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Contourlet and Nearest Feature Line Based Feature Extraction Approach for One Prototype Sample Problem

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Abstract. *In this paper, a novel algorithm for face recognition with one sample per person is proposed. The proposed algorithm is based on contourlet transformation. For simple prototype sample problem, many discriminant learning methods can not work. Because for most discriminant learning methods, the within class scatter of the prototype samples are very important. However, simple prototype sample problem does not have within class scatter. To enhance the representative capability of the prototype samples set, some new samples are generated using contourlet transformation. Multiple prototype samples for each class are constructed through the decomposition and reconstruction of original training images by contourlet transformation. Thus neighborhood discriminant nearest feature line analysis can be performed on the new database. The experimental results demonstrate the efficiency of the proposed algorithm.*

Keywords: Image classification, Contourlet, Neighborhood discriminant nearest feature line analysis.

1. **Introduction.** As one of a few biometric methods, face recognition and related technology [1-2] have a variety of potential applications in access control, smart card, information security, etc. For this reason, face recognition received a lot attention from both industrial and academic communities during the past 20 years. Face recognition aims to verify or identify one or more persons from still images or video images of a scene using a stored database of face images. Many approaches have been presented to improve the efficiency of the face recognition system. During the last two decades, there have been a lot of schemes for face recognition from the frontal face images, with many encouraging results, reported in the literature. A recent study shows that computer algorithms are capable of outperforming people on recognition of face images, when large and representative training data set is available. These algorithms represent faces in the derived

face images feature space before verification. The variability of individuals across changes in illumination, expression, and light condition can be extracted from the representative training images by these algorithms.

However, machine learning based algorithms are still limited in the number of image variations they can generalize across. One of most clear differences between person and machine is the ability to learn from very few, even single, examples. After a close look at a certain face, people can memorize and recognize that face in many unseen situations, such as lighting, new pose, and ages. Compared to person, machine lacks the ability of generalization to new complex situations. Recently, the problem of one sample per person (or one sample problem for short)[3-5] in face recognition are focused on by some researchers. So-called the problem of one sample per person is defined as follows: given a database of faces images with only one sample per person, the goal is to identify a person from the database later in time in any different and unpredictable expression, lighting and aging, etc. from the individual image. Also there are some other simple sample problem in the world. Due to the within class scatter of the prototype samples does not exists. So some powerful subspace learning algorithms can not be used directly, such as Linear Discriminant Analysis based algorithms [6-7]. Many methods have been proposed to attempt to address this problem, such as several extensions of the principal component analysis[3-4], the synthesization of the virtual samples, and the high-dimensional local feature based methods. Many methods have reported promising results on the one sample problem. However, a recent study pointed out that many previously proposed methods cannot improve the simplest PCA method when the complex image variations are presented. So the robust and applicable algorithms for one sample problem are still being studied.

Nearest Feature Line [8] is a classifier which was proposed in 1999. Some NFL based classifiers are designed in the following decades [9]. Neighborhood discriminant nearest feature line analysis (NDNFLA)[10] is a powerful NFL-based subspace learning algorithm. Its drawback is it requires three prototype samples per class for one sample problem due to the construction of the feature line. In order to solve this problem, a novel feature extraction algorithm, based on contourlet [11] is proposed in this paper. In the proposed algorithm, the images for training are decomposed into several subbands by contourlet, and then more than one images can be reconstructed by using different subbands. The reconstructed images form a new training set. NDNFLA can perform well on this training set.

The rest of this paper is organized as follows. Section 2 briefly reviews NDNFLA and contourlet. Section 3 describes the proposed algorithm in detail. Some experiments are performed on two image database in section 4. Section 5 gives the conclusions of this paper.

2. The review of contourlet and NDNFLA.

2.1. **The contourlet transform.** The contourlet transform is also known as the pyramidal directional filter bank which is a 2-D transform technique. There are two filter banks in it. First of all, the Laplacian pyramid is utilized to get a multiscale representation of an image. Subsequently, subband images from the multiscale decomposition are processed by a directional filter bank (DFB) [13] to analyze the directional details at each specific scale level. The so-called "contourlet coefficients" are the output values from the DFB. The overall result is an image expansion using basic elements like contour segments. In particular, contourlet has elongated supports at various scales, directions and aspect rations, offering a flexible multiscale and directional decomposition for images. The contourlet transform is illustrated in Fig. 1.

