FACE RECOGNITION USING ENERGY PROBABILITY IN DCT DOMAIN

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ABSTRACT

In this paper, we propose a novel feature extraction method for face recognition. This method is based on Discrete Cosine Transform (DCT), Energy Probability (EP), and Linear Discriminant Analysis (LDA). We define an energy probability as magnitude of effective information. It is used to create a frequency mask in DCT domain. Our method consists of three steps. First, the spatial domain of face images is transformed into the frequency domain called DCT domain. Second, for energy probability is applied on DCT domain which acquires from face image, dimension reduction of data and optimization of valid information. At last, in order to obtain the most significant feature of face images, LDA is applied to the extracted data using frequency mask. Our experimental results show that the proposed method improves on the dimension reduction of feature space and the face recognition over the previously proposed methods.

1. INTRODUCTION

In face recognition, feature extraction is one of the most important steps, and it performs the reduction that high dimensional image data into low dimensional feature vectors. A common way to resolve high dimensional problem have used dimension reduction techniques, and one of the most frequently used techniques is Principal Components Analysis (PCA). Hafed and Levine [1] used Discrete Cosine Transform (DCT) feature for face recognition. They pointed out that DCT obtains the optimal performance of PCA in facial information compression and the performance of DCT is superior to conventional transforms. By manually selecting the frequency bands of DCT, their recognition method achieves similar recognition results as the Eigenface method which is based on PCA. [2] Nevertheless, their method can not provide a rational band selection rule or strategy, and it can not outperform the classical Eigenface method.

In this paper, we propose a new feature extraction method to enhance the image classification information and improve the recognition results. We introduce energy probability to construct the frequency mask which is useful for face recognition. The organization of the paper is as follows. In Section 2, we present proposed the frequency mask and the background of DCT and energy probability. Section 3 describes the procedures of our approach, which is based on the frequency mask. Experimental results are presented and discussed in Section 4. Finally, conclusions are drawn in Section 5.

2. ENERGY PROBABILITY IN DCT DOMAIN

In this section, we explore the frequency mask including the background of DCT and energy probability.

2.1. Discrete Cosine Transform (DCT)

DCT is a frequently used solution of various problems in image and signal processing. It expresses data to ad the sum of cosine function for reduced size of data. Under the assumption that gray scale matrix of face image as *f(x, y)* of size $N \times N$, its DCT, *F(u, v)* of size $N \times N$, is obtained by the following equation:

$$F(u,v) = \alpha(u)\alpha(v)\sum_{x=1}^{N}\sum_{y=1}^{N} f(x,y) \times \cos\left[\frac{(2x+1)u\pi}{2N}\right]\cos\left[\frac{(2y+1)v\pi}{2N}\right] \tag{1}$$

where,

$$\alpha(u), \alpha(v) = \begin{cases} \sqrt{\dfrac{1}{N}}, & u, v = 1 \\ \sqrt{\dfrac{2}{N}}, & otherwise \end{cases} \qquad (2)$$

with *u, v, x, y = 1, 2, 3,…, N*, where, *x* and *y* are spatial coordinates in the sample domain while u, v are coordinates in the transform domain[1].

The first element, value of *F(1, 1)* is the average of all the samples in the input image and is referred to as Direct Current (DC) component. The remaining elements in *F(u, v)* each indicate the amplitude corresponding to the frequency component of *f(x, y)*, and are defined as Alternate Current (AC) coefficients. It is well-known that the DC coefficient is only dependent to the brightness of the image. Consequently, it becomes DC-*free* (i.e., zero mean) and invariant against uniform brightness change by simply removing the DC coefficient. [3] The proposed method uses zero-valued DC coefficient and the remaining AC coefficients for eliminating illumination characteristic of the image.

