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An Efficient Method for Face Feature Extraction and Recognition based on Contourlet Transforms and Principal Component Analysis

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Abstract

In this paper, an efficient face recognition method based on the discrete contourlet transform using PCA and the Euclidean distance classifier is proposed. Each face is decomposed using the contourlet transform. The contourlet coefficients of low and high frequency in different scales and various angles are obtained. The frequency coefficients are used as a feature vector for further processing. PCA (Principal Component Analysis) is then used to reduce the dimensionality of the feature vector. Finally, the reduced feature vector is adopted as the face classifier. The test databases are projected onto contourlet-PCA subspace to retrieve reduced coefficients. These coefficients are used to match the feature vector coefficients of the training dataset using a Euclidean distance classifier. Experiments are carried out using the Face94 and IIT_Kanpur databases.

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Keywords : Discrete Contourlet Transform; Euclidean Distatnce; Principal Component Analysis;Feature Extraction.

1. Introduction

In the last two decades, object detection and classification received a growing attention by researchers concerned with Human-Machine communication. Face detection and classification is always a complicated and uncertain area within mobile robotics as well as any surveillance system due to the interference of illumination and blurriness. Moreover, the performance requirements are no longer confined to a prototype at research lab but exposed to the real world problems. That demand makes the task greatly challenging for requirements of speed and accuracy.

1.1. Related Works

Object detection and classification have been done in different ways. Gupte etc al. [1] uses a background subtraction and tracking updates to identify the vehicle positions in different scene. Kirby and Sirovhich [2] proposed the use of the Principal Component analysis in reducing dimensions and extract featured parts of objects. A concept of Eigen picture was defined to indicate the Eigen functions of the covariance matrix of a set of face images. Turk and Pentland [3] have developed an automated system using Eigen faces with a similar concept to classify images in four different categories, which help to recognize true/false of positive of faces and build new set

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of image models. Use of Eigen spaces and Support Vector Machine for nighttime detection and classification of vehicles has been mentioned by Thi et al. [4]. S.Zehang, G.Bebis, and R.Miller [6] used PCA based vehicle classification framework. Harkirat S.Sahambi [7] and K.Khorasani used a neural network appearance based 3-D object recognition using Independent component analysis.

Recently, a theory for high dimensional signals called multiscale geometric analysis (MGA) has been developed. Several MGA tools were proposed such as Curvelet [9, 10], bandlet and Contourlet [8, 11, 12, 14, 15] etc. Nonsubsampled Contourlet was pioneered by Do and Zhou as the latest MGA tool [11, 12], in 2005. Contourlet transform can effectively represent information than wavelet transform for the images having more directional information with smooth contour [18] due to its properties, viz. directionality and anisotropy.

Ch.Srinivasa Rao [5] used feature vector using Contourlet Transform for Content Based Image Retrieval System. Yan et al. [16] proposed a faced recognition approach based on Contourlet transform. Yang et al. [13] proposed a multisensor image fusion method based on nonsubsampled Contourlet transform. Extensive experimental results show that proposed scheme performs better than the method based on stationary wavelet transforms.

1.2 .Our Approach

In our system the detection of features of object is particularly of interest mainly for mobile robotics application as well as visual surveillance system. We have proposed and implemented a feature based classification approach using the Discrete Contourlet transform. The coefficient of CT is used as a feature vector. This feature vector is used to extract the Eigen value and Eigen vector using PCA method. These Feature vector is used to match with Testing feature vector using Euclidean distance Classifier. This framework can be used for classification of different types like traffic surveillance system, biological cells, or human activities.

This paper is organized as follows. Section 2 & 3 provides brief background information on use for multi-level decomposition using the Discrete Contourlet transform and Principal Component Analysis. Section 4 describes our Methodology for feature extraction and recognition of the face image. Section 5 describes our experiment results of the proposed technique using the face94 and IIT-Kanpur databases. Section 6 concludes the paper and gives future directions of work.

