Feature Image Generation Using Energy Distribution for Face Recognition in Transform Domain

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Abstract. In this paper, we propose a feature image generation method for face recognition. Feature extraction is done using three transforms viz. Discrete Cosine Transform, Slant Transform and Walsh Transform. Energy distribution defined as magnitude of effective information is used to create a feature image in transform domain by retaining high energy distribution coefficients. The proposed method consists of three steps. First, the face images are transformed into the frequency domain. Second, transformed coefficient matrix and energy distribution matrix is divided into three equal regions. Thresholds are selected in each region to retain the most significant features. Finally feature image is generated from these coefficients. Recognition is performed on generated feature images using Mahalanobis distance. Experimental results shows that the proposed method improve the face recognition rate as compared to previously proposed methods.

Keywords: Face Recognition, Discrete Cosine Transform (DCT), Slant Transform (ST), Walsh Transform (WT), Energy Distribution (ED), Mahalanobis distance.

1 Introduction

In Biometrics inherent characteristics of human beings are used for verification and validation. Face recognition use biometric features for Identifying or verifying one or more persons in the scene using a stored database of faces if a still or video image of a scene is given. There is an increasing need for face recognition technology due to concerns in security such as in identification for authentication, Law enforcement and surveillance, smart cards, access control, for perceptual user interfaces. However, the general problem of face recognition remains to be solved, since most of the systems to date can only successfully recognize faces when images are obtained under prescribed conditions. The problem added due to effects of illumination could cause the system to degrade the performance and are larger than the difference between individuals. The most common issues are expression, aging, distractions such as glasses or changes in hairstyle, illumination problem and the pose problem as proposed by Ramanathan N, et al., [13]. To cope with the issues and to construct a computational model is quite difficult. While designing a system certain issues are needs to be challenged since faces are complex, multidimensional, and subject to change over

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time. Thus, face recognition is an unsolved problem under the conditions of pose and illumination variation, but still attracts significant research efforts.

In face recognition, feature extraction is most important, and it involves the reduction of high dimensional image data into low dimensional feature vector. Principal Components Analysis (PCA) technique resolve high dimensional problem giving dimension reduction, and is one of the most frequently used technique. Mathematical transforms such as Discrete Fourier Transform (DFT), Discrete Wavelet Transform (DWT), Discrete Cosine Transform (DCT) has been widely used to generate feature vectors. Weilong Chen, Meng Joo Er, and Shiqian Wu, [15] use DCT to generate feature image by using PCA and Linear Discriminant Analysis. In particular, many data compression techniques employ the DCT, which has been found to be asymptotically equivalent to the optimal Karhunen-Loeve Transform (KLT) for signal decorrelation. In DCT, coefficients with large magnitude are mainly located in the upper-left corner of the DCT matrix. They are the low spatial frequency DCT components in the image. M. J. Er, W. Chen, and S. Wu.[11] states that the DC or the first three low frequency coefficients have been truncated in order to decrease the effects of the illumination variation. C. Sanderson and K. K. Paliwal [2] shows that the polynomial coefficients are derived from the 2D-DCT coefficients obtained from the spatially neighboring blocks. Jiang and Feng [10] showed that removal of DC element enables the reconstructed facial image to be robust to lighting changes and removal of high-frequency DCT coefficients to be robust to scaling variations. X.Y. Jing and D. Zhang [16] proposed an approach to find discriminant bands (a group of coefficients) in the transformed space. Their approach searches the discriminant coefficients in the transformed space group by group. In this case, it is possible to lose a discriminant coefficient placing beside the non- discriminant coefficients in a group as shown by Dabbaghchian, S., Aghagolzadeh, A., and Moin M.S.[3]. DCT obtains the optimal performance of PCA in facial information compression and the performance of DCT is superior to conventional transforms. Jean Choi et al. [7] proposed face recognition using energy probability to generate a frequency mask without attention to the class.

Slant and Walsh transforms are also popular transforms used in the face recognition techniques. In Slant transform the coefficient selection affects the performance of the face recognition scheme significantly. The high frequency components are relatively vulnerable to compression operations, while the low frequency components must be retained for visual quality of the face image. The middle frequency band retains the overall information as stated by Anthony T. S. Ho, et al. [1]. The Slant transform has more useful middle and high frequency bands. The concept of an orthogonal transformation containing Slant basis vector was introduced by Enomoto and Shibata [4]. The Slant vector is a discrete saw tooth waveform decreasing in uniform steps over its length. Slant vectors are suitable for efficiently representing gradual brightness change in a face image. Walsh kernel is separable and symmetric and its function holds unique sequency value. Jia, Xiaoguang and Nixon, Mark S. [9] has used the Walsh Transform to extract the facial profile from a frontal view to provide a measure for automatic face recognition. The Walsh power spectrum is used to derive profile from the intensity projection of the face image. The work proposed by H B Kekre, et al. [6] used transform based technique and compares the performance with vector quantization (VQ) technique. Transform based face recognition technique considers full and partial feature vector of an image. Jia, X. and

Nixon, M. S. [8] describes a measure of the facial profile feature from a frontal view of the face for automatic face recognition.

