Face Recognition Using Discrete Cosine Transform and Nearest Neighbor Discriminant Analysis

Surya Kant Tyagi and Pritee Khanna

***Abstract*—In this paper we have proposed a new combination of DCT with Nearest Neighbor Discriminant Analysis (NNDA) for face recognition. Discrete Cosine Transform (DCT) is a powerful transform to extract features from a face image. It is requisite to discriminate classes using extracted DCT features. Some low frequency DCT coefficients are selected and given as input for Discrimination analysis. We used DCT for feature extraction, low frequency DCT coefficients are selected since they carry most of the information, then NNDA is used for discrimination analysis. We applied 2-level Discrete Wavelet Transformation(DWT) only for non-match faces and smoothed those images by zeroing vertical coefficients of DWT, since those coefficients are responsible for the effect of small expressions and edges in facial images, considering this, image is reconstructed after zeroing its vertical DWT coefficients and classified once again. When experimented, we achieved 99% (at 50 features) and 98.5% (at 70 features) recognition rate on ORL and Yale databases respectively. This method is found to be robust for expressions and small pose variations of facial images.**

***Index Terms*—Discrete cosine transform (DCT), nearest neighbor discriminant analysis (NNDA), discrete wavelet transform (DWT), inverse discrete wavelet transform (IDWT), face recognition.**

I. Introduction

Face Recognition is been widely studied field for last several decades and hence many techniques have been developed so far, complete review can be found in [1]. People are been attracting towards this field with alacrity. Its application towards security and surveillance, law enforcement and commercial, motivates and encourages researchers to make it the subject of their research.

Face Recognition techniques can be categorized into three types: Generative methods, Feature based methods and holistic methods. Generative methods are used to address the problem of varying illumination in face recognition. Feature based methods extract local features from a face image like eyes, nose, mouth and chin. Holistic methods are based on global appearance of a face image. Features are extracted and augmented into a signal vector and can be considered as point in the feature space [13]. Spatial domain does not give much information about a face image; hence face image is first transformed from spatial domain to frequency domain using FFT, DWT and DCT like transformations. DCT is found to be the powerful transformation for feature extraction due to its data compaction property. For appearance based methods features are extracted then data redundancy is reduced by applying some dimensionality reduction methods like PCA, LDA and ICA. Recently other discrimination methods are also evolved. Saeed Dabbaghchian, Masoumeh P. Ghaemmaghami and Ali Aghagolzadeh used DCT for feature extraction and proposed a Discrimination Power Analysis technique for face recognition in [2]. Ziad M Hafed and Martin D. Levine used DCT for face recognition along with geometrical and illumination normalization techniques in [3]. He also suggested that DCT could be used as first stage transformation followed by linear discrimination analysis. DCT is used as feature extraction then probability energy is calculated along with data reduction using LDA in [4]. Dattatray V. Jadhav, Raghunath S. Holambe used Radon Transform and DCT for feature extraction in [5]. They applied Radon Transform to enhance the low frequency component and then DCT is applied for dimensionality reduction. Nan Liu, Han Wang proposed a method based on trace transform and DCT [6]. They proposed a fusion scheme on DCT filtered trace transformed face images. Various dimensional reduction methods are present in literature recently a new dimensionality reduction method based on non-parametric scatter matrix was proposed in [7] by Y.-J. Zheng, J.-Y. Yang, J. Yang, X.-J. Wu and Z. Jin. It seems to be more intuitive because it uses point to line distance which is gained by Nearest Neighbor Line (NNL) algorithm, to evaluate the class difference. Kadir Kırtaç, Onur Dolu, Muhittin Gokmen utilized the power of NNDA along with Gabor wavelet in [8]. Power of NNDA was evident in their work. We were interested in simpler feature extraction method and hence we chose DCT for fast feature extraction and then applied NNDA for dimensionality reduction..

In this paper we propose a new combination of Discrete Cosine Transform (DCT) and Nearest Neighbor Discriminant Analysis (NNDA) in [7], DCT+NNDA for face recognition. First, features from facial images are extracted using DCT, then it applies to NNDA to learn NNDA projection then data is projected onto the feature space. We have also proposed a smoothing technique based on Discrete Wavelet Transform (DWT) for smoothing images and that would be applied at post classifying stage i.e. we are doing smoothing only for the non-matched images. We observed that non-match faces were not matching due small face expressions and vertical edges. In order to smooth such face we applied Discrete Wavelet Transform and reconstructed those faces after zeroing there DWT vertical components and matched again. Similar kind of image smoothing technique was proposed in [10] by A. Abbas, M. I. Khalil, S. Abdel-Hay and H. M. Fahmy, they reconstructed images after zeroing all high frequency components while we have

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Authors are with the Computer Science and Engineering at Indian Institute of Information Technology, Design and Manufacturing Jabalpur, 482 005 India. (e-mail: suryakantt@iiitdmj.ac.in; pkhanna@iiitdmj.ac.in).

