 130 million from the photoreceptors) are projected to the lateral geniculate nucleus (LGN) for further processing, resulting in data compression of the order of 100 1 (Sekuler and Blake, 1994)

Earlier studies (Harmon 1973, Ginsburg 1978) concluded that information in low spatial frequency bands play a dominant role in face recognition as low-frequency components contribute to the global description, while the high-frequency components contribute to the finer details In the following sections, we analyzed the existing frequency domain algorithms viz, Discrete Fourier Transform (DFT), Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT) based face recognition methods which have been developed where low frequency feature extraction through novel methods is employed to achieve better results The existing Discrete Fourier Transform based face recognition is extended (Liu and Wang 2011) to fractional DFT for face recognition Motivated by the results of these extended face recognition models, we have proposed two novel extensions i e, Fractional Discrete Cosine Transformation and Discriminative Fractional Discrete Cosine Transformation for accurate representation and recognition of faces

5.2. Frequency Domain Based Face Recognition: A Review

The term "transform" means to change form or appearance In terms of signal processing, a transform is normally a tool that is used to convert the signals from time domain or spatial domain to the frequency domain There are various instances when it is pertinent to have the signal in the time domain and on the other instances it is important to have the signal in the frequency domain For most of the image processing applications, it is better to have the signal in the frequency domain In others words, a transformation can be described as the process of mapping the correlated data to no-correlated data Each pixel in an image is correlated with its neighbor pixels The information represented by any pixel should be predicted by its neighbors because of the fact that they are all correlated In the literature, various frequency domain transforms are proposed by researchers

The Fourier transform plays a critical role in a broad range of image processing applications including enhancement, analysis, restoration and recognition The DFT is used to decompose an image into its sine and cosine components The output of the transformation represents the image in the Fourier or frequency domain, while the input image is the spatial domain equivalent In the Fourier domain image, each point represents a particular frequency contained in the spatial domain image and it produces a complex number valued output image which can be displayed with two images, either with the real and imaginary part or with magnitude and phase In image processing, often only the magnitude of the Fourier Transform is displayed, as it contains most of the information of the geometric structure of the spatial domain image However, if we want to re-transform the Fourier image into the correct spatial domain after some processing in the frequency domain, we must make sure to preserve both magnitude and phase of the Fourier image Almas and Javed (2006) applied the Discrete Fourier Transform on Face databases viz , YALE and ORL In this approach, high frequency facial features are discarded through image decimation and secondly images are transformed through DFT and low frequency feature extraction is carried out by using square and circular feature extraction methods Results reflects that only 121 features out of 10304 are used for recognition which is a considerable dimension reduction with improved computing speed and found that the results are encouraging

Another important and the most popular frequency domain technique is the discrete cosine transform (DCT) It is a sinusoidal unitary transform The DCT has been used in digital signal and image processing and particularly in transform coding systems for data compression/decompression This type of frequency transform is real, orthogonal and separable Algorithms for its computation have proved to be computationally efficient

Ahmed et al (1974) first introduced the discrete cosine transform (DCT) in the early seventies Ever since, the DCT has grown in popularity, and several variants have been proposed (Rao and Yip, 1990) In particular, the DCT was categorized by Wang (1984) into four slightly different transformations named DCT-I, DCT-II, DCT-III, and DCT-IV Of the four classes, Wang defined, DCT-II was the one first suggested by Ahmed et al , and it is the most popular type The DCT is a mathematical operation that transforms a set of data which is sampled at a given sampling rate to its frequency components The number of samples should be finite and power of two for optimal computation time The DCT is a widely used frequency transform because it closely approximates the optimal Karhunan-Loeve Transform (KLT) while not suffering from the drawbacks of applying the KLT However, KLT is constructed from the eigenvalues and the corresponding eigenvectors of a covariance matrix of the data to be transformed It is signal-dependent and there is no general algorithm for its fast computation The DCT does not suffer from various drawbacks due to data-independent basis functions and existence of several algorithms for fast implementation The DCT provides a good trade-off between energy packing ability and computational complexity In the DCT based face recognition, main idea is to compute the DCT coefficients of a face image and select only a limited number of the coefficients (this limited selection corresponds to low spatial frequency coefficients) and use them as input to the recognition model The locations of the transformed coefficients retained for each image remain unchanged from one image to another It is computationally easier to implement and more efficient to regard the DCT as a set of basis functions which gives a known input array size (8x8) which can be pre-computed and stored An accurate and robust face recognition system was developed and tested Hafed and Levine (2001) proposed the system which exploits the feature extraction capabilities of the discrete cosine transform (DCT) and invokes certain normalization techniques that increase its robustness to variations in facial geometry and illumination The method was tested on a variety of available face databases The system was shown to perform very well when compared to other approaches