In this paper, we propose a new feature image generation method to enhance the image classification and improve the recognition. We consider different transform (DCT, Walsh, or Slant), and information of different frequency bands is retained separately. Energy distribution is used to set the parameters for the selection of different frequency bands to construct feature image. Using this we retain the important coefficients of each band generating the feature image suitable for recognition. The recognition achieves better recognition results compared to traditional approaches of face recognition.

The rest of the paper is organized as follows. In Section 2, the methodologies used are briefly introduced. This includes the different transforms used (DCT, Slant Transform, Walsh Transform). Also the energy distribution and Mahalanobis distance are defined. Section 3 describes the proposed technique and experimental results are described in Section 4. At end in Section 5 conclusions are mentioned.

2 Methodology

2.1 Energy Distribution (ED)

Energy is one of the important characteristic of image defined by following equation

$$Energy_C = \sum_{u=1}^{N} \sum_{v=1}^{N} \left| F(u,v) \right|^2$$

Where, *F(u,v)* represents image in transform domain.

Energy Distribution *ED(u, v)* represents the energy contribution of each transformed coefficient and is given by following equation:

$$ED(u,v) = \frac{\left| F(u,v) \right|^2}{Energy_C}$$

The magnitude of *ED(u, v)* gives Energy Distribution matrix.

3 Proposed Technique

In the proposed technique we consider two datasets viz. training datasets containing set of face images for extracting the relevant information and test dataset for the face image to be recognized. The face images in the training dataset are converted to transform domain (DCT, Slant or Walsh). The transformed coefficients after zigzag scan are divided equally into three bands, namely low frequency, middle frequency and high frequency and are represented by *TCvector*. This is shown diagrammatically in Figure 1.Low frequency coefficients are related to illumination variation and smooth regions (like forehead, cheeks etc) of face. High frequency coefficients represent noise and detailed information of edge. The middle frequency coefficients represents the basic structure of the of face image. It shows that each band contains important information. Hence we cannot ignore the low frequency components to compensate illumination variations if the image is not so much affected by lighting conditions. Similarly we cannot truncate the high frequency coefficients to remove noise as they are responsible for details and edge information of the image.

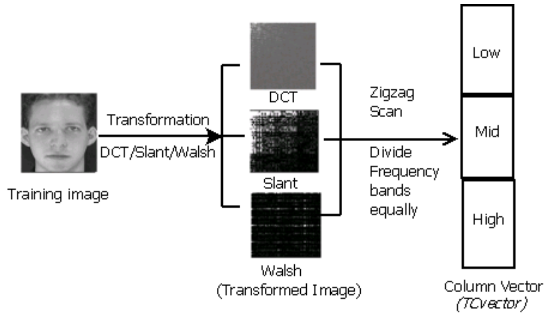

Fig. 1. Formation of Column Vector (*TCvector*)

Energy is used to describe a measure of "information" in an image. *E*nergy *D*istribution represented by *ED(u, v)* as described in section 2.1 gives the contribution of individual transformed coefficients. Let M be the total number of facial images of training dataset and N as width and height of all images. The *ED*, of size NxN, is converted into the column vector by performing Zigzag scan of length N*N represented by *EDvector*. The *EDvector* is divided into three equal regions similar to the *TCvector*.

