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Face Recognition using Curvelet Transform and $(2D)^2$PCA

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Abstract

This paper proposes a novel algorithm for face recognition, which is based on curvelet transform and $(2D)^2$PCA. Contrast to traditional tools such as wavelet transform, curvelet transform has better directional and edge representation abilities. Inspired by these attractive attributes, we decompose face images to get low frequency coefficients by curvelet transform. $(2D)^2$PCA with an exponential decay factor is applied on these selected coefficients to extract feature vectors, which will achieve dimension reduction as well. The nearest neighbor classifier is adopted for classification. Extensive comparison experiments on different data sets are carried out on ORL and Yale face database. Results prove that the proposed algorithm has high recognition accuracy and short recognition time, and it is also robust to changes in pose, expression and illumination.

Index Terms: human face recognition, curvelet transform, exponential decay factor, $(2D)^2$PCA, the nearest neighbor classifier

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1. Introduction

Face recognition is one of the biometric identification technologies and has many potential applications such as human identity authentication, access control and human-computer interface [1]. After 20 years of development, the technique can reach 90% accuracy in an ideal environment and has been applied in many practical fields [2]. But when conditions such as illumination, gesture and expression are not ideal, recognition accuracy suffers dramatically. So the most challenging task in face recognition technique is to eliminate effects of these changing conditions.

One of the most popular techniques used to eliminate the effects is wavelet transform. It divides changes in illumination and expression into different frequency bands, and then extracts the robust feature to recognize [3, 4]. However, wavelet transform reflects the point singularity of images, and the various basis functions are isotropic,so it cannot accurately express the direction of images' edge, and cannot form a sparse representation. To solve the above problem, curvelet transform is proposed to improve directional capability, which can better represent edges and other singularities along curves as compared to other traditional multiscale transforms [5, 6]. Recently, some pioneer work has been done to explore the potential of curvelet transform to solve face recognition problems [7-10]. In 2007, J. L. Zhang studied the combination of curvelet transform and SVM [7], and

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T. Manda studied the method of curvelet transform and PCA in 2008 [8]. Both studies achieved significantly higher recognition accuracy than wavelet transform methods.

In this paper, we propose a face recognition algorithm based on curvelet transform and $(2D)^2$PCA. For face images, we firstly apply curvelet transform on face images and get low frequency coefficients, which contain most energy. Then $(2D)^2$PCA with an exponential decay factor is introduced to reduce the dimensions and extracts feature vectors. Finally, the face recognition is realized by the nearest neighbor classifier. The rest of the paper is organized as follows: Section II describes curvelet transformation. Section Ⅲ describes the concept of $(2D)^2$PCA. A face recognition system based on the proposed method is discussed in section Ⅳ. Experimental results are presented in section Ⅴ. We conclude in section Ⅵ.

2. Curvelet transform

Wavelet transform has been profusely employed to pattern recognition and computer vision, because of its ability to capture localized time-frequency information of image extraction. But wavelet transform can only detect point singularities in 1D and 2D images, it fails to represent curved singularities efficiently.

To overcome these weaknesses, Candes and Donoho proposed curvelet transform. The basic idea of curvelet transform is based on anisotropic scaling principal, and it directly takes edges as the basic representation elements, so curvelet transform is useful for representing the edges of images efficiently, and it has a better prospect than wavelet in human face recognition. The main technique presented in current curvelet transform literature is numerically tight FDCT Wrapping, as this is the fastest curvelet transform algorithm currently available.

The curvelet transform of function *f* can be expressed as:

$$c(j,l,k) := \langle f, \varphi_{j,l,k} \rangle \tag{1}$$

In (1), $\varphi_{j,l,k}$ is the curvelet expression, and *j, l* and *k* are the scale, direction and position parameters respectively. For a input of the Cartesian matrix $f[t_1,t_2], 0 \le t_1,t_2 < n$, the discrete curvelet transform can be expressed as:

$$c^D(j,l,k) := \sum_{0 \le t_1,t_2 < n} f[t_1,t_2]\,\overline{\varphi^D_{j,l,k}[t_1,t_2]} \tag{2}$$

Implementation steps of FDCT via Wrapping are as follows:

1. 2D FFT (Fast Fourier Transform) is applied to $\hat{f}[n_1,n_2]$ to obtain Fourier samples: $\hat{f}[n_1,n_2], -n/2 \le n_1,n_2 < n/2$.