2.2. Energy Probability (EP)

The energy is one of the image properties using signal processing technique, and it means characteristics of images. From the result of DCT transformed from image, *F(u, v)* of size $N \times N$, the energy using DCT coefficients is defined as following equation [4]:

$$Energy_F = \sum_{u=1}^{N} \sum_{v=1}^{N} \left| F(u,v) \right|^2 \qquad (3)$$

$Energy_f$ is a value concerned with an image and a property of each image. It cannot be suited our purpose, dimension reduction and optimization of valid information, because we need the property about available pixel information. For the extracted features of face, we define energy probability, *EP(u, v)*. We can obtain *EP(u, v)* using following equation:

$$EP(u,v) = \frac{\left| F(u,v) \right|^2}{Energy_F} \qquad (4)$$

The magnitude of *EP(u, v)* is used as criterion of valid information. The total number of *EP(u, v)*, $N \times N$ indicates the ratio of an energy value holding a whole face image to an energy value held a pixel of position *(u, v)*. Thus the large value *EP(u, v)* means more valid information than face features have. We assume that M is the number of total facial images and N as width and height of all images. The original image is transformed using DCT. The *EP*, 2-D vector of size $N \times N$, is converted into the column vector *S* arranged length of $N \times N$ by the size of energy probability in

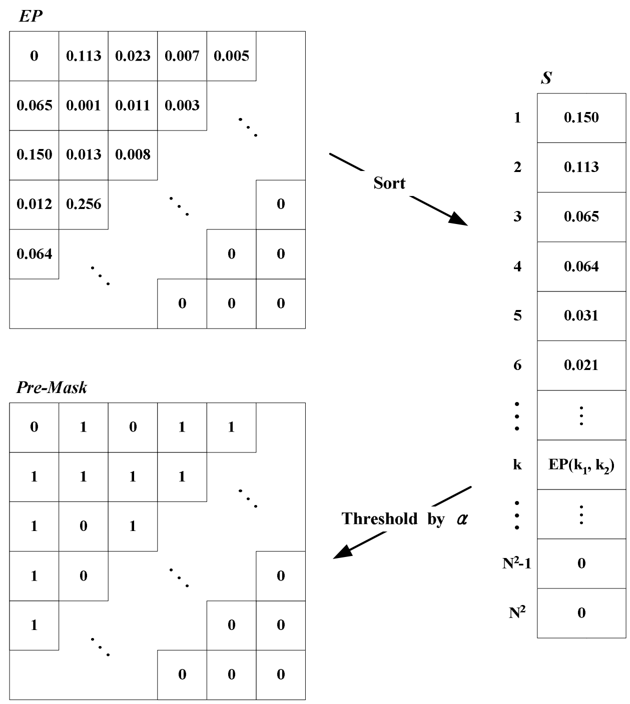
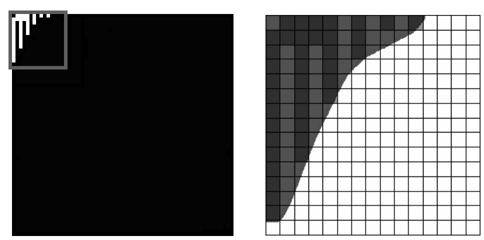


Figure 1. The creation procedure of frequency mask.



(a) (b)

Figure 2. (a) is the generated the frequency mask and (b) is its magnification of 15x15 block.

descending order and assume the value of *S(k)* is K. If we select the first *k*-th energy probability, then we will be remained 1.Otherwise set the value of *EP(u, v)* to change to zero.

$$Pre\text{-}Mask(u,v) = \begin{cases} 1, & if\ EP(u,v) \le K \\ 0, & otherwise. \end{cases} \qquad (5)$$

The *Pre-Mask*s of size M are generated from face image of size M. To obtain the final frequency mask, we combine *Pre-Mask*s by pixel by pixel and divide it into M. Figure 2 shows the generated frequency mask and its magnification of 15x15 block. From the diagram, we can perceive the extended lengthwise shape has a characteristic of large horizontal variation in facial images.