The high value of *ED(u, v)* means more valid information. To achieves reduction in data while retaining the important features we set different thresholds in three regions of *EDvector*. Energy distributions below the different thresholds in different regions of *EDvector* are set to zero.

$$Featureimage(u,v) = \begin{cases} 0 & , \quad if \;\; ED(u,v) < threshold \\ F(u,v) & , \quad otherwise \end{cases}$$

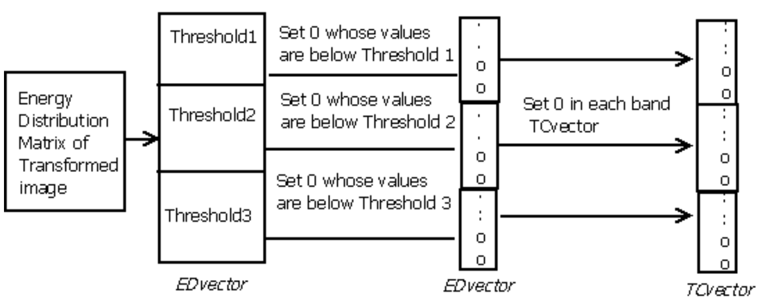

Fig. 2. Feature Image Generation

Finally we generate Feature image represented as *Featureimage(u,v)* by retaining corresponding coefficients of *TCvector* that we retained in the *EDvector*. This is shown diagrammatically in Figure 2.

Figure 3 depicts the whole procedure of face recognition by Feature Image Generation. Face images in the training set are converted into Transform domain. The Energy distribution is defined as criterion of selecting effective facial features. Energy distribution is calculated for the dimension reduction of data and optimization of valid information. Similar procedure is carried out for test image to form *TFeatureimage(u,v)*. Mahalanobis distance between set of *Featureimage(u,v)* and the test image formed as *TFeatureimage(u,v)* is calculated. The *Featureimage(u,v)* which gives minimum distance from the set of training images and test image will give recognized face.

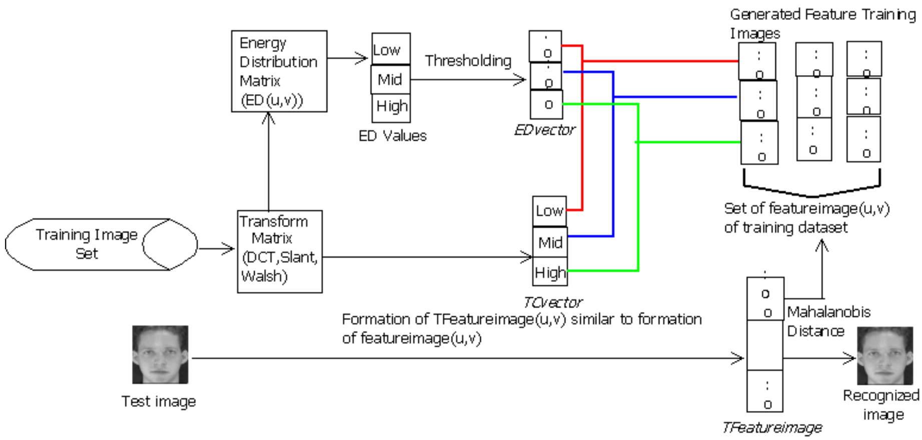

Fig. 3. Proposed Technique for face Recognition

4 Experimental Results

To validate the results we implement the proposed technique in MATLAB 2010. The experimentation is carried out on ORL dataset and Yale dataset. To prove the robustness of the technique, we considered only two poses of each individual (out of 10 poses of each individual in the training dataset) i.e., 80 images of 40 individuals are considered in case of ORL training dataset [5]. Similarly in case of Yale dataset 30 images (two poses of each individual) of 15 people in the training dataset are considered. Test dataset contains poses that are different than the training dataset.

4.1 Experimental Result Analysis Based on ORL Face Dataset

We implement our technique by using DCT, Slant and Walsh Transform. Figure 4 shows test image and its correctly recognized image. All the input test images correctly recognizes the face from the training dataset even if there is change in emotions like- neutral, smile, laughter, sad/disgust and poses like looking front, looking left, looking right, looking up, looking up towards left, looking up towards right, and looking down.

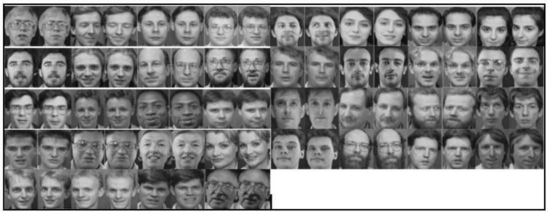

Fig. 4. Test image and corresponding recognized faces of ORL dataset

Table 1 shows the recognition rate using DCT transform with different thresholds in low, mid and high frequency bands. The experimentation is carried out on different threshold combinations to decide the correct threshold for the better recognition rate. But due to space limitations we had shown only two set of thresholds with threshold1 30 in low frequency band, threshold2 7 in mid frequency band and threshold3 0.4 in high frequency band for the first set. The second set of different thresholds is prepared with threshold1 as 35, threshold2 as 10 and threshold3 as 0.7. The second set thresholds show the improvement in the recognition rate. The proposed technique is also compared with standard PCA as introduced by M. Turk and A. Pentland [12] and DCT normalization technique as used by Štruc, V. and Pavešić, N [14]**.** Table shows that the proposed technique has high recognition rate as compared to other techniques.