2. For each pair of scale j and angle l, the product $\tilde{U}_{j,l}[n_1,n_2]\hat{f}[n_1,n_2]$ is formed, where $\tilde{U}_{j,l}[n_1,n_2]$ is the discrete localizing window.

3. This product is wrapped around the origin to obtain $\tilde{f}_{j,l}[n_1,n_2] = W(\tilde{U}_{j,l}\hat{f})[n_1,n_2]$; where the range for n_1 and n_2 is now $0 \le n_1 < L_{1,j}, 0 \le n_2 < L_{2,j}$. Here $L_{1,j}$ is about 2^j and $L_{2,j}$ is about $2^{j/2}$.

4. Apply the inverse 2D FFT to each $\tilde{f}_{j,l}$, hence creating the discrete curvelet coefficients $c^D(j,l,k)$.

3. $(2D)^2$PCA

$(2D)^2$PCA [11] is based on 2D image matrices rather than 1D vectors and it does not need to be transformed into a vector prior to feature extraction. When compared with PCA and 2DPCA, $(2D)^2$PCA works not only in the row direction of face images, but also in the column direction. It also has smaller number of coefficients for face representation and recognition.

Consider an image matrix $A^{m\times n}$. Let $X \in R^{n\times d}$ be a matrix with orthonormal columns, which $n \geq d$. Projecting A onto X yields an $m\times d$ matrix $Y=AX$. In 2DPCA, the total scatter of the projected samples was used to determine a good projection matrix X. That is, the following criterion is adopted:

$$\begin{aligned} J(X) &= trace\{E[(Y-E(Y))(Y-E(Y))^T]\} \\ &= trace\{E[(AX-E(AX))(AX-E(AX))^T]\} \\ &= trace\{X^T E[(A-E(A))^T(A-E(A))]X\} \end{aligned} \tag{3}$$

where the last term in (3) results from the fact that *trace(AB)=trace(BA)*. Define the image covariance matrix $G=E[(A-E[A])^T(A-E[A])]$, which is an $n\times n$ nonnegative definite matrix. Suppose that there are N training samples $A_i(i=1,2,\cdots\cdots,N) \in R^{m\times n}$, and denote the mean image as $m=\frac{1}{N}\sum_{i=1}^{N} A_i$, then G can be evaluated by:

$$G=\frac{1}{N}\sum_{i=1}^{N}(A_i-m)^T(A_i-m) \tag{4}$$

It has been proved that the optimal value for the projection matrix X_{opt} is composed of the orthonormal eigenvectors $X_1, X_2, ..., X_d$ of G corresponding to the d largest eigenvalues, which is $X_{opt}=[X_1, X_2, ..., X_d]$.

An alternative 2DPCA works simultaneously. $Z_{opt} \in R^{m\times q}$ is a matrix with orthonormal eigenvectors $Z_1, Z_2, ..., Z_q$ of G' corresponding to the q largest eigenvalues, that is $Z_{opt}=[Z_1, Z_2, ..., Z_q]$, which $m \geq q$. Projecting A onto Z_{opt} yields a $q\times n$ matrix $B=Z_{opt}^T A$. Here the alternative definition of image covariance matrix G' is:

$$\begin{aligned} G' &= E[(A-E(A))(A-E(A))^T] = \frac{1}{N}\sum_{i=1}^{N}(A_k-\overline{A})(A_k-\overline{A})^T \\ &= \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{n}(A_k^{(j)}-\overline{A}^{(j)})(A_k^{(j)}-\overline{A}^{(j)})^T \end{aligned} \tag{5}$$

