Face Recognition using Curvelet Based PCA

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Abstract

This paper identifies a novel feature space to address the problem of human face recognition from still images. This is based on the PCA space of the features extracted by a new multiresolution analysis tool called Fast Discrete Curvelet Transform. Curvelet Transform has better directional and edge representation abilities than widely used wavelet transform. Inspired by these attractive attributes of curvelets, we introduce the idea of decomposing images into its curvelet subbands and applying PCA (Principal Component Analysis) on the selected subbands in order to create a representative feature set. Experiments have been designed for both single and multiple training images per subject. A comparative study with wavelet-based and traditional PCA techniques is also presented. High accuracy rate achieved by the proposed method for two well-known databases indicates the potential of this curvelet based feature extraction method.

1. Introduction

Face recognition has been studied extensively for more than 20 years now. Since the beginning of 90's the subject has became a major issue; mainly due to its important real-world applications in areas like video surveillance, smart cards, database security, internet and intranet access [1].

Multiresolution analysis tools, notably wavelets, have been found quite useful for analyzing the information content of images; hence they enjoyed wide-spread popularity in areas like image processing, pattern recognition and computer vision. Over the past two decades, following wavelets, other multiresolution tools like contourlets, ridgelets etc. were developed. 'Curvelet Transform' is a recent addition to this list of multiscale transforms. It has already been used to resolve image processing problems like image compression [2], texture classification [3] and image denoising [4]; but not much work has been done to explore the potential of curvelet transform to solve pattern recognition problems. In some recent works, Majumdar showed that curvelets can serve the basis for pattern recognition problems like character recognition [5].

In our previous work [6] curvelet transform has been employed to extract features from bit quantized facial images and we showed that curvelets can indeed supersede the performance of wavelets. However, working with large number of features can be computationally expensive. So, in this experimental study we aim at reducing dimensionality using Principal Component Analysis. The proposed method has been evaluated by setting up different experiments. For some experiments only one image per subject has been used as prototype, which is a common scenario in practice. Thereafter, multiple sample images have been used to increase the recognition rate. Besides, it has also been studied how eigenvector-selection affects the system's performance. Experiments have been carried out on two well-known databases: Essex Grimace and ORL (AT&T) Database.

The methodology is discussed in the following section and experimental results are listed in section 3. Finally, section 4 concludes and suggests the future prospect of this work.

2. Proposed Method

PCA, the basis of standard eigenface technique [7] is widely used in face recognition. Traditionally, each image is first converted to a vector by row (or column) concatenation. Then PCA is applied for dimensionality reduction. Though it provides effective approximation, the method suffers from high computational load and poor discriminatory power [8]. In order to resolve these limitations, application of PCA on curvelet domain is

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suggested. Due to limited scope of this paper, we are unable to delve into the mathematical details of curvelet transform. A brief description of curvelet transform is given below for ready reference. Interested readers may refer to the works of Candes and Donoho [4, 9-10].

2.1 Curvelet Transform

The development of Curvelet Transform by Candes and Donoho in 1999 was motivated by the need of image analysis [10]. Curvelets present highly anisotropic behavior as it has both variable length and width. At fine scale the relationship between width and length can be expressed as $width \approx length^2$; anisotropy increases with decreasing scale, in keeping with power law.

Second generation curvelet transform [9] has two different digital implementations: curvelets via USFFT (Unequally Spaced Fast Fourier Transform) and curvelets via Wrapping. These new discrete curvelet transforms are simpler, faster and less redundant compared to their first generation version. Both the digital implementations use the same digital coronization but differ in the choice of spatial grid. Curvelets via Wrapping has been used for this work as this is the fastest curvelet transform currently available [9]. If $f[t_1, t_2]$, $0 \le t_1, t_2 < n$ is taken to be a Cartesian array and $\hat{f}[n_1, n_2]$ to denote its 2D Discrete Fourier Transform, then the architecture of curvelets via wrapping is as follows [9]:

1. 2D FFT (Fast Fourier Transform) is applied to obtain Fourier samples $\hat{f}[n_1, n_2]$.
2. For each scale j and angle ℓ, the product $\tilde{U}_{j,\ell}[n_1, n_2]\hat{f}[n_1, n_2]$ is formed, where $\tilde{U}_{j,\ell}[n_1, n_2]$ is the discrete localizing window [9].
3. This product is wrapped around the origin to obtain $\tilde{f}_{j,\ell}[n_1, n_2] = W(\tilde{U}_{j,\ell}\hat{f})[n_1, n_2]$; where the range for n_1 and n_2 is now $0 \le n_1 < L_{1,j}$ and $0 \le n_2 < L_{2,j}$; $L_{1,j} \sim 2^j$ and $L_{2,j} \sim 2^{j/2}$ are constants.
4. Inverse 2D FFT is applied to each $\tilde{f}_{j,\ell}$, hence creating the discrete curvelet coefficients.