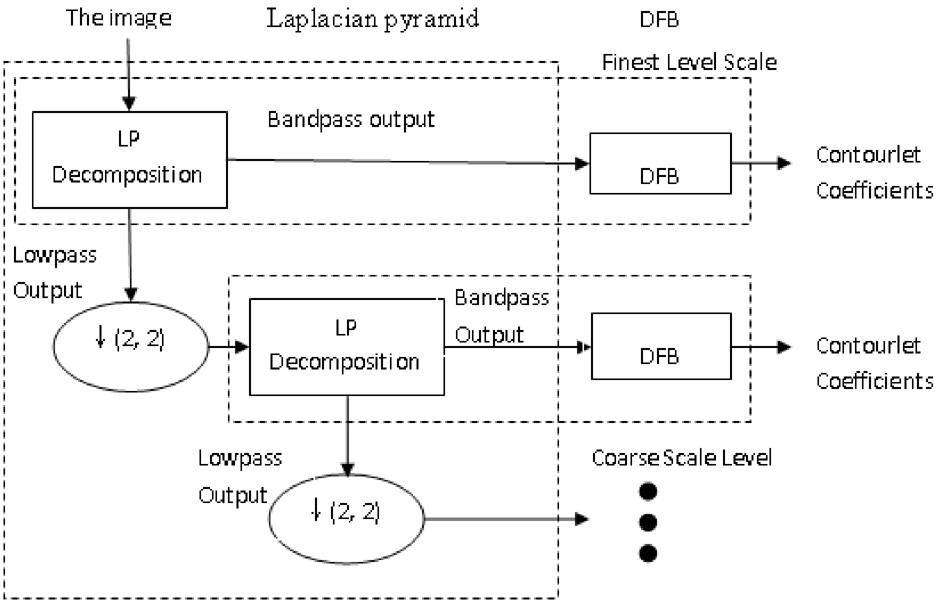

FIGURE 1. The construction of contourlet

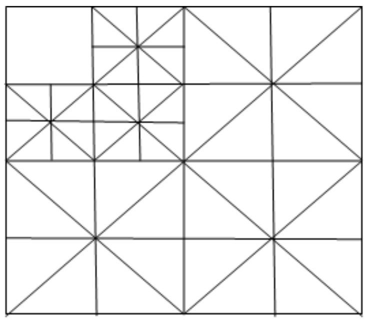

FIGURE 2. An example of the frequency spectrum partition of the Contourlet Transform

The contourlet transform provides a multiscale multidirectional representation of images. The directional filter bank of contourlet is easily adjustable to have any number 2^n of directions for detecting fine details. Also, its basis functions have elongated supports rather than square supports as with 2-D wavelets, which makes it more efficient in describing curvature details along smooth contours. Further, the decoupling of the multiscale decomposition and the multidirectional decomposition guarantees a flexible structure for image analysis, because the number of directional subbands can vary at different scale levels. Fig. 2 shows an example of the contourlet multiscale multidirectional representation of images.

2.2. **The review of NNDFLA.** Given a training samples set,$X = \{x_n \in R^M : n = 1, 2, \cdots, N\}$, NFL generalizes each pair of prototype feature points belonging to the same class: $\{x_m, x_n\}$ by a linear function $L_{m,n}$, , which is called the feature line. The line $L_{m,n}$ is expressed by the span $L_{m,n} = span(x_m, x_n)$. The query x_i is projected onto $L_{m,n}$ as a point $x^i_{m.n}$. This projection can be computed as

$$x^i_{m,n} = x_m + t(x_n - x_m) \tag{1}$$

where $t = [(x_i - x_n)(x_m - x_n)]/[(x_m - x_n)^T(x_m - x_n)]$. The Euclidean distance of x_i and $x^i_{m,n}$ is termed as FL distance. The less the FL distance is, the more probability that x_i belongs to the same class as x_m and x_n. Define two types of neighborhoods.

Definition 2.1. (Homogeneous neighborhoods). For a sample x_i, its k nearest homogeneous neighborhood N_i^o is the set of k most similar data which are in the same class with x_i.

Definition 2.2. (Heterogeneous neighborhoods). For a sample x_i, its k nearest heterogeneous neighborhood N_i^e is the set of k most similar data which are not in the same class with x_i.