Wavelets are used to achieve multiresolution which is a powerful signal analysis tool and widely used in image compression and facial feature extraction applications Images have locally varying statistics that result from different combinations of abrupt features like edges, of textured regions and of relatively low-contrast homogeneous regions While such variability and spatial non stationary defies any single statistical characterization, the multiresolution components are more easily handled Wavelet transform can be performed for every scale and translation (resulting in continuous wavelet transform (CWT)), or only at multiples of scale and translation intervals (resulting in discrete wavelet transform (DWT)) An appropriate wavelet transform can result in robust representations with regard to lighting changes and is capable of capturing substantial facial features while keeping computational complexity low The DWT is computed by successive low pass and high pass filtering of the discrete time-domain signal

Wavelet transform techniques achieve optimal decomposition without affecting much of the image quality At the same time wavelet transform and wavelet packet analysis have provided a new subspace for image recognition Fotlyniewiez (1996) proposed an automatic face recognition using nonlinear filtering to enhance intrinsic features of face and used a high order neural network classifier for training and recognition of faces Lee and Chung (2000) employed the wavelet-based Fisher Linear Discriminant (FLD) recognition process Zhu and Orchard (2000) captured local discriminative features in the space frequency domain for face detection using wavelet packet analysis Ma and Tang (2001) used discrete wavelet face graph matching approach for the purpose Liu (2001) used Haar wavelet for effective human face detection Yang et al (2002) presented an application of nonlinear wavelet approximation to recognize faces and the advantages of nonlinear wavelet approximation compared to its linear counterpart L Wiskott (1997) used labeled graph based on Gabor wavelet transform for face recognition application

Wavelet analysis is useful for the purpose of face recognition since it offers good spatial-frequency localization characteristics Among various wavelet bases, Gabor wavelets provide a favorable tradeoff between spatial resolution and frequency resolution There is a strong biological relevance for processing images using Gabor wavelets (Daugman

1980) Gabor wavelets, whose kernels are similar to the 2-D receptive field profiles of the mammalian cortical simple cells (Field, 1987) have been proven to be capable of deriving desirable features in face recognition, mainly spatial frequency (scale), spatial locality, and orientation selectivity The Gabor wavelet transform possesses useful properties such as invariance to illumination, rotation, scale, and translation The available literature has demonstrated that using Gabor wavelets at the front end of an automated face recognition system is effective (Wiskott et al 1997, Daugman et al 1988, Lee 1996, Liu at al 2001) The Gabor wavelet representation of an image involves convolution of the image with a family of Gabor kernels at different spatial frequencies and different orientations To encompass the different spatial frequencies, spatial localities, and orientation selectivities, the resulting convolution representations are normally concatenated as an augmented feature vector (Liu at al 2002) A face image is typically represented as the convolution result of the face image with 40 Gabor wavelets (five scales, each with eight orientations) (Liu et al 2002, Liu 2004) Keeping only the magnitude values in the representation, this gives a "$h \times w \times 40$" vector, where $h \times w$ is the length of the face vector Unfortunately, the "$h \times w \times 40$" vector usually has a very large dimensionality To reduce the dimensionality of the vector, uniform sampling of the original Gabor features is traditionally used The drawback of using uniform sampling is that it falsely assumes that all Gabor features equally contribute to the face recognition task (Du and Ward, 2009) As a result, it may lead to a loss of features that are important while preserving many redundant ones If the original Gabor features are finely sampled, the resulting vector will still remain too large and will preserve many redundant or trivial features The required system resources (i e , central processing unit and memory) will be large, and the processing speed will be slow On the other hand, if the features are coarsely sampled, some important features may be lost, and the recognition rate will be low