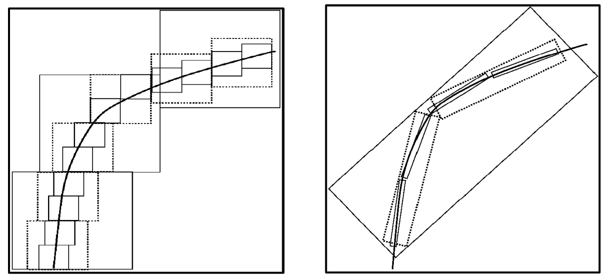

Figure 1: Edge representation by wavelets and curvelets [14]

2.2 Curvelet based Feature Extraction

PCA has been successfully applied on wavelet decomposed images in [8, 11]. However, wavelets, though suitable for detecting point singularities in images, fail to represent curved discontinuities. On the contrary, curvelet transform has been developed especially to represent objects with *'curve-punctuated smoothness'* [9] i.e. objects which display smoothness except for discontinuity along a general curve; images with edges are good examples of this kind of objects. In a two dimensional image two adjacent regions can often have differing pixel values. Such a gray scale image will have a lot of "edges" i.e. discontinuity along a general curve and consequently curvelet transform will capture this edge information. To form an efficient feature set it is crucial to collect these interesting edge information which in turn increases the discriminatory power of a recognition system.

Our face recognition system is divided into two stages: training stage and classification stage. In training stage, the images are decomposed into its approximate and detailed components using curvelet transform. These sub-images thus obtained are called *curvefaces*. These *curvefaces* greatly reduces the dimensionality of the original image. Then PCA is applied on selected subbands, which further reduces the dimension of image data. Thereafter only the approximate components are selected to perform further computations, as they account for maximum variance. Thus, a representative and efficient feature set is produced. In classification stage, test images are subjected to the same operations and are transformed to the same PCA representational basis. A simple distance (L1 Norm) based classifier like k-Nearest Neighbor classifier is employed to perform the classification task. Figure 2 shows the curvelet coefficients of a face from ORL dataset decomposed at scale = 2 and angle = 8.

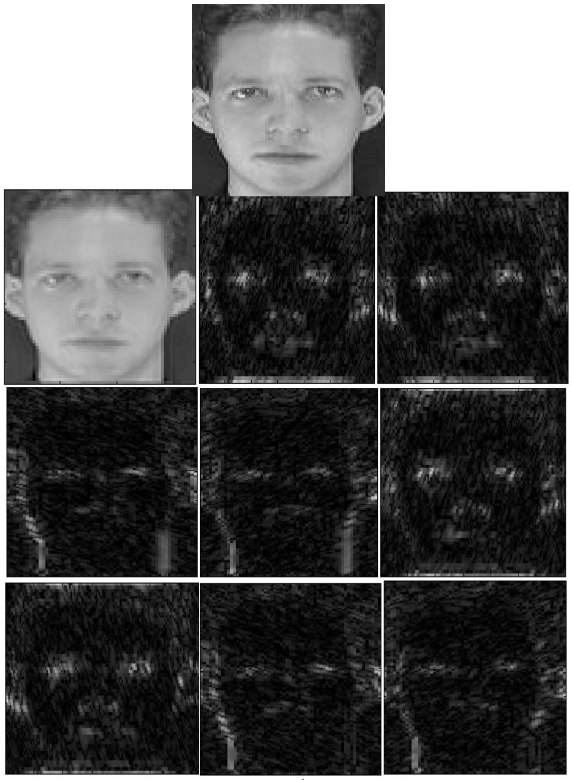

Figure 2: Curvefaces: 1st image is the original image, 1st image in the 2nd row is the approximate coefficient and others are detailed coefficients at eight angles

3. Experiments

3.1 Datasets

Essex Grimace database [12] contains a sequence of 20 images (180 x 200) each for 18 individuals consisting of male and female subjects, taken with a fixed camera. During the sequence, the subject moves his/her head and makes grimaces which get more extreme towards the end of the sequence. Images are taken against a plain background, with very little variation in illumination. Sample images of this database are shown in figure 3.