The aim of NDNFLA is to find the discriminant feature of samples based on nearest feature line, at the same time, the feature extracted by NDNFLA can preserve neighborhood information. The optimization criterion of NDNFLA is

$$\begin{aligned} \max J(W) = (&\sum_{i=1}^{N} \frac{1}{NC^2_{\left|N_i^e\right|}} \sum_{x_m, x_n \in N_i^e} \left\| W^T x_i - W^T x^i_{m,n} \right\|^2 \\ -&\sum_{i=1}^{N} \frac{1}{NC^2_{\left|N_i^o\right|}} \sum_{x_m, x_n \in N_i^o} \left\| W^T x_i - W^T x^i_{m,n} \right\|^2) \end{aligned} \tag{2}$$

where $|\cdot|$ represents the cardinality of a set. The above problem can be transformed into the problem as follows:

$$\max J(W) = \mathrm{tr}[W^T(A - B)W] \tag{3}$$

where

$$A = \sum_{i=1}^{N} \frac{1}{NC^2_{\left|N_i^e\right|}} \sum_{x_m, x_n \in N_i^e} [(x_i - x^i_{m,n})(x_i - x^i_{m,n})^T] \tag{4}$$

$$B = \sum_{i=1}^{N} \frac{1}{NC^2_{\left|N_i^o\right|}} \sum_{x_m, x_n \in N_i^o} [(x_i - x^i_{m,n})(x_i - x^i_{m,n})^T] \tag{5}$$

Then, the projection W of NDNFLA can be obtained by solving the following eigenvalue problem

$$(A - B)w = \lambda w \tag{6}$$

Let $w_1, w_2, \cdots, w_q$ be the eigenvectors of Eq. 6 corresponding to the q largest eigenvalues ordered according to $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_q$. An $M \times q$ transformation matrix $W = [w_1, w_2, \cdots, w_q]$ can be obtained to project each sample $M \times 1$ x_i into a feature vector $q \times 1$ y_i as follows:

$$y_i = W^T x_i, i = 1, 2, \cdots, N \tag{7}$$

3. **The proposed method.** NDNFLA is an efficient algorithm. However, for the one sample problem, it does not work because it needs more than one sample per person. In order to apply NDNFLA to the one sample problem, some new samples are constructed in our algorithm. Given a training image, the contourlet is performed on it. The multiscale multidirectional representation is got. Then let some directional subband equal to zero matrix. The reconstructed images can be calculated by the remaining subbands. So multiple images for each class are constructed by setting the different subbands to equal to zero matrix. Through this method, enough images can be computed even there is only

one training sample per person. Since there are multiple prototype samples, the feature line of each subject can be constructed, and the NDNFLA can be performed.

The procedure of the proposed algorithm is as follows:

Input: The training images set

Output: The optimal projection matrix

Step 1, the contourlet is performed on each training images;

Step 2, for each training images, set some directional subband to zero matrix, then a new image can be got from reconstruction;

Step 3, let the new training set contains all the images got from Step 2;

Step 4, perform NDNFLA on the new training set, and calculate the optimal projection matrix.

4. **Experimental results.** To evaluate the performance of the proposed algorithm, some experiments are implemented on ORL database [14] and Finger-Knuckle-Print (FKP) [15] with two-manners. In the following, we assess the feasibility and performance of the proposed method for face recognition with one sample problem. Comparative performance is carried out against some popular face recognition algorithm such as the PCA, two-dimensional principal component ananlysis (2DPCA), projection-combined principal component analysis $(PC)^2A$, enhanced $(PC)^2A$ ($E(PC)^2A$), and SVD perturbation algorithm[16]. In all the experiments, the nearest-neighbor (NN) algorithm is applied as the classifier for its simplicity. The following experiments are implemented on a PC with Athlon 2.5GHz CPU and 768MB RAM and programmed in the MATLAB platform. In the following experiments, the 1-level contourlet is applied, a 2-level DFB is performed in the contourlet, so for each training image, four images are reconstructed by set each directional subband to zero matrix, respectively.

4.1. **Experimental results on ORL face database.** The ORL face database contains 400 face images, 10 different face images per person for 40 individuals. Some face images are captured at different times . There are facial expressions (open or closed eyes, smiling or non-smiling) and facial details (glass or no glasses). These face images are taken with a tolerance for some tilting and rotation of the face up to 20 . All face images are gray with 256 levels and size of 112×92. Yale face database contains 165 images of 15 individuals (each person has 11 different images). These images are under variations with following facial expressions or configurations: center-light, with glasses, happy, left-light, without glasses, normal, right-light, sad, sleepy, surprised and wink. All images are gray with 256 levels and size of 100×100 pixels.