As we have discussed in previous sections, the Fourier transform is one of the most important mathematical tools used in physical optics, linear system theory, signal processing, and so on (Bracewell, 1986) The generalization of Fourier transform called Fractional Fourier transform (FRFT) was first introduced by Namias in 1980 The conventional Fourier transform can be regarded as a $\pi/2$ rotation in the time-frequency plane, and the FRFT performs a rotation of signal to any angle Moreover, fractional Fourier transform serves as an orthonormal signal representation for chirp signal The fractional Fourier transform is also called rotational Fourier transform or angular Fourier transform in some documents Besides being a generalization of Fourier transform, the FRFT is also related to other time-varying signal processing tools, such as Wigner distribution (Hlawatsch 1992), short-time Fourier transform, Wavelet transform and so on Liu and Wang (2011) successfully applied Fractional DFT to perform face recognition task To overcome the problems associated with conventional Fourier transform, fractional discrete Fourier Transform is introduced by Jing et al (2006) and subsequently this fractional discrete Fourier transform is employed in many applications including face recognition Firstly, facial images are processed by using Fractional DFT and then PCA/FLD are combined to extract discriminative features Finally, the Euclidean distance based nearest neighbor classifier is employed for classification purpose

5.3. Proposed Models

Inspired by the work on fractional discrete Fourier Transform, Pei and Yeh (2001) introduced fractional discrete cosine transform that finds many applications in the field of signal processing such as image compression, watermarking etc It is observed that the recognition accuracy of Fractional Discrete Cosine Transformation (FDCT) is good when compared to other models of frequency domain FDCT is general form of DCT which has an additional free parameter and with this free parameter it finds its place in many applications where DCT is found to be useful Motivated by this, in our work, we explored the application of fractional DCT to face recognition problem Further, we proposed the cascaded model which uses Linear discriminant analysis as the classifier

5.3.1 Face recognition using Fractional DCT: This section presents the brief introduction to 2D-DCT followed by the application of fractional discrete cosine transform to face recognition

A 2-Dimensional DCT

The 2-D DCT is a direct extension of the 1-D case and is given by

$$C\,(u,v) = \alpha\,(u)\,\alpha\,(v)\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} f(x,y)\cos\left[\frac{\pi(2x+1)u}{2N}\right]\cos\left[\frac{\pi(2y+1)v}{2N}\right] \quad (5.1)$$

for u, v =0,1,2, ,$N-1$ and $\alpha(u)$ and $\alpha(v)$ *are given by*

$$\alpha(u) = \begin{cases} \sqrt{\frac{1}{N}}, & for\ u = 0 \\ \sqrt{\frac{2}{N}}, & for\ u \neq 0 \end{cases}$$

The inverse transform is defined as

$$f(x,y) = \sum_{x=0}^{N-1}\sum_{y=0}^{N-1} \alpha\,(u)\,\alpha\,(v)\,C(u,v)\cos\left[\frac{\pi(2x+1)u}{2N}\right]\cos\left[\frac{\pi(2y+1)v}{2N}\right] \quad \ldots(5\ 2)$$

for x, y =0,1,2, ,$N-1$

B Feature extraction using Fractional Discrete Cosine Transform

The kernel matrix of the DCT-I transform (Pei and Yeh, 2001) is

$$\left[M = \sqrt{\tfrac{2}{N}}\,k_m\,k_n\cos\left(\frac{mn\pi}{N}\right)\right] \quad (5\ 3)$$

for m, n = 0,1, ,$N-1$, where k_m is defined as

$$Km = \begin{cases} \frac{1}{\sqrt{2}}, & m = 0 \; and \; n = 0; \\ 1, & otherwise \end{cases}$$