Table 1. Recognition rate of ORL Face dataset using DCT

ORL Dataset Recognition				
Test Images	No. of correctly recognized faces			
	Proposed DCT[30,7,0.4]	Proposed DCT[35,10,0.7]	PCA (Mahalanobis)	DCT Normalization
Images(1-10)	9	9	8	8
Images(11-20)	9	9	8	8
Images(21-30)	7	8	5	5
Images(31-40)	10	10	8	8

Table 2 shows the face recognition rate using Slant and Walsh transform with different thresholds. Here a set of threshold with values [35, 7 and 0.4] are considered and tested on Slant transform and the Walsh transform. The result is also compared with PCA and DCT normalization techniques. From the table it is clear that the proposed technique gives approximately same results on DCT, Slant as well as Walsh transforms. This shows that the technique is robust to any kind of transform used.

The comparative study of different transforms with different set of thresholds is done by plotting the No. of training images tested against the corresponding recognition rate. Figure 5 shows the plot for DCT transform with Thresholds [30, 7, 0.4] and Figure 6 with Thresholds [35, 10, 0.7] respectively. Figure 7 shows the plot for Slant and Walsh Transform with Thresholds [35, 10, and 0.7].

Table 2. Recognition rate of ORL Face dataset using Slant and Walsh transform

ORL Dataset Recognition				
Test Images	No. of correctly recognized faces			
	Proposed Slant[35,7,0.4]	Proposed Walsh[35,7,0.4]	PCA Mahalanobis	DCT Normalization
Images(1-10)	9	9	8	8
Images(11-20)	9	9	8	8
Images(21-30)	7	7	5	5
Images(31-40)	10	10	8	8

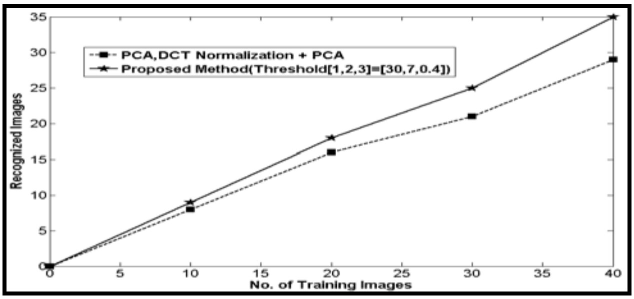

Fig. 5. Plot of No. of training images tested Vs. recognition rate [DCT (30, 7, 0.4)]

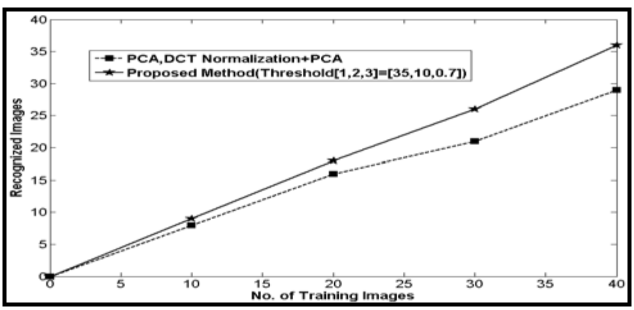

Fig. 6. Plot of No. of training images tested Vs. recognition rate [DCT (35, 10, 0.7)]

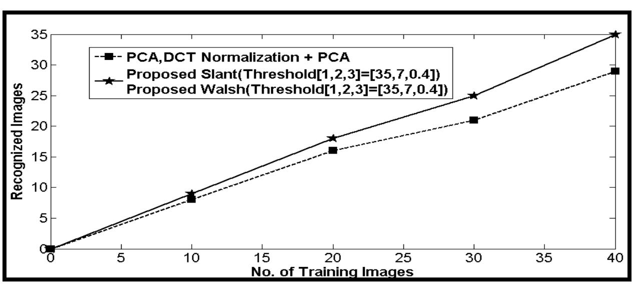

Fig. 7. Plot of No. of training images tested Vs. recognition rate (Slant & Walsh transform)

4.2 Experimental Result Analysis Based on YALE Face Database

Yale face dataset comprises eleven frontal images of each of fifteen people, wherein the images have different face expressions, with or without glasses, and these images are taken under different illumination conditions [17]. Figure 8 shows test image and its correctly recognized image. The test image and the recognized images vary in facial expressions with or without glasses, etc.