2. Discrete Contourlet Transform

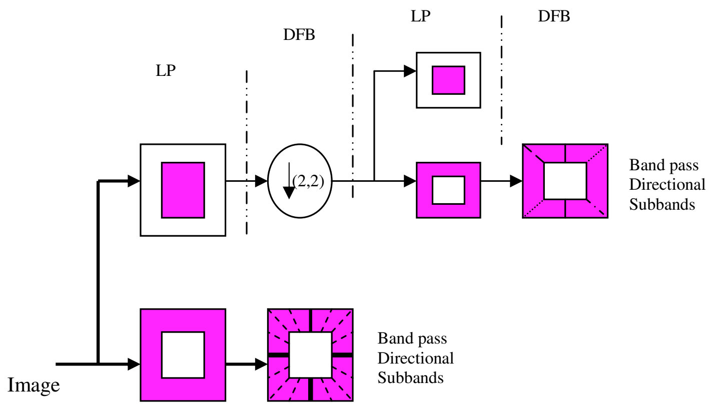

Figure 1. Double Filter Bank Decomposition of Contourlet Transform

Multiscale and time-frequency localization of an image is offered by wavelets. But, wavelets are not effective in representing the images with smooth contours in different directions. Contourlet Transform (CT) addresses this problem by providing two additional properties viz., directionality and anisotropy [17, 18].

Contourlet transform can be divided into two main steps: Laplacian pyramid (LP) decomposing and directional filter banks (DFB) as shown in the Figure 1. The original image is divided to a lowpass image and a bandpass image using LP decomposing. Each bandpass image is further decomposed by DFB. Repeating the same steps upon the lowpass image, the multiscale and multidirection decomposition of the image will be obtained [14 –16]. Contourlet transform is a multi scale and directional image representation that uses first a wavelet like structure for edge detection, and then a local directional transform for contour segment detection.

A double filter bank structure of the Contourlet is shown in Figure 1 for obtaining sparse expansions for typical images having smooth contours. In the double filter bank structure, Laplacian Pyramid (LP) [13] is used to capture the point discontinuities, and then followed by a Directional Filter Bank (DFB), which is used to link these point discontinuities into linear structures.

The Contourlet have elongated supports at various scales, directions, and aspect ratios. This allows Contourlet to efficiently approximate a smooth contour at multiple resolutions. In the frequency domain, the Contourlet transform provides a multiscale and directional decomposition.

2.1. Pyramid frames

One way to obtain a multiscale decomposition is to use the Laplacian pyramid (LP) introduced by Burt and Adelson [23]. The LP decomposition at each level generates a down sampled lowpass version of the original and the difference between the original and the prediction, resulting in a bandpass image. The LP decomposition is shown in Figure 1. Here, the band pass image obtained in LP decomposition is then processed by the DFB stage. LP with orthogonal filters provides a tight frame with frame bounds equal to 1.

2.2. Iterated directional filterbanks

DFB is designed to capture the high frequency content like smooth contours and directional edges. The DFB is implemented by using a k-level binary tree decomposition that leads to 2^k directional sub- bands with wedge shaped frequency partitioning as shown in Figure 2. But, the DFB used in this work is a simplified DFB [13], which is constructed from two building blocks. The first is a two-channel quincunx filter bank with fan filters [11]. It divides a 2-D spectrum into two directions, horizontal and vertical. The second is a shearing operator, which amounts to the reordering of image pixels. Due to these two operations, directional information is preserved. This is the desirable characteristic in CBIR (Content Base Image Retrieval) system to improve retrieval efficiency.

Combination of a LP and DFB gives a double filter bank structure known as Contourlet filter bank. Band pass images from the LP are fed to DFB so that directional information can be captured. The scheme can be iterated on the coarse image. This combination of LP and DFB stages result in a double iterated filter bank structure known as Contourlet filter bank .The Contourlet filter bank decomposes the given image into directional sub-bands at multiple scales. Figure 2 shows the decomposition of image using Contourlet Transform for level-2 using ‘pkva’ filter for both low pass filter and direction filter bank.

Let S is the dataset having P images. Let f (m, n) is a gray level image of size N1 x N2 is resized into N x N. The Contourlet Transform of two levels with ‘pkva’filter is applied on the face images. Resulting image gives the decomposed coefficients with the same size kxk as $C_1, C_{2\text{-}1}, C_{2\text{-}2} \ldots C_{n\text{-}1}, \ldots C_{n\text{-}v}$,where V is the number of directions. These Coefficients are used to reorder the column vector I_i of the images. Image Vector I_i is constructed by converting coefficients to a column vector and then concatenation of all coefficient vectors. Let $I = [I_1, I_2, I_3, \ldots I_P]$ is the Feature Image Matrix constructed by Discrete Contourlet Coefficient.

