Face Recognition Based on Coarse Sub-bands of Contourlet Transformation and Principal Component Analysis

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ABSTRACT:
In this paper, a face recognition system is implemented by using Contourlet transformation (CT) as a two dimensional transformation defined in discrete form and principal component analysis (PCA) as a subspace method to form the feature vectors, is implemented. Every input image is decomposed by CT up to three levels and the CT coefficients are obtained at three scales and 15 orientations. The obtained CT coefficients are used by PCA to form the feature vectors. At the end, the Euclidean distance is used for classification. Our experimental results on ORL data base show the appropriate performance in comparison with other approaches**; E**ven though for each subject only one image is used for training and other 9 images are used for testing. The average accuracy of our proposed algorithm for face recognition is 96.07%.

KEYWORDS: Discrete Contourlet Transformation, Principal Component Analysis, Coarse Sub-Sand and Euclidean Distance.

1. INTRODUCTION

Human face recognition is an important issue in many application such as public security, human computer interface [1], and human authentication [2]. These applications range from static matching of controlled format photograph (e.g. passport, credit card and driver license) to real time matching of intelligent video images' surveillance [3]. The main challenges for any face- recognition system are pose, illumination, age and facial expressing variation and also face exclusion by hair, scarf and glasses. Some classical techniques for face recognition are the geometrical-measurement [4], Eigen face [5], manifold learning [6], and elastic graph matching [7]. Xie et.al [8] proposed a method that image blocks are reconstructed by using the local image block of other face image. Then an elastic local constructional method is proposed to measure the similarities between the images of block pairs in order to measure the difference between the two face images. Wang et. al [9] proposed a face recognition system based on Contourlet transformation (CT) and supportive vector machine (SVM). Xiao et. al [10] proposed the spatial enhanced multi-level boosting by using the uniform local binary and multi-level ad boost algorithm. Two dimensional linear discrimination analyses were proposed in [11]. In general, these mentioned methods have appropriate performance under well-controlled conditions.

In this paper, we use the CT for face recognition. For this purpose, the original image is decomposed to 3 levels, and the CT coarse coefficients, because of having maximum energy, are used for obtaining the feature vectors. The Eigen-values and Eigen-vectors of feature vectors are obtained by using the principle component analysis (PCA) and indeed the sub bands are projected to PCA for the dimensionality reduction. The Euclidean distance is used for classification. The proposed method is easy for implementing because only coarse sub-bands of CT are used and it has appropriate performance even when there is only one sample training per subject.

This paper is organized as follows. In Section 2, CT and PCA are expressed briefly. Our proposed method for feature extraction and face recognition is explained in Section 3. Section 4, shows the experimental results of the proposed method by using ORL face database which is shown and compared with other methods. Conclusion is given in section 5.

2. BACKGROUND

In this section, at first, we have a short review on CT as a new multi-resolution transformation in image processing, and then we briefly explain the PCA.

2.1. Discrete Contourlet Transformation

The CT is a new image DE compositional scheme, which provides the flexible multi-resolution representation for two dimensional signals [12]. The two properties that make CT superior to other transformations such as wavelet are directionality and anisotropy [12]. The block diagram of CT for two level decomposition is shown in Figure 1 which includes two sub-blocks, laplacian pyramid (LP) [13] for multi-resolution and multi-scale representation and directional filter bank (DFB) [14] for multi-direction DE compositional.