Suppose the projection matrices $X_{opt}^{n\times d}$ and $Z_{opt}^{m\times q}$ are obtained by projecting the image $A^{m\times n}$ onto $X_{opt}^{n\times d}$ and $Z_{opt}^{m\times q}$ simultaneously. We can get a $q\times d$ matrix C:

$$C = Z_{opt} A X_{opt} \tag{6}$$

When used for face recognition, the matrix C is also called the feature matrix. After projecting each training image A_k onto $X_{opt}^{n\times d}$ and $Z_{opt}^{m\times q}$, we obtain the training feature matrices $C_i(i=1,2,\cdots\cdots,N) \in R^{q\times d}$. Given a test face image A, first use (6) to get the feature matrix C, then a nearest neighbor classifier is used for classification. Here the distance between C and C_k is defined by:

$$d(C,C_k)=\|C-C_k\|=\sqrt{\sum_{u=1}^{q}\sum_{v=1}^{d}(C^{(i,j)}-C^{(i,j)})^2} \tag{7}$$

4. The proposed method

In view of the comparisons between wavelet and curvelet and between PCA and $(2D)^2$PCA, we proposed a face recognition algorithm based curvelet transform and $(2D)^2$PCA.

For a given set of training face images, we firstly get low frequency coefficients through curvelet transform. Because majority of the image energy is included in low frequency coefficients, it can express the basic characteristics of human face images easily. We can figure out that the size of low frequency coefficient is 37 × 31 for a 112 × 92 image. Here the images are decomposed using curvelet transform at *scale = 3* and *angle=8*. The experiments have proved that this scale can balance between recognition accuracy and recognition time, and larger scales of the transformation will not significantly improve recognition accuracy. Fig. 1 shows the curvelet coefficients of a face from ORL dataset decomposed at *scale = 3* and *angle = 8.* The 1st image is the original and the 2nd is low frequency coefficients in the first row. Other images are detailed coefficients at 8 angles.

$(2D)^2$PCA is a global feature extraction method more sensitive to illumination changes, so before the dimension reduction with 2DPCA, we introduce a exponential decay factor a to make the elements of image matrix decay exponentially:

$$h = h^a, 0 < a < 1 \tag{8}$$

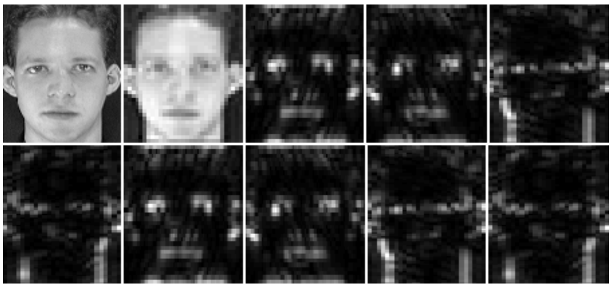

Figure 1. Curvefaces: 1st is the original image and 2nd is low frequency coefficients in the first row, others are detailed coefficients at 8 angles

In (8), h is the image pixel gray value and a is the exponential decay factor. This process is similar to the gamma correction in image display by increasing the contrast between overall brightness and part darkness to restrain the range of illumination change. As a result, recognition accuracy is enhanced.

To further reduce the dimensionality, $(2D)^2$PCA is applied on low frequency coefficients only. Thus, a representative and efficient feature set is produced. A nearest neighbor classifier is employed to perform the identification task.

5. Experiments and Analysis of results

This paper uses ORL and Yale standard human face database for face recognition experiments. ORL face database has 400 grayscale images (112 × 92) of 40 individuals with 10 different postures and expressions for each individual. Yale face database puts more focus on the change of illumination. It contains 165 grayscale images (320 × 243) of 15 individuals.

Experimental conditions are as follows: Intel P4-3.0GHz CPU, and 512M memory under Windows XP. Experimental parameters are listed below: Wavelet radix is sym7, decomposition levels are 3, curvelet transform scales are 3, and angles are 8.

We performed three groups of experiments. Fig. 2 shows how recognition accuracy of our proposed algorithm varies with the different values of exponential decay factor a . Because the introduction of a is intended to eliminate the illumination effects, we test a with our method on the Yale face database. Results show that when a =0.4, the algorithm will achieve the best recognition accuracy. So during the following experiments, we set a =0.4.