The eigenvalues of DCT-I transform matrix, λ_i are 1 or -1 and the unique eigenvectors v_i can be obtained from the even Hermite-Gaussian eigenvectors of the Fourier matrix in the cosine case The eigen decomposition of an $N \times N$ DCT-I transform matrix M can be expressed by

$$M = V \Lambda V^T \quad (5.4)$$

where $V=[v_1|v_2| \quad |v_N]$ and $\Lambda=\text{diag}(\lambda_1,\lambda_2, \quad ,\lambda_N)$

With these eigenvalues and eigenvectors, the fractional transform matrix M_α is constructed by

$$M_\alpha = V \Lambda V^T \quad (5\ 5)$$

To design a real fractional transform matrix, a method is presented (Venturini and Duhamel, 2004) Set $N=2^b$ (b is an integer and $b \geq 2$) and $\lambda_1= \quad =\lambda_{N/2}=-1$, a block-diagonal matrix Λ_α is computed by

$$\Lambda_\alpha = \begin{bmatrix} G1_{\frac{N}{2}}(\theta(\alpha)) & 0 \\ 0 & G2_{\frac{N}{2}}(\eta(\alpha)) \end{bmatrix} \quad (5.6)$$

where G_1 and G_2 are block-diagonal matrices whose blocks are

$$G1_2(\theta(\alpha)) = \begin{bmatrix} \cos(\theta(\alpha)) & \sin(\theta(\alpha)) \\ -\sin(\theta(\alpha)) & \cos(\theta(\alpha)) \end{bmatrix}$$

and analogously for G_2 with the angle η θ and η are functions of the real fraction α Among the choices for θ and η, we consider the one with $\theta(\alpha)=2\pi\alpha$ and $\eta(\alpha)=\pi\alpha$

Once the given face image is transformed to an image in the frequency domain with the kernel specified, first few coefficients are used as feature values To summarize, the proposed face recognition algorithm with the multiple-order FDCT for a given face image F of size M×N is as follows

ALGORITHM: FACE RECOGNITION

Training Phase:

Step-1 Each row of the face image F is transformed by one-dimensional FDCT, with the transform fractional order of p_i for the i^{th} row, $i = 0,1, \ldots, M - 1$, and the transformed image is F_1

Step-2 Each column of F_1 is transformed by another one-dimensional FDCT, with the transform fractional order of q_j for the j^{th} column, $j = 0,1, \ldots, N -1$, and the resulting image, F_2.

Step-3 Extract the first r fractional DCT coefficients to form a feature vector for a face image F

Recognition Phase:

Step 1 Given the test face image, say T, use Step-1 and Step-2 specified in Training phase to obtain the face image, say T_F in frequency domain.

Step-2 Extract the first r fractional DCT coefficients from T_F to form a feature vector for a test face image T

Step-3. Take the nearest neighbor classifier to classify T_F Here, the distance between two arbitrary samples, z_1 and z_2, is defined by: $d(z1, z2) = \|z1 - z2\|_2$ where $\| \|_2$ denotes Euclidian Distance

ALGORITHM ENDS.

Experimental results: This section presents the results of the experiments conducted to corroborate the success of the proposed model We have conducted experimentation on AT&T face image databases All experiments are performed on a P-IV 2 99GHz Windows machine with 1 GB of RAM The experiments on the above database has been conducted by setting parameters values of α=5 and p = N/2 where N is the length of the row/column vector

We have considered AT&T face database and chosen alternate five samples for training and the remaining samples for testing and the recognition performance is obtained On the similar line, we have considered alternate four samples, three samples and two samples for training and the remaining samples for testing and the recognition accuracy is computed The results are tabulated in Table 5 1 Recognition accuracy of proposed fractional DCT algorithm on UMIST face database is given Table 5 2 It shall be observed that the proposed model possess best recognition accuracy