Fig. 3 gives some samples in ORL face database. An example is shown in Fig. 4. Fig. 4(a) is the original prototype sample. Fig. 4(b) is the new sample generated by the contourlet transformation using the low frequency sub-band and the first high frequency sub-band. The reconstructed image looks similar to the original image, yet, They are different. For both database, one image is taken from one individual for training randomly. And the system runs 20 times. The average recognition rates (ARR) of different algorithms on ORL face database are shown in the Table 1. From Table 1, the recognition rate of the proposed algorithm is higher than those of the other algorithms.

TABLE 1. ARRs of different algorithms on ORL face database.

Different Approaches	PCA	2DPCA	$(PC)^2A$	$E(PC)^2A$	SVD	Proposed algorithm
ARR	0.5435	0.5421	0.5617	0.5698	0.5523	0.7072

FIGURE 3. Examples of ORL face database

FIGURE 4. An example of the new sample generated by the Contourlet Transformation

4.2. **Experimental results on FKP database.** In this experiment, one image sample per subject were selected as prototype samples randomly and the others were used as query samples in each run. the system ran ten times in order to reduce the variation on the database. Therefore, (ARR) is used to evaluate the different algorithms.

The Biometric Research Centre (UGC/CRC) at the Hong Kong Polytechnic University created FKP database. There were 165 people's fingers collected in FKP database, 125 were from men and 40 were from women. Each person provided 12 images on middle finger and index finger from both hands. First instead of treating each person's fingers as one subject, we treated each finger as one subject. Therefore, there are 660 subjects with 12 images per subjects. In the experiments, we find there are some duplicate samples in the database. To evaluate various algorithms better, the categories with duplicate samples are removed from the database during the experiments. Besides, in order to reduce the complexity of the experiment and experimental time, PCA were taken to reduce the dimension of the samples. And 97% of energy is retained in PCA stage.

TABLE 2. ARRs of different algorithms on FKP database.

Different Approaches	PCA	2DPCA	$(PC)^2A$	$E(PC)^2A$	SVD	Proposed algorithm
ARR	0.6051	0.6247	0.6148	0.6353	0.6244	0.7332

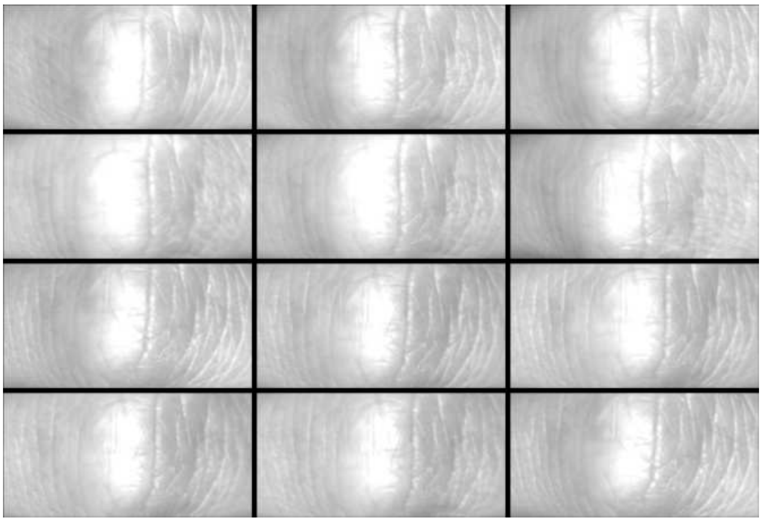

Figure 5. Examples of FKP image database

Table 2 gives the ARRs of different algorithms on FKP image database. The Experimental results show that the proposed algorithm outperforms the other approaches. FKP database is bigger than ORL face database and has more classes. However, from the Table 1 and Table 2, the ARR of the proposed algorithm on FKP database is higher than that on ORL face database. In fact, image samples in ORL face database contain more conditions, such as light, angle, and so on. Therefore, it is a more complex classification task compared with FKP database.

5. **Conclusions.** In this paper, a novel contourlet based algorithm for one sample problem is presented. The main contribution of this paper is to solve NDNFLA cannot be applied to one sample problem. Image prototype sample can be decomposed by contourlet transformation. Then a new sample can be generated using the low-frequency subband and part of high-frequency subband. Multiple training samples for each class are produced through the decomposition and reconstruction of original training images. Experimental results show that the proposed method outperforms the other popular algorithms.

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