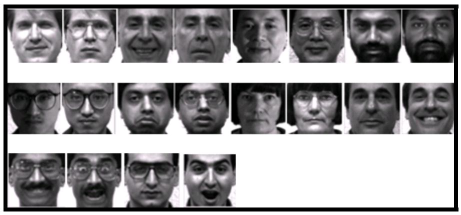

Fig. 8. Test image & corresponding recognized images of YALE dataset

The proposed technique is tested on YALE dataset using DCT, Slant and Walsh transform. Table.3 shows the experimental results using DCT transform with set of different thresholds [30, 7, and 0.4] and [35, 7, 0.4]. As seen from the Table 3 the proposed technique using DCT on YALE dataset gives maximum recognition rate with threshold set of [30, 7, and 0.4].

Table 3. Recognition Table of YALE Face Dataset

Recognition Table of YALE Face Dataset				
Range of Images	Proposed DCT [30,7,0.4]	Proposed DCT [35,7,0.4]	PCA (Mahalanobis)	DCT Normalization
Images(1-15)	10	9	7	7

Table.4 shows recognition rate on Slant and Walsh transform with thresholds [35, 7, and 0.4]. From the table 3 and 4 it is evident that the face recognition rate on thresholds [35, 7, and 0.4] for Slant and Walsh transform and on thresholds [30,7,0.4] for DCT transform is same.

Table 4. Recognition Table of YALE Face Dataset

Recognition Table of YALE Face Dataset				
Range of Images	Proposed Slant [35,7,0.4]	Proposed Walsh [35,7,0.4]	PCA (Mahalanobis)	DCT Normalization
Images(1-15)	10	10	7	7

The comparative study of different transforms with different set of thresholds is done by plotting the No. of training images tested. Figure.9 shows the plot for DCT with Thresholds [35, 7, and 0.4] and [30, 7, and 0.4]. Similarly Figure 10 shows the plot for Slant and Walsh transform with Thresholds [35, 10, and 0.7].

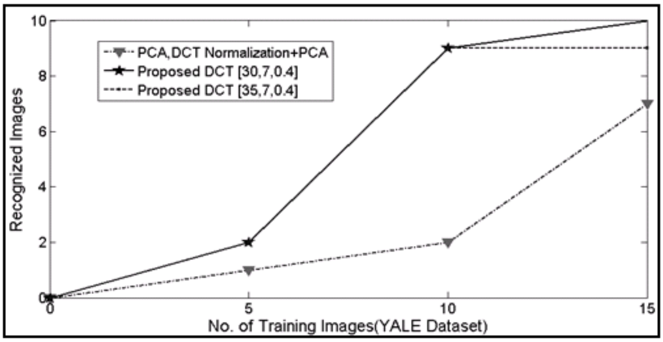

Fig. 9. Recognition Graph of proposed work using DCT transform on YALE Face Dataset

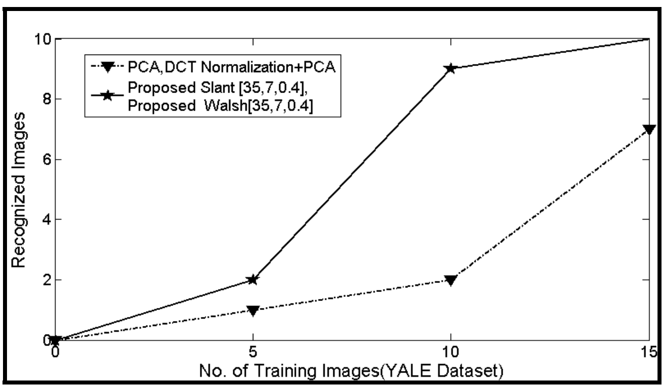

Fig. 10. Recognition Graph of proposed work using Slant and Walsh transform on YALE Face Dataset

5 Conclusion

Transform based feature image is generated for face recognition. Our method consists of three steps. First, face images are transformed into Transform domain. Second, Transform coefficients acquired from face image is applied on energy distribution for the selection of different thresholds. Third, in order to obtain the most expressive features only higher value energy distribution coefficients are kept, this facilitates the selection of useful Transform coefficients for face recognition. For the purpose of retaining most distinctive features of individual we optimize information by different thresholds. At last, distance measure is done directly on generated feature image by

Mahalanobis distance without using PCA. As PCA is not used, efficiency also get increased. The experimental results with ORL face database shows that the proposed method has shown better recognition performance than existing methods.

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