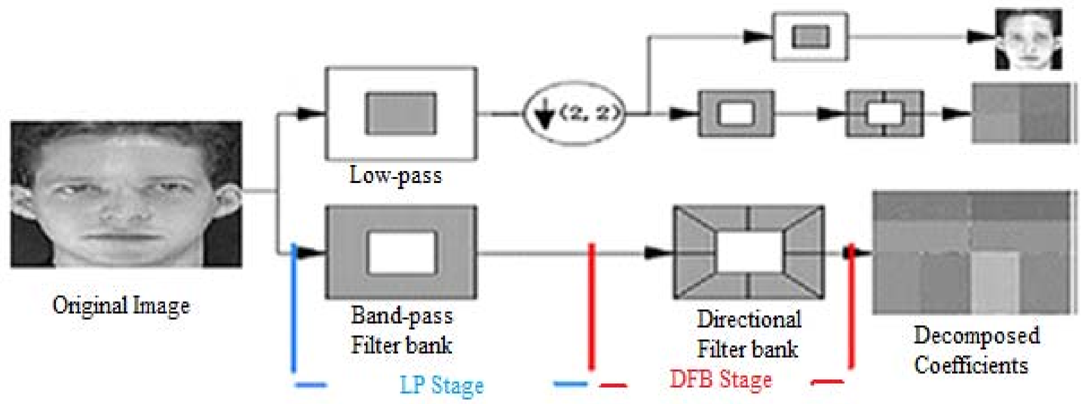


Fig. 1. The block diagram of two levels CT

The block diagram of LP is shown in Figure 2. where H and G are analysis and synthesis filters, respectively and MS denotes the sampling matrix. As it is seen, the output of LP at each level includes the sampled low-pass and the band pass version of the original signal. The band pass image is then processed by the DFB and repeating the same steps upon the low-pass image until the multi-scale and multi-directional decomposition of an image are obtained. The DFB is implemented via an *l*-level tree-structured decomposition that leads to $k = 2^l$ multi-bands with wedge-shaped frequency partition as shown in Figure 3. Directional information obtained by two operators [15]; a two-channel quincunx-filter bank with fan-filter which divide a 2-D spectrum into two directions of vertical and horizontal, and a shearing operator which reorders the image pixels. In general, LP decomposes the input image into the low-pass- and band pass-image, then, DFB decomposes the band pass image in order to capture the directional information. The same above procedures are repeated on the low-pass image at the second level of CT. Combination of LP and DFB gives a double filter bank structure known as Contourlet filter bank. The Contourlet filter bank decomposes the given image into directional multi-bands at multiple scales. Figure 4 shows samples of a sub-band image and Contourlet coefficients at 3 scales and 15 orientations.

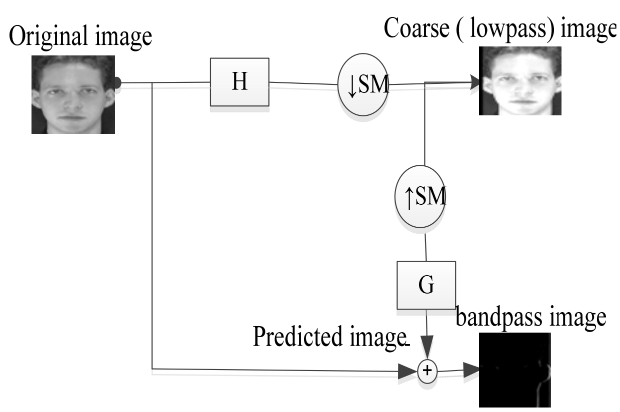


Fig. 2. The block diagram of LP

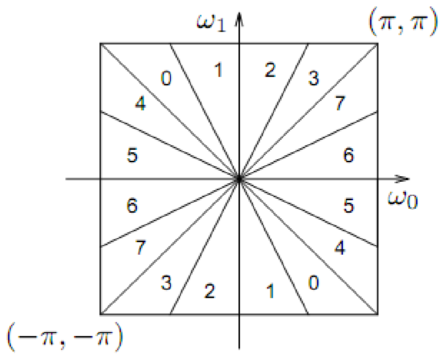


Fig. 3. The k real wedge-shape frequency bands of DFB for *l*=3, and $k = 2^3$ [12].