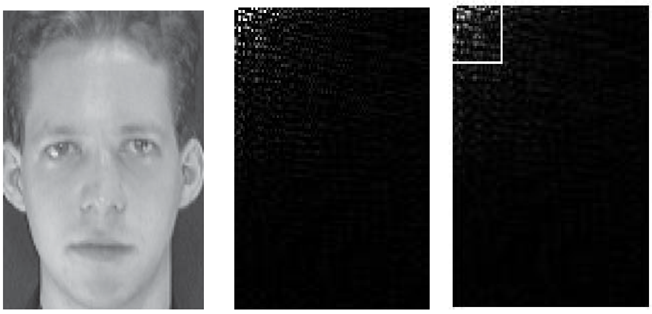
considered vertical coefficients only. We achieved 99 % and 98.5% recognition rate on ORL[12] and Yale Database [11] respectively.

Rest of the paper is organized as follows: Section 2 defines DCT, NNDA and DWT; Section 3 describes proposed method, Section 4 discusses the results, and Section 5 presents conclusions and future direction.

II. Definition

A. Discrete Cosine Transform

DCT is been highly used in image processing and signal analysis due to its 'energy compaction' property. It compresses most signal information in some coefficients. Considering this, here DCT is chosen for feature extraction. First DCT is applied on entire face image which is in result gives low and high frequency coefficients feature matrix of same dimensions, Fig. 1(b). Secondly, few low frequency DCT coefficients are selected as feature vector from each image to construct feature space.



(a) (b) (c)

Fig. 1. (a) A face image from ORL database (b) its DCT transformed image (c) Top-left (low frequency) rectangle carries maximum information

Assuming a face image can be considered as a matrix $f(x,y)$ of dimensions $M \times N$, , then its DCT transform $F(u,v)$ having dimensions $M \times N$, , can be obtained by:

$$F(u,v) = \frac{1}{MN}\alpha(u)\alpha(v) \times \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y) \times \cos\left(\frac{(2x+1)u\pi}{2M}\right) \times \cos\left(\frac{(2y+1)v\pi}{2N}\right) \quad (1)$$

where, $u = 0,1,2,\ldots\ldots\ldots M$, $v = 0,1,2,\ldots\ldots\ldots N$ and $\alpha(w)$ is defined as:

$$\alpha(w) = \begin{cases} \frac{1}{\sqrt{2}} & w = 0 \\ 1 & otherwise \end{cases} \quad (2)$$

Here, x and y are coordinates in special domain while u and v are the frequency coordinates in transformed domain. The first coefficient $F(1,1)$ is named as DC (Direct Current) while remaining coefficients are AC (Alternate Current). DC coefficient depends on the average image brightness while AC coefficients indicate the amplitude corresponding to the frequency components of $f(x,y)$.

B. Nearest Neighbor Discrimination Analysis

Nearest Neighbor Discriminant Analysis (NNDA) is nonparametric feature extraction method which forms the between class and within class scatter matrices in a nonparametric way [7]. Considering a c-class problem with classes $C_i\{i= 1, 2\ldots.c\}$ and training samples $\{x_1, x2,\ldots\ldots.x_N\}$, the extra-class and intra-class neighbor of a sample $x_n \in C_i$ is defines as,

$$x_n^E = \arg\min_z \| z - x_n \|, \qquad \forall z \notin C_i, \quad (3)$$

$$x_n^I = \arg\min_z \| z - x_n \|, \qquad \forall z \in C_i, \quad z \neq x_n \quad (4)$$

The nonparametric extra class and intra class distances are defined as;

$$\Delta_n^E = x_n - x_n^E \quad (5)$$

$$\Delta_n^I = x_n - x_n^I \quad (6)$$

Using extra class and intra class and intra class distances defined above, the nonparametric between class and within class scatter matrices are defined as follows,

$$S_B = \sum_{n=1}^{N} w_n (\Delta_n^E)(\Delta_n^E)^T \quad (7)$$

$$S_W = \sum_{n=1}^{N} w_n (\Delta_n^I)(\Delta_n^I)^T \quad (8)$$

where w_n is defines as,

$$w_n = \frac{\| \Delta_n^I \|^\alpha}{\| \Delta_n^I \|^\alpha + \| \Delta_n^E \|^\alpha} \quad (9)$$

w_n is introduced to emphasize the samples in class boundaries and deemphasize the samples in class centers. Qiu and Wu [9] reached to the following solution for the computation of the projection matrix *W*,

$$W = \arg\max tr(W^T(S_B - S_W)W) \quad (10)$$

To keep the nonparametric extra-class and intra-class differences of the high dimensional space consisted with the projected extra-class and intra-class differences, Qiu and Wu [9] proposed stepwise dimensionality reduction process. In this scheme, the nonparametric between-class and within-class matrices are recomputed each time in the current dimensionality. This process is repeated until reaching the desired dimensionality.