In order to test the reliability of the proposed method, we have compared it against well-established techniques such as standard eigenface and wavelet methods. We set the training and testing ratio as 5:5 for ORL and 6:5 for

Yale, and calculated the averages out of 10 random experiments. The results are reported in Tab. 1 and they show that on the ORL and Yale database, the recognition accuracy and speed of our algorithm are superior to those of other algorithms. The results also indicate that our method has better robustness and less time complexity under different pose, illumination and expression conditions.

In the next group of experiment, performances under different training samples are compared. We selected two higher recognition accuracy algorithms from the previous experiment, and then made a comparison. Tab. 2 and Tab. 3 report the results of different training samples on ORL and Yale face database. The results indicate that with the different training samples, the recognition accuracy of our method is better than that of the other two algorithms. On the Yale face database, which has more complicated illumination conditions, the recognition accuracy of our algorithm is higher than other method by about 8%, and the recognition accuracy can reach 68.4% with only one training sample. This indicates that our method can effectively reduce the impact of illumination changes, and has a good adaptability.

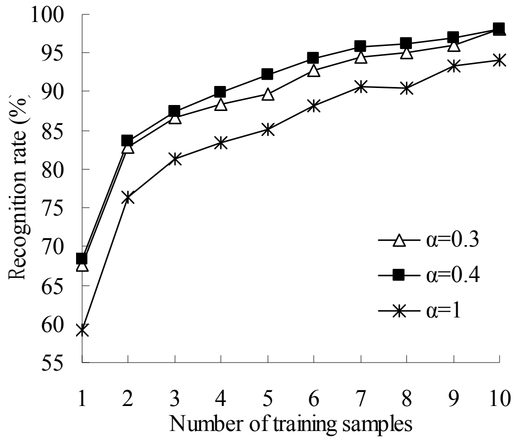

Figure 2 Result of proposed method in different value of a on Yale database

TABLE 1 The comparison of Curvelet and Wavelet on ORL and Yale human face database

Algorithm	**ORL Face Database**		**Yale Face Database**	
	recognition	***recognition time***	***recognition***	***recognition***
Standard eigenface	91.8 %	0.042 s	75.7 %	0.093 s
Waveletface	92.3 %	0.045 s	83.2 %	0.147 s
Wavelet+PCA	93.5 %	0.048 s	83.9 %	0.155 s
Wavelet+2DPCA[4]	95.3 %	0.047 s	85.8 %	0.144 s
Curveletface	92.9 %	0.038 s	82.5 %	0.138 s
Curvelet+PCA[8]	94.6 %	0.043 s	86.7 %	0.144 s
Our method	95.8 %	0.041 s	92.5 %	0.140 s

TABLE 2 Recognition accuracy of different training samples on ORL

Training : Testing	1:9	3:7	5:5	7:3	9:1
Wavelet+2DPCA[4]	73.8 %	91 %	95.3 %	97.8 %	96.5 %
Curvelet+PCA[8]	71.2 %	88.1 %	94.6 %	96.7 %	98 %
Our method	78.6 %	94.8 %	95.8 %	98.6 %	99.2 %

TABLE 3 Recognition accuracy of different training samples on Yale

Training : Testing	1:10	3:8	5:6	7:4	9:2
Wavelet+2DPCA[4]	56.7 %	77.6 %	82.3 %	87.7 %	90.4 %
Curvelet+PCA[8]	55.2 %	79.3 %	84.1 %	88.2 %	89.6 %
Our method	68.4 %	87.5 %	92.1 %	95.8 %	97.6 %

6. Conclusion

This paper proposes a face recognition algorithm based on Curvelet transform and $(2D)^2$PCA. Using the ORL and Yale face database, our method achieves higher recognition accuracy and shorter recognition time than the Wavelet +2DPCA[4] and Curvelet + PCA[8] methods. Our method also demonstrated better robustness for changing conditions in gestures, facial expressions and especially illuminations. In future projects, we will study how to use the high frequency components extracted by the curvelet transform and how to combine curvelet transform with 2DLDA and $(2D)^2$LDA.

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