Fig. 4. CT coefficients of a sample face image for the first, second, and third decomposition level

2.2. Principal Component Analysis

Principal component analysis (PCA) is a well-known statistical method, which is often applied as the pre-processing stage of face recognition [16]. In general, PCA is, first, reducing the dimension and therefore computational complexity, and second, extracting the input data important features [17]. Suppose, the size of the input data for PCA is $M \times N$. The procedures of PCA for the input data are written as follows,

1. arrange the input data

   $$A = \{A_i\} \ ; \ i = 1,2,...,N \tag{1}$$

   where A_i denotes the original vectored image, with the size $M \times 1$ then clearly A is a matrix with the size $M \times N$.
2. compute the mean vector of the matrix,

   $$\mu = \frac{1}{N}\sum_{i=1}^{N} A_i \tag{2}$$

3. subtract the mean vector, μ , from every vectors,

   $$\varphi_i = A_i - \mu \ , \ i = 1,2,...,N \tag{3}$$

4. compute the covariance matrix ,

   $$C = \frac{1}{N}\sum_{i=1}^{N} \varphi_i \varphi_i^T \tag{4}$$

   with the size of $M \times M$ and of φ^T , it denotes the transposition of φ .
5. ddetermine the eigen values, $\{\lambda_i\}_{i=1:M}$, and eigen vectors, $\{V_i\}_{i=1:M}$, of covariance matrix,where $\lambda_1 > \lambda_2 > ... > \lambda_M$, $|C - \lambda I| = 0$, $CV_M = \lambda_M V_M$.
6. use the Eigen vectors corresponding to the K largest Eigen values,

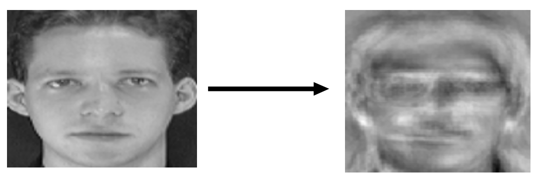
   $$U_K = \sum_{i=1}^{k} V_i \tag{5}$$

   where $K << M$, $U_K = \{U_{ji}\}_{j=1:K, i=1:N}$.

   It was shown in [18], considering a small set of Eigen vectors that corresponds to the largest Eigen values still store the image characteristics
7. project the feature vectors to linear subspace,

   $$E = U_K^T B \tag{6}$$

where $B = \{\varphi_i\}_{i=1:N}$ and U_K^T denotes the transposition of U_K . The above linear transformation is used to reduce the dimension and prepare the data for classification as well. Figure 5 shows the original image and the Eigen face image after applying PCA where only the 20 largest Eigen vectors among 400 Eigen vectors are used. Although the dimension is reduced considerably, the image main features are already preserved.



(a) (b)

Fig. 5. (a) The original image, (b) The Eigen face by using the first 20 largest principal components

3. FACE RECOGNITION BASED ON CT

In this work, we use the low-pass multi-band coefficients belong to the first, second and third levels of CT. Then, we employ the PCA in order to extract the texture features that are robust to pose, illumination, facial-expression variation and hair variation. There are N subspace Contourlet coefficients for N images, size of subspaces are $\{p_n \times r_n\}_{n=1:3}$ in each level. Subspace is set as a column vector with size $M \times 1$ for each image, where $M = p_1 \times r_1 + p_2 \times r_2 + p_3 \times r_3$. So, the size of the input data for PCA is $M \times N$ for the all of N images. The feature dimension is usually large compared to the size of the training data, $\varphi\varphi^T$ is very large. Therefore, we calculate $C = \varphi^T \varphi$ instead, and then we find the Eigen vectors and Eigen values from the new defined C. In the following, we select the Eigen vectors corresponding to the K largest Eigen values, then we compute the coefficient matrix,

$$F = \frac{BU_K}{\sqrt{L}} \tag{7}$$

where $L = diag(\lambda_1, \lambda_2, ..., \lambda_K)$, and $B = \{\varphi_i\}_{i=1:N}$.