ORL (AT&T) database [13] contains 10 different images (92 x 112) each for 40 distinct subjects. For some subjects, images were taken at different times varying the lighting, facial expression (open / closed eyes, smiling / not smiling) and facial details (glasses / no glasses). All the images were taken against a dark homogeneous background with the subjects in an upright, frontal position (with tolerance for some side movement). Sample images of this dataset are shown in figure 4.

Figure 3: Sample faces from Essex Grimace

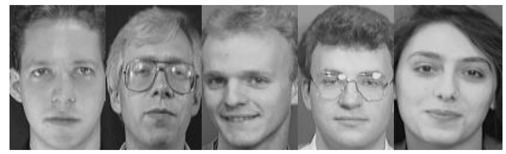

Figure 4: Sample images from ORL database

3.2 Results

In the first part of our experimental study, 5 images per subject for ORL and 8 images per subject for Essex Grimace database are randomly selected as prototype; the rest construct the test set. Color images of Essex dataset are converted to gray-scale images. No other preprocessing is done. The original images are decomposed using curvelet transform at scale = 3 and angle = 8. Thus 25 components are produced, including 1 approximate and 24 detailed subbands. The resolution of the approximate subband is reduced to 31x37 and 60x67 for images of ORL and Essex database respectively. To further reduce the dimensionality, PCA is applied on these approximate components only. After curvelet sub-images are projected to eigenspace, k-NN (for this entire work, k=1) is employed to perform the identification task. Number of principal components is varied to display how recognition rate changes with selection of eigenvectors. The results are shown in Table 1. The recognition rates shown in all the tables are the results achieved by averaging the recognition rates of 5 different rounds of face recognition.

Table 1: Curvelet based recognition result

Principal Components	Recognition Rate (%)	
	Essex Grimace	ORL
10	99.8	94.6
20	99.8	96.2
30	99.8	96.6
50	100	96.6
70	100	96.6
90	100	96.6
110	100	96.6

In practice, only a few sample images per subject are available for training; hence it is necessary to note the effect of number of prototype per subject on recognition rate. The number of training images per subject is varied and corresponding recognition accuracy is listed in table 2 and 3. First 50 principal components are selected in each case for comparison.

Table 2: Recognition Rate vs. no. of prototype (ORL)

Prototype per subject	1	2	3	4	5
Recognition Rate (%)	70.0	85.3	88.9	91.2	96.6

Table 3: Recognition Rate vs. no. of prototype (Essex Grimace)

Prototype per subject	1	2	4	6	8
Recognition Rate (%)	93.8	95.3	99.6	99.6	100

3.3 Comparative Study

In the previous section, different results of curvelet-based PCA technique have been presented. In order to establish the capability of the proposed method we have compared it against two popular existing techniques: standard eigenface and wavelet based PCA. A 3-level wavelet decomposition using 'Haar' wavelet was performed for wavelet based PCA technique. The best 50 eigenvectors were selected for both curvelet and wavelet based PCA; training images for Essex and ORL being 8 and 5 per subjects respectively.

Table 4: Comparative study

Recognition Method	Recognition Rate (%)	
	Essex Grimace	ORL
Eigenface	69.4	92.6
Waveletface + PCA	98.5	94.5
Proposed method	100	96.6

4. Conclusion

We have introduced a new feature extraction technique from still images using PCA on curvelet domain which has been evaluated on two well-known databases. Our technique has been found to be robust against extreme expression variation as it works efficiently on Essex database. The subjects in this dataset make grimaces, which form edges in the facial images and curvelet transform captures this crucial edge information. The proposed method also seems to work well for ORL database, which shows significant variation in illumination and facial details.

From the comparative study, it is evident that curvelet based PCA completely outperforms standard eigenface technique; it also supersedes wavelet based PCA scheme. The promising results indicate that curvelet transform can emerge as an effective solution to face recognition problem in future. We have investigated the possibility of curvelet transform to be used in combination with one linear analysis tool. Future work is suggested towards exploring the combination of curvelets with LDA, ICA etc. Different classification techniques can also be employed.

Acknowledgment

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