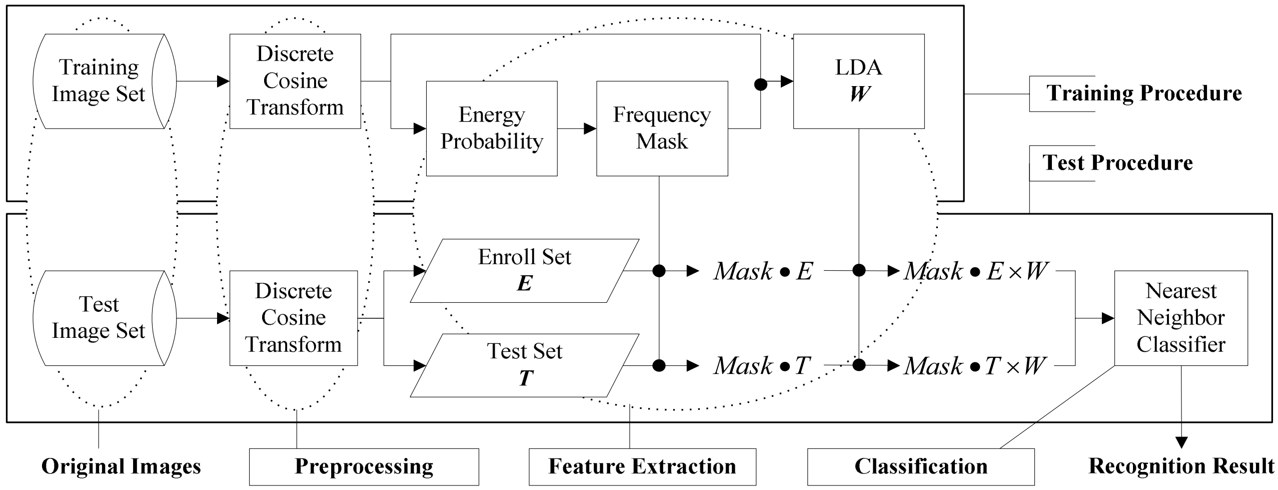


Figure 3. Block diagram of proposed method.

3. FACE RECOGNITION PROCEDURE

Figure 3 depicts the whole procedure of face recognition. First, face images are transformed into DCT domain. Second, DCT domain that acquires from face image is applied on energy probability for the dimension reduction of data and optimization of valid information. The energy probability is defined as criterion of effective facial features in section 2.2. Third, in order to obtain the most silent and invariant feature of face images, the LDA is applied in the data extracted from the frequency mask that can facilitate the selection of useful DCT the frequency pixels for image recognition, since not all the pixels are useful in classification. At last, it will extract the linear discriminative features by LDA and perform the classification by the nearest neighbor classifier.

We divide original images into two parts of the training and test image set. The training image set is applied to DCT and it is computed energy probability. Then, we generate the frequency mask. When the number of pixels in valid information in the frequency mask is n and the total number of training images is *M*, it creates *Mask* vector of size n x M.

In feature extraction, The LDA is one of the most popular linear projection methods. It is used to find a linear projection of the original vectors from a high dimensional space to an optimal low dimensional subspace in which the ratio of the between-class scatter and the within-class scatter is maximized. The W is the LDA optimal projection matrix and calculated by *Mask* vector. In the same way, the test image set is applied to DCT and divide test image set into two parts of the enroll set E and test set T. $Mask \bullet E$ denotes that E applied on the frequency mask. The extracted final feature vectors are $Mask \bullet E \times W$ and $Mask \bullet T \times W$ and is calculated from the Euclidian distance between them.

4. EXPERIMENTAL RESULTS

To verify the efficiency of out suggested method through face recognition experiments, we used images from a group of 55 people and a few images are shown in Figure 4. In our experimental environments, for each person, 20 facial images were taken. To construct bases for feature extraction, the images of 20 randomly selected people from the group were used. Among the images that were not used in base construction, 10 images for each person were used for training, and the rest were used for testing. The size of image is 64 x 64, and the experiments were conducted using the Euclidian distance.