The subspace Contourlet coefficients were normalized so that the variance along each of the K dimensions becomes equal. This is done by dividing the subspace coefficients within the square root of the respective Eigen values. Now, matrix F project is under linear subspace,

$$E = F^T B \tag{8}$$

where F^T denotes transposition of F. The above mentioned procedures, as it is shown in Figure 6 are performed for training and testing images as well. At the end, we use Euclidean distance as a simple classifier.

We convert each colorful image into gray scale and we also normalize them. We decompose the input image by CT into 3 levels and set the coefficients of three low-pass bands in order to construct the column vector, A_i. Using PCA reduces the dimensional subspace of the feature matrix, A. At the end, suppose q and t represent the query/test and train image respectively. In h dimensions, the Euclidean distance between two points t and q is,

$$d_{Euc}(t,q) = \sqrt{\sum_{i=1}^{h} (t_i - q_i)^2} \tag{9}$$

That it is used for classification. t_i or q_i is the coordinate of t or q in dimension i.

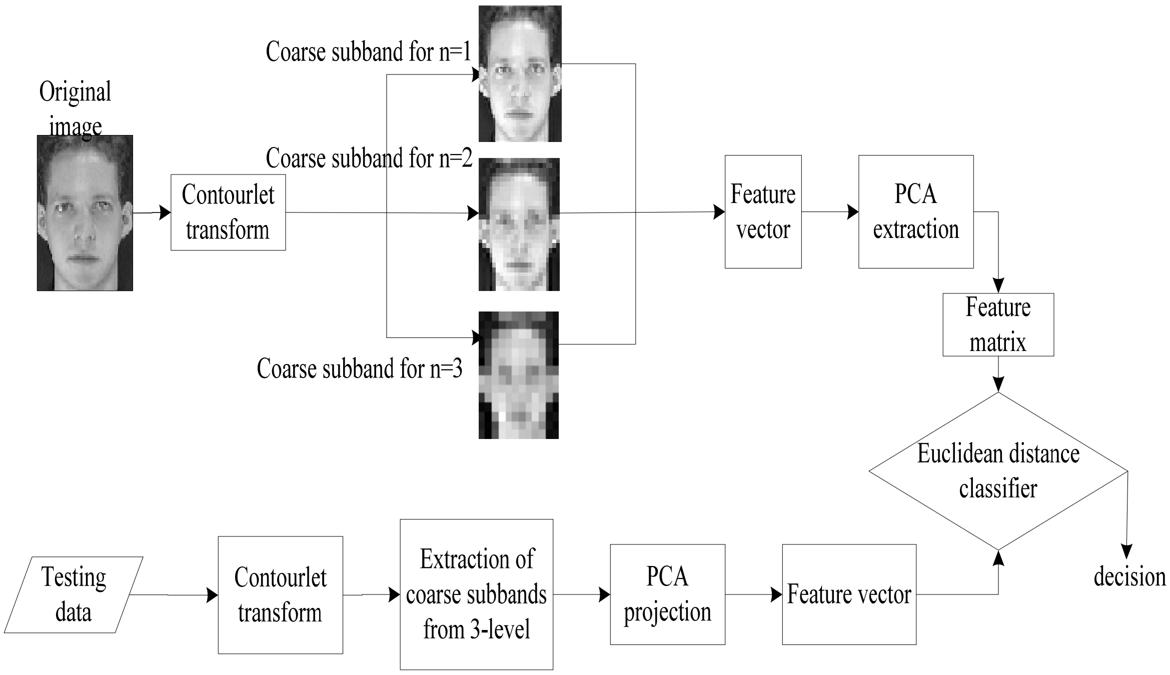


Fig. 6. The block diagram of our proposed method for a sample training data

4. EXPERIMENTAL RESULTS

In this work, for implementing the CT, the “pkva” filters [19] are used and in order to evaluate the performance of our proposed method and have a comparison with some other methods, the ORL data set [20] is used. The ORL dataset includes 10 different images of 40 subjects at different lighting conditions, facial expression (open/closed eyes, smiling/not smiling) and perspectives (looking to the right, left, up or down) and facial details (glasses/no glasses), the background is dark homogeneous, and the image size is 112×92 pixels, with 256 gray levels. Three sample images of two subjects are shown in Figure 7.