Table 5 1 Recognition accuracy of Fractional DCT on AT & T face database

Step size	No of Training Faces	Dimension of Feature Vector							
		5	10	15	20	25	30	35	40
2	**200**	94 5	96 5	96 0	96 0	96 0	96 0	96 0	96 5
3	**160**	96 0	98 5	98 5	98 5	98 5	98 0	98 0	98 0
4	**120**	89 5	94 0	93 0	92 5	92 5	92 5	92 0	92 0
5	**080**	70 5	70 0	70 0	70 0	69 5	70 0	70 0	69 5

Table 5 2 Recognition accuracy of Fractional DCT on UMIST face database

Step size	Number of Training Faces	Dimension of Feature Vector			
		10	20	30	40
2	**260**	99 4	99 4	99 4	99 4
3	**180**	99 2	99 2	99 2	99 2
4	**140**	99 2	99 4	99 4	99 4
5	**100**	98 4	98 0	98 0	98 0

5.3.2 Discriminative Fractional Discrete Cosine Transform for Face Recognition

Motivated by the results of frequency domain based face recognition, we have proposed a new cascading model which is called as Discriminative Fractional DCT In this model, we propose a robust and an accurate face recognition concept which uses the feature extraction capabilities of fractional discrete cosine transform (FDCT) followed by Linear Discriminant analysis (LDA) for compact representation of feature vectors The proposed model is tested on publicly available standard AT&T and YALE face databases to exhibit the superiority of fractional DCT technique in terms of recognition accuracy.

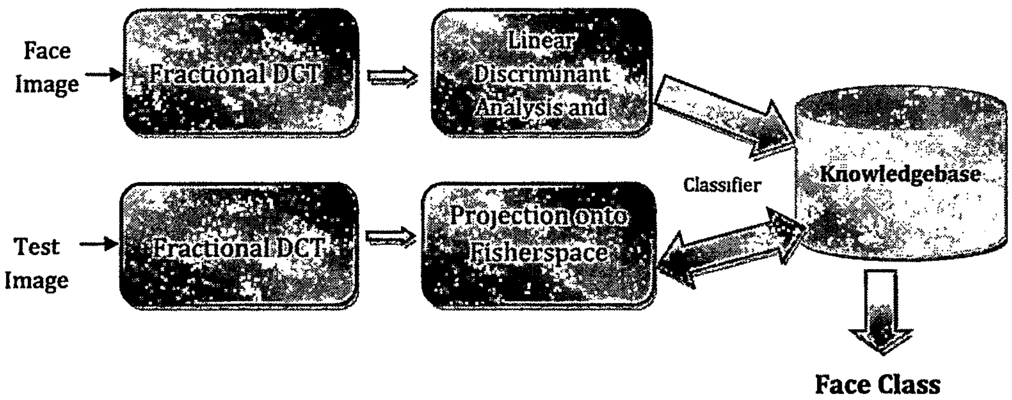

Fig 5 1 Discriminative Fractional DCT based model

The block diagram of new proposed model is shown in the Figure 5 1 In the first stage, we extract the first *r* fractional DCT coefficients to form a feature vector for a face image F In the second stage using linear discriminant analysis (LDA), compute the optimal projection axes (dominant eigen vectors) Project these feature vectors onto dominant eigen vectors to create knowledgebase For classification use the nearest neighbor classifier

Fisher Linear Discriminative Analysis:

Training scheme Let there be N number of training images Let there be T number of classes each with k_i, i=1 T, number of training images Therefore we have totally $N=\sum_{i=1}^{T} k_i$ number of training images Let A_i^j be an image of size $m \times n$ representing j^{th} sample in i^{th} class Let $\overline{A}_i$ be the average image of all k_i training images of the i^{th} class and represented in the column vector form Each image A_i^j is converted into a column vector c_i^j of length M (= m× n) Let $\overline{A}$ be the average image of all N training images and represented as a column vector Let us consider a linear transformation function mapping the original M dimensional image space into d-dimensional feature space, where M << d Since the learning set is labeled, by using class-specific linear methods for dimensionality reduction, one may get better recognition rates than eigenfaces method FLD is a well-known example of a class-specific method and hence the linear transformation function shall be chosen in such a way that the ratio of the between-class scatter matrix and the within-class scatter matrix is maximized Let the between-class scatter matrix G_b and the within-class scatter matrix G_w are computed as follows

$$G_b = \frac{1}{N}\sum_{i=1}^{T} k_i(\overline{A}_i - \overline{A})(\overline{A}_i - \overline{A})^T \tag{5.7}$$

$$G_w = \frac{1}{N}\sum_{i=1}^{T}\sum_{j=1}^{k_i}(A_i^j - \overline{A}_i)(A_i^j - \overline{A}_i)^T \tag{5.8}$$

Once G_b and G_w are computed, it is recommended to find the optimal projection axis X so that the total scatter of the projected samples of the training images is maximized If G_w is non-singular, the optimal projection X is chosen as the matrix with orthonormal columns which maximizes the ratio of the determinant of the between-class scatter matrix of the projected samples to the determinant of the within-class scatter matrix of the projected samples, i e ,

$$X = \arg\max_{X} \frac{\left|X^T G_b X\right|}{\left|X^T G_w X\right|} \tag{5.9}$$

Here, $X = \{x_1, x_2 \; x_d\}$ is the set of generalized eigenvectors of G_b and G_w corresponding to the first d largest eigenvalues $\lambda_1, \lambda_2, \; , \lambda_d$ i e ,

$$G_b x_i = \lambda_i G_w x_i,\; i=1,2, \; ,d \qquad .. (5.10)$$

It shall be noticed here that there are at most T-1 nonzero generalized eigenvalues, and hence an upper bound on d is T-1, where T is the number of classes (Duda and Hart, 1973) Though all the M eigenvectors are needed to represent images exactly, only a small number, $d << T$, is generally sufficient for capturing the primary characteristics of the objects The d eigenvectors, corresponding to the d largest eigenvalues, constitute the *fisherspace* Thus fisherspace analysis can drastically reduce the dimension (M) of the images to the fisherspace dimension (d) while keeping several of the most effective features that summarize the original images

Recognition Procedure

The proposed face recognition approach contains three steps feature extraction through FDCT, discriminative feature extraction using a Fisherface method and classification using the nearest neighbor classifier It is described as follows

ALGORITHM: FACE RECOGNITION

Training Phase:

Step-1 Each row of the face image F is transformed by one-dimensional FDCT, with the transform fractional order of p_i for the i^{th} row, $i = 0,1,..,M-1$, and the transformed image is F_1.

Step-2 Each column of F_1 is transformed by another one-dimensional FDCT, with the transform fractional order of q_j for the j^{th} column=0,1, . ,N-1, and the resulting image, F_2.

Step-3 Extract the first r fractional DCT coefficients to form a feature vector for a face image F.

Step-4: Compute the optimal projection axes (dominant eigen vectors) using LDA as described in section 5 4

Step-5: Project the feature vectors obtained in step-4 onto dominant eigen vectors to create **knowledgebase**.

Recognition Phase:

Step 1: Given the test face image, say T, use Step-1 and Step-2 specified in Training phase to obtain the face image, say T_F in frequency domain

Step-2: Extract the first r fractional DCT coefficients from T_F to form a feature vector for a test face image T

Step-3 Project T_F dominant Eigen vectors onto T_F'.

Step-4: Take the nearest neighbor classifier to classify T_F. Here, the distance between two arbitrary samples, z_1 and z_2, is defined by: $d(z_1, z_2) = \|z_1 - z_2\|_2$ where $\| \|_2$ denotes Euclidian Distance

ALGORITHM ENDS.