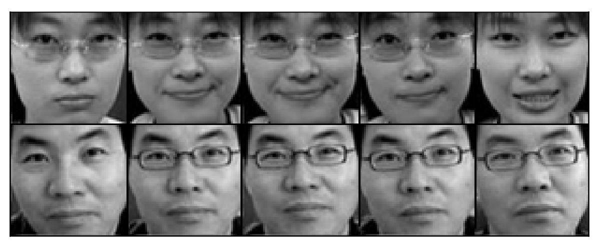
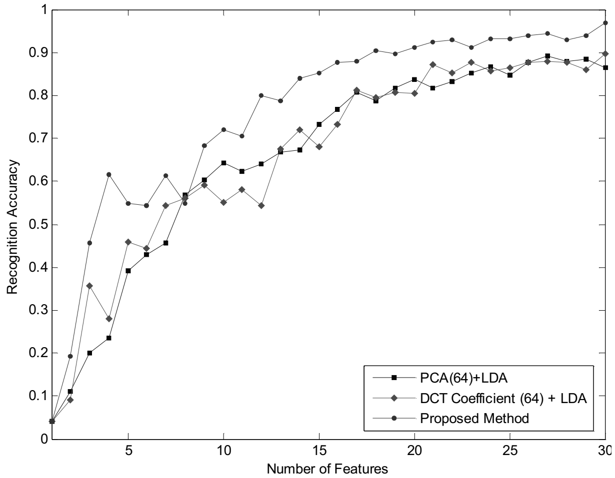
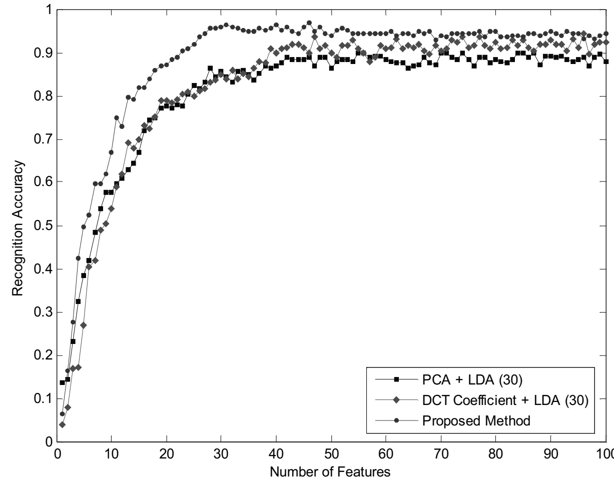


Figure 4. Example faces in our database.

Throughout the experiments, we have compared the results from the following feature extraction methods: (a) PCA plus LDA, (b) existing DCT method, and (c) proposed method. Figure 5 (a) and (b) show recognition rate with the increments of the number of the dimension reduction data and the final features applied to the LDA. For the rank 1, the best recognition rates of PCA plus LDA, existing DCT method, and proposed method are 90.0%, 94.4%, and 96.8%, respectively (Table1). Accuracy which test images are matched within rank 1 using the number of reduced data in



(a)



(b)

Figure 5. (a) is recognition accuracy with the number of reduced data, 64 and the increments of the number of extracted features (b) is recognition accuracy with the increments of the number of reduced data and number of extracted features, 30.

the second row and the number of extracted features in the third row in Table 1.The recognition accuracies in the forth row are the minimum number of reduced data with the best performance of the rank 1. (a) PCA plus LDA, (b) existing DCT method, and (c) proposed method.

Table 1. Comparison of classification performance

Method	(a)	(b)	(c)
Reduced Data	74	96	46
Extracted Features	30	30	30
Recognition Accuracy	0.900	0.944	0.968

5. CONCLUSION

Based on energy probability, we propose a new feature extraction method for face recognition. Our method consists of three steps. First, face images are transformed into DCT domain. Second, DCT domain acquired from face image is applied on energy probability for the purpose of dimension reduction of data and optimization of valid information. Third, in order to obtain the most silent and invariant feature of face images, the LDA is applied in the data extracted from the frequency mask that can facilitate the selection of useful DCT frequency bands for image recognition, because not all the bands are useful in classification. At last, it will extract the linear discriminative features by LDA and perform the classification by the nearest neighbor classifier. For the purpose of dimension reduction of data and optimization of valid information, the proposed method has shown better recognition performance than PCA plus LDA and existing DCT method.

6. REFERENCES

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