C. Discrete Wavelet Transform

Wavelet is a most widely used multi-resolution tool in image processing area [6]. Wavelet families $X(a, b)$ is the set of basic functions generated by dilation and translation of a unique mother wavelet $X(t)$:

$$X_{a,b} = |a|^{-1/2} X\left(\frac{t-b}{a}\right)$$

where t is the time, a and b is the scale and translation parameter respectively. The joint spatial frequency resolution obtained by wavelet transform makes it a good candidate for the extraction of details as well as approximations of images.

At each level j, there is a j-level approximation A_j, or approximation at level j, and a deviation signal called the j-level detail D_j. We can consider the original signal as the approximation at level 0, denoted by A_0. The words approximation and detail are justified by the fact that A_1 is an approximation of A_0 taking into account the low frequencies of A_0, whereas the detail D_1 corresponds to the high frequency correction. If an image X is decomposed into approximation X_l and details X_h; if X_l is further decomposed into A_1 and H_1 and X_h is further decomposed into V_1 and D_1 as in Fig. 1, we can obtain the original signal X by using A_1, H_1, V_1, and D_1. This can be seen in [14].

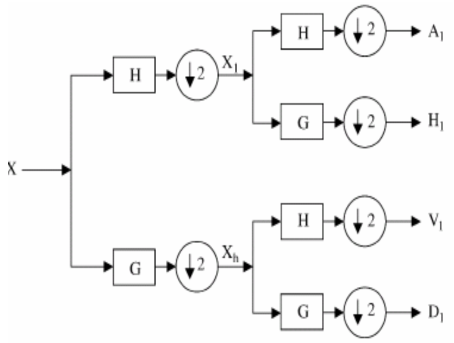


Fig. 2. Wavelet transform

III. Face Recognition Using DCT+NNDA

First, DCT is applied on entire image in order to extract features. Few low-frequency DCT coefficients are selected using a window mask of size 16×16. Training algorithm for DCT+NNDA is given in Table 1. Consider we are having C classes and S samples per classes that give $C \times S$ samples in training database. Complete training algorithm can be seen in Fig. 1. and recognition algorithm is presented in Fig. 2. Overall method is shown graphically in Fig. 3.

TABLE I: Training Algorithm of DCT+NNDA

1. Calculate DCT coefficient matrix of each image of size M×N.
2. Apply mask of size 16×16 to extract low frequency DCT coefficients from each image as shown in Fig. 1(c).
3. Augment extracted features into a training data matrix A row/column wise.
4. Apply NNDA on A to learn the NNDA projection Matrix.

$$T_{nnda} = [\varphi_1 | \varphi_2 | \varphi_3 | \dots | \varphi_d], T_{nnda} \in R^{d \times N} \quad (12)$$

5. Finally, Project feature matrix A with Learned NNDA de

$$Y = T_{nnda}^t A \quad (13)$$

TABLE II: Testing Algorithm of DCT+NNDA

1. For test image repeat step 1 to 2 of training algorithm shown in Fig. 1 and calculate the feature matrix I.
2. Project the feature matrix I with learned NNDA projection matrix T_{nnda} calculated

$$X = T_{nnda}^t I$$

3. Classify X using Euclidian distance measure to identify X with the label of closest feature vector in DCT+NNDA feature space.
4. If test image is matched correctly then stop else Move to step 5.