Experimental Results: This section presents the results of the experiments conducted to corroborate the success of the proposed model We have conducted experimentation on AT&T which has 400 face images of 40 individuals with 10 different views and YALE face image databases The YALE face image database contains 165 images of 15 subjects that include variation in both facial expression and lighting The experiments on the above data bases has been conducted by setting parameters values of α=0 75 for YALE database and α=5 for AT &T database All experiments are performed on a P-IV 2 99GHz Windows machine with 1 GB of RAM

In the first experimental set up, we have considered AT&T face database and chosen alternate five samples for training and the remaining samples for testing and the recognition performance is obtained On the similar line, we have considered alternate four samples, three samples and two samples for training and the remaining samples for testing and the recognition accuracy is computed The results are presented in Table 5 3

Table 5 3 Experımental results of Dıscrımınatıve FDCT on AT&T face database

STEP SIZE:2	Dımensıon of feature vector				
	3×3	4×4	5×5	6×6	7×7
20×20	94 5	97 0	98 0	97 7	98 2
30×30	94 5	96 7	97 7	97 7	98 2
40×40	94 5	96 2	97 5	97 7	98 0
50×50	94 2	96 5	97 2	98 0	98 2
STEP SIZE·3					
20×20	94 0	97 7	98 5	98 5	99 2
30×30	93 0	97 0	98 0	98 0	99 0
40×40	92 5	98 0	98 0	98 0	98 7
50×50	92 2	98 5	98 7	99 0	99 7
STEP SIZE:4					
20×20	87 3	90 2	93 5	95 5	96 2
30×30	87 7	92 0	94 0	96 5	96 5
40×40	85 8	90 0	95 0	96 5	97 0
50×50	85 0	362	90 5	95 8	96 0
STEP SIZE:5					
20×20	76 5	80 0	86 2	86 2	85 8
30×30	75 0	82 3	84 3	85 5	85 7
40×40	71 7	80 0	84 5	85 3	85 7
50×50	74 0	83 3	83 3	85 2	86 5

Similar process of experimentation on YALE database is conducted Table 5 4 shows the results of discriminative FDCT on YALE face database

Table 5 4 Experimental results of Discriminative FDCT on YALE Face Database

	Dimension of feature vector				
STEP SIZE:2	3×3	4×4	5×5	6×6	7×7
20×20	92 2	93 4	95 2	96 4	97 4
30×30	91 6	94 5	95 8	95 8	97 6
40×40	91 6	94 5	94 5	94 5	96 7
50×50	91 2	93 3	93 4	95 2	95 8
STEP SIZE:3					
20×20	85 1	85 5	91 6	92 2	94 5
30×30	86 5	86 7	91 2	94 5	93 3
40×40	85 3	87 3	92 2	94 5	96 7
50×50	83 5	84 9	95 2	93 3	95 2
STEP SIZE:4					
20×20	82 1	82 5	86 1	89 7	91 0
30×30	83 6	84 4	87 9	90 3	90 3
40×40	83 6	84 0	91 6	91 6	92 2
50×50	83 6	86 1	92 2	94 5	95 8
STEP SIZE:5					
20×20	80 1	84 3	89 1	91 6	90 0
30×30	80 1	85 5	86 7	91 6	92 2
40×40	83 1	85 5	88 5	92 0	92 2
50×50	83 1	86 7	91 0	93 4	93 4

5.4 Conclusion

A known problem in performing face recognition is to determine what facial features constitute the most relevant dimensions of a face In attempting to solve this problem, there has been controversy with respect to the relevance of various spatial frequency bandwidths for face perception and processing The structure and internal geometry of face images describes that only low-frequency spectrum is sufficient for the processing of faces for recognition, whereas high frequency components of facial image convey facial information which does not contribute much in recognition process In this direction, we have proposed new robust and an accurate face recognition algorithms which work in the frequency domain The proposed models are based on fractional discrete cosine transform which is generalized version of discrete cosine transform and linear discriminant analysis Experimentation on the standard face databases have been conducted and comparative analysis is provided with well known recent algorithms to demonstrate the superiority of the proposed models for face recognition problem