Fig. 7. Three sample images of two subjects belong to ORL face database

In this work, we use all 400 images belong to the ORL database. As the ORL data set image size is 112×92, the size of three low-pass images belong to the first, second, and the third levels of CT that are in order (56×46), (28×23), and (14×21). The CT coefficients of the three coarse sub-bands are used for obtaining the column vectors, A_i, with size 3388×1. In this paper, different number of images for each subject is used for training and the rest is used for testing. For each subject 6, 5, 4, 3, 2, 1 images are considered as the training set, and the rest of the images are the test set. As the number of images for each subject is 10, decreasing the training image set is equivalent to increasing the test image set. Obviously, the number of CT coefficients, which are extracted from the coarse sub-bands of the first, second, and third level decomposition, are minimum and maximum in order when the train image for each subject is considered one and six, respectively. The recognition rate gets the maximum value by using only 200 coefficients and 5 train images. The face recognition accuracy based on the number of CT coefficients is written in Table 1.

Table. 1. Recognition rate of our proposed method when the ORL data set is used

No. of training samples	No. of coefficients used	Face recognition accuracy (%)
1	40	81.94
2	80	95.62
3	120	99.28
4	160	99.58
5	200	100
6	240	100

The performance of our proposed method, based on CT by using 6 images as training and 4 images as testing, in comparison with six different methods [11], [21] are written in Table 2. The performance of our proposed method, based on CT by using 6 images as training and 4 images as testing, in comparison with six different methods [11], [21] are written in Table 2.

Table .2. Recognition rate of our proposed method in comparison with other approaches where six images for each subject are used for training

Different methods	Face recognition accuracy (%)
PCA-SVM [21]	86.88
2DLDA [11]	92.50
2DLog's [11]	93.00
XU's [11]	93.00
W-2DLDA [11]	93.10
KPCA-SVM [21]	95.00
Our Algorithm	100

The ORL data set is used in all methods and our proposed approach gets the best accuracy. In addition, the achieved accuracy when only one and two images are used for training, are written in Table 3, where other approaches in comparison are elastic local reconstruction (ELR) [8], PCA [8], elastic graph matching (EGM) [22], and Gabor wavelet (GW) [23]. It is known that PCA preserves the global structure of the image space, where as GW and EGM adopt the image of local information and ELR considers the human face manifold structure. Two sets of parameters are used for GW and named as GW3 and GW5. GW3 denotes using the three center frequencies, i.e. $\pi/2$, $\sqrt{2}\,\pi/4$ and $\pi/4$, and eight orientations, i.e. range $[0,7\,\pi/8]$ with steps of $\pi/8$, where as GW5 also uses two center frequencies, i.e. $\sqrt{2}\,\pi/8$ and $\pi/8$. The experimental results according to the different numbers of training set show that our algorithm based on CT is robust even if, only one image is used for training and nine images are used for testing. In this case, the recognition rate is obtained with only 40 coefficients.

Table.3. The achieved accuracy by using different approaches where one and two images for each subject are used for training

	Face recognition accuracy (%)					
No. of Training	EGM [22]	PCA [8]	GW3[23]	GW4 [23]	ELR [8]	Our Algorithm
1 sample	68.6	71.1	72.2	76.4	77.2	81.94
2 samples	82.8	82.5	88.1	89.1	94.4	95.62

5. CONCLUSION

In this work, we present a novel facial recognition system based on CT and PCA. We decompose an input image up to 3 levels for high precision and use the coarse sub-bands coefficients because of comprising the highest energy. PCA is used in order to reduce the dimension of input data and to extract the feature vectors as well. Our proposed algorithm is superior to other methods under choosing different number of images for training and it is easy to implement.

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