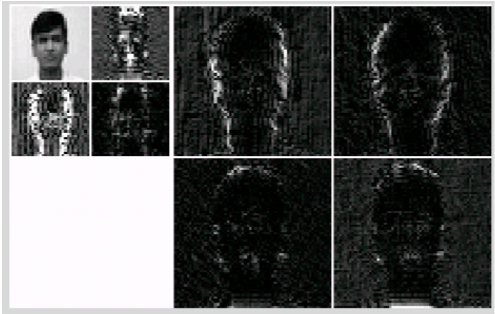

Figure 2. Decomposition of image using Contourlet Transform(2-level and 'pkva' filter for pyramid and directional filter)

3. Principal Component Analysis

As described in general face recognition application [5, 7], Principal Component analyses are used with two main purposes. First, it reduces the dimensions of data to computationally feasible size. Second, it extracts the most representative features out of the input data so that although the size is reduced, the main features remain, and still be able to represent the original data [10].

We got first the covariance matrix from the set of feature image matrix. Then the Eigen vectors of covariance transformation were obtained. The Eigen vectors are those that invariant in direction during a transformation, which can be used as a representation set of the whole big dataset. Those components are called Eigenfaces in Turk and Pentland face detection application [7] and Eigen vehicles in Zhang et al. vehicle detection application [9]. The covariance matrix of the input data is calculated starting from the algorithmic mean Ψ of all vectors I_1, $I_{2,}$ …… and $I_{P.}$, where M is the no of test image in the dataset.

$$\Psi = \frac{1}{M}\sum_{i=0}^{M} I_i \tag{1}$$

The difference image vector I_i and meanΨ is called Φ with

$$\Phi_i = I_i - \Psi \tag{2}$$

The theoretical covariance matrix C of all Φ_i is

$$C = \frac{1}{M}\sum_{i=0}^{M} \Phi_i \Phi_i^T \tag{3}$$

All Eigenvectors ν_i and Eigenvalues λ_i of this covariance matrix are derived from the relationship:

$$\lambda_i = \frac{1}{M}\sum_{i=0}^{M} (\upsilon_i^T \Phi_i^T)^2 \tag{4}$$

The collection of M eigenvectors ν_i can be seen as the reduced dimension representation of the original input data (with size N^2) when M << P^2. This set of eigenvectors will have a corresponding Eigenvalues associated with it, with indicates the distribution of this eigenvector in representing whole dataset. Many papers have shown that, only a small set of eigenvectors with top Eigenvalues is enough to build up the whole image characteristic. In our system, we keep Q top eigenvectors where Q represents the number of important features from the faces Eigenspace. The value of vehicle Eigenspace is represented by

$$\varepsilon = \sum_{i=0}^{P} v_i \tag{5}$$

Representative features of the Eigenspace will be used to derive the transformed version of each separated vehicle image in this vehicle space. In our system we call this transformed version the vehicle "weight" ω of each image in respect to the whole vehicle Eigen space, and can be used to judge the relationship between the each image with the model vehicle spaces. The weight ω_i of each input image Vector I_i is calculated from the matrix multiplication of the difference $\Phi_i = I_i - \Psi$ with the Eigenspace matrix ε. The weight ω_i of each input image vector I_i is calculated from the matrix multiplication of the different Φ_i with the Eigenspace matrix ε.

$$\omega_i = \Phi_i \times \varepsilon \tag{6}$$

The image weight calculated from the (6), is the projection of an image on the Face Eigenspace, which indicates relative "weight" of the certainty that whether such image is an image of a Face Dataset. Our initial training set S consists of P different Face Images. These images are transformed into a new set of vector T^w of all input training weight. Figure 3 shows the Eigen value after applying PCA to the Contourlet transform of the face images. This transformation has showed how PCA has been used to reduce the original dimension of the dataset (PX N^2) to T^w (Size (PXP)) where generally P <<N^2. Thus the dimensions are greatly reduced and the most representative features of the whole dataset still remain within only P Eigen features.

Figure 3. Eigen Value of Face94 Dataset

4. Methodology

The objective of the proposed work is to extract the texture features in image Identification. Figure 4 illustrates overall process of calculating Contourlet transform and PCA applied to the training images and recognition of testing dataset.