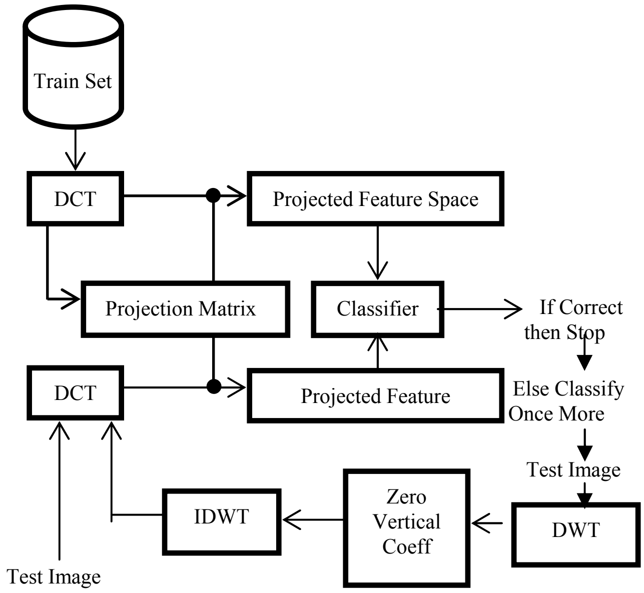


Fig. 3. Complete method

IV. Results and Discussions

First, we performed experiment on ORL Database [12]. ORL database consists of 400 facial images of 40 subjects and 10 samples per subject with variations in expression and small variation in pose. We kept 5 images per subject for training and other 5 for testing purpose, value of α is set to 0. After applying DCT+NNDA on this database, we investigated non-matched faces we observed that most of them were not matching because they comprise facial expressions and small edges; hence they need to be smoothened. In order to reduce this effect we applied a simple technique to smooth such images. We assumed that most of the expression part lies in edges and that constitute to vertical coefficient of the DWT transformed image. So we applied 2nd level DWT on non-matched images then reconstructed images after zeroing their vertical coefficients and matched again as shown in Fig. 3. We applied this technique only for the non-matched faces and we achieved 99% recognition rate at 50 features, Fig. 5. shows performance on different no of features. We have also compared this method with LDA. An example of reconstructed image after zeroing its vertical DWT coefficients is shown in Fig. 4.

(a) (b)

Fig. 4. (a) Original image from ORL database (b) reconstructed image.

Second experiment was performed on Yale Database [11]. Yale database consist of 165 facial images of 15 different people with 11 samples per people. It has images with small variations in pose, illuminated images and images with facial expressions like happy, sad, surprise, angry etc. We kept 6 images from each class into training set while remaining 5 are kept for testing. After applying proposed method on this database we achieved 98.5 % recognition rate when we selected 70 no. of features while value of α is set to 0, performance on this database can be seen in Fig. 6.

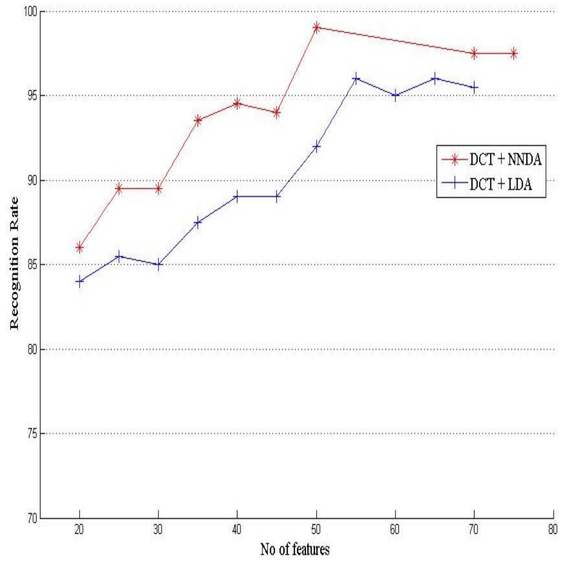


Fig. 5. Recognition rate on orl database.

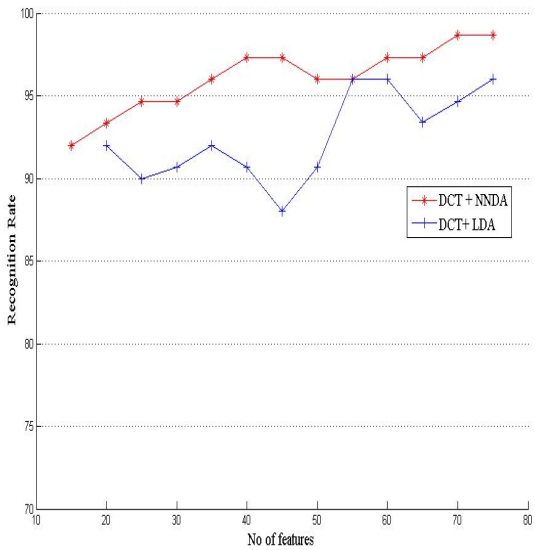


Fig. 6. Recognition rate on yale database..

V. Conclusion

A new combination of DCT+NNDA was proposed in this paper, along with image smoothing technique for non-match faces. Since NNDA is an efficient tool for feature extraction. We have utilized the power of DCT and NNDA for face recognition, along with DWT for image smoothing, and achieved 99% accuracy on ORL database and 98.5% accuracy on Yale database respectively. Our method is found to be robust to expressions and small pose variations. In future, more sophisticated kernel-NNDA approach can be proposed. We will also work on some illumination reduction technique and look forward to make our proposed method invariant to illumination also.

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