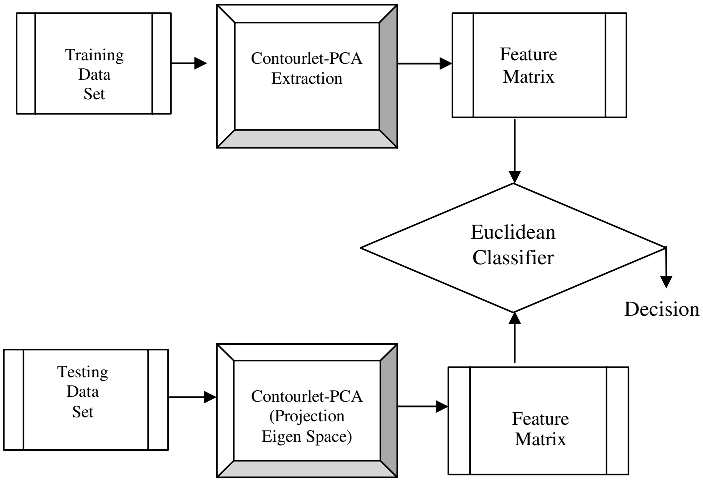

Figure 4. Block diagram of the proposed Technique

4.1. Feature Extraction

Let X_face and Y_Face represent the training and testing dataset. For gaining the best feature vector from the training dataset, at first, all images are normalized.

The following steps are performed for feature extraction.

- RGB image is converted into gray scale image and resize to 128x128.
- Filtering is applied to remove noise and sharpening the image. Unsharp Contrast Enhancement filter and Multidimensional filtering is used as a Preprocessing.
- Decompose each image into the Contourlet transform. As a result of performing CT, coefficients of low frequency and high frequency in different scales and various directions will be obtained. Decomposed coefficients with the same size kxk as $C_1, C_{2\text{-}1}, C_{2\text{-}2} \ldots . C_{n\text{-}1}, \ldots . C_{n\text{-}v}$,where $_V$ is the number of directions. These Coefficients are used to reorder the column vector I_i of the images. In our method we use 2 level of decomposition C_1, $C_{2\text{-}1}, C_{2\text{-}2}, C_{2\text{-}3}$ coefficients to construct the feature matrix. Each coefficient is having 32x32 (total 1024) points. All the coefficients are arranged to make a column vector of 4028x1.
- The Feature image matrix I= $[I_1, I_2, I_3 \ldots .. I_P]$ is constructed from the coefficients column vector I_i. Where i represent the no of image.
- Feature matrix I is transformed to lower dimension subspace T^w using PCA.
- T^w consists of Weight calculated for each image of the respective Dataset.

4.2. Classification

For the classification, each image transformed to a lower order subspace using Contourlet-PCA using the above steps. Upon observing an unknown test image X, the weights are calculated for that particular image and stored in the vector W_X. Afterwards, W_X is compared with the weights of training set T^w using the Euclidean distance. If the distance does not exceed some threshold value, then the weight vector of the unknown image W_X is matched with the training dataset. The optimal threshold value has to be determined empirically.

5. Experimental Results

All the algorithms are implemented in MATLAB 7.0.1, Contourlet Toolbox and executed on thePentium–IV, 3.00GHz CPU with 2 GB RAM. For the Contourlet transform, pyramidal filter and directional filter the "pkva" filter is used. The two level subbands are used to find the coefficients. To validate the accuracy of the proposed algorithm, we used two different databases: Face94 and IIT_Kanpur Datasets.

5.1. IIT_Kanpur Dataset[20]

IIT_Kanpur dataset consists of male and female images having 22 images of female faces and 38 images of male faces having 40 distinct subjects in up right, frontal position with tilting and rotation. Therefore this is a more difficult database to work with. From these dataset we have selected 10 individuals from male dataset and 10 individuals from female dataset. For each individual we have selected 3 images for training, chosen randomly and 10 images for testing out of 11 face images. Figure 5 (a) shows gray scale images after filtering is applied as a preprocessing stage using male IIT_Kanpur dataset. Figure 5 (b) shows the Eigen faces after applying PCA value to the Contourlet Transform of Training dataset. Figure 6 shows some of the gray scale face images used from the male IIT_Kanpur dataset.

(a) (b)

Figure 5. (a) Filtering is applied on Face dataset of IIT_Kanpur (b) Eigen faces after applying PCA to the Contourlet Transform

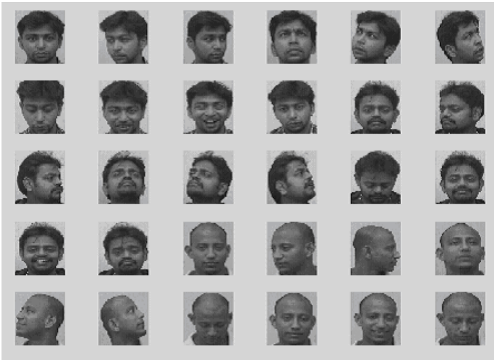

Figure 6. Some of the face images from Testing dataset from IIT_Kanpur

5.2. Face94 Datast[21]

Face94 dataset consists of 20 female and 113 male face images having 20 distinct subject containing variations in illumination and facial expression. From these dataset we have selected 17 individuals from male dataset and 11 individuals from female dataset. For each individual we have selected 3 images for training, chosen randomly and 10 images for testing out of 20 face images. Figure 7 shows some of the gray scale face images used from faces94 dataset.

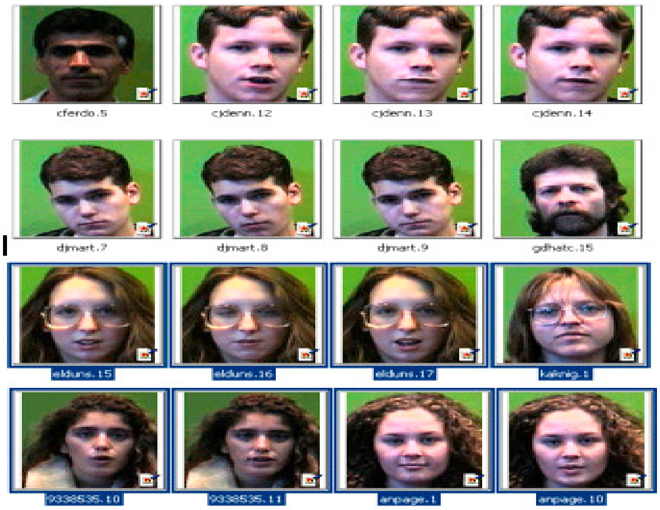

Figure 7. Face Images from Face94 dataset.

In order to assess the efficiently of the proposed technique describe above, we carried out series of experiments using face94 dataset and IIT_Kanpur dataset for Euclidean Distance Classifier. Table 1 reports the performance result obtained for all database. For face_94 female Dataset we selected 33 images for Training Set and 110 images are used for Testing purpose. As shown in the table the feature matrix for 33 image becomes 4096x 33=135168 points. After applying PCA to the Feature Matrix I the weight matrix T^w becomes of size 33x33=1089 Points. Thus for the classification of the image required to match only 1089 points (33 x33) and not 135168 points. Thus the computational cost greatly reduced by applying PCA. For the other dataset the values are listed in the Table 1. For face_94 male dataset 51 images are used for training set and 170 images are used for testing dataset. For IIT_Kanpur dataset, for male and female both 30 images are used for training as well as 100 images are used for testing purpose. The Recognition rates shown in the table 1 indicates the efficiency of the method. We got very good results for Face 94 and IIT_kanpur female dataset. Due to much variation in the IIT_Kanpur male dataset, we got only 82 % result.

Table.1. Recognition Rate using different Dataset.

Dataset (JPEG Image)	Original Size of the Image	No of Images used for Training	Size of Feature Matrix I using Contourlet Transform	Final Weight Matrix T^w required for classification (after applying PCA)	No. Of Images used for Testing	Recognition Rate (%)
Faces_94 female	180 x 200	33	4096 x 33	33 x 33	110	97.27%
Faces_94 Male	180 x 200	51	4096 x 51	51 x 51	170	98.24%
IIT_Kanpur Female	640 x 480	30	4096 x 30	30 x 30	100	96%
IIT_Kanpur Male	640 x 480	30	4096 x 30	30 x 30	100	82%

6. Conclusion

Feature extraction using Contourlet-PCA is very fast and its accuracy is very high on recognition rate. It also provides low dimensionality to reproduce and compare the results. The method is very fast and suitable for real time application for visual surveillance and robotics systems and also can be used for any other classification. Different run of Face images have proved face classification framework as robust, both in accuracy as well as processing speed.

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