GABOR-BASED IMPROVED LOCALITY PRESERVING PROJECTIONS FOR FACE RECOGNITION

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ABSTRACT

A novel Gabor-based Improved Locality Preserving Projections for face recognition is presented in this paper. This new algorithm is based on a combination of Gabor wavelets representation of face images and improved Locality Preserving Projections for face recognition and it is robust to changes in illumination and facial expressions and poses. In this paper, Gabor filter is first designed to extract the features from the whole face images, and then a locality preserving projections, which is improved by two-directional 2DPCA to eliminate redundancy among Gabor features, is used to subject these feature vectors onto locality subspace projection. Experiments based on the ORL face database demonstrate the effectiveness and efficiency of the new method. Results show that our new algorithm outperforms the other popular approaches reported in the literature and achieves a much higher accurate recognition rate.

Index Terms— Face Recognition, Gabor wavelets, two-directional 2DPCA, Locality Preserving Projections, Gabor-based Improved Locality Preserving Projections

1. INTRODUCTION

In the last several years, automatic face recognition technology has developed rapidly for the need of surveillance and security, human-computer intelligent interaction, access control, telecommunication and digital libraries, and smart environments. Numerous algorithms have been proposed for face recognition, such as principal component analysis (PCA) [1] and linear discriminant analysis (LDA) [2] and so on. As known, Gabor wavelets have proven to be good at local and discriminate image feature extraction as they have similar characteristics to those of the human visual system.

Gabor wavelet transform [5]-[7] allows description of spatial frequency structure in the image while preserving information about spatial relations which is known to be robust to some variations, e.g., pose and facial expression changes. Although Gabor wavelet is effective in many domains, it nevertheless suffers from a limitation. The dimension of the feature vectors extracted by applying the Gabor wavelet to the whole image through a convolution process is very high. To solve this dimension problem, subspace projection is usually used to transform the high dimensional Gabor feature vectors into a low dimension one. Principal component analysis (PCA)[1] and linear discriminant analysis (LDA)[2], which are typical subspace projection methods for feature extraction and dimension reduction , has been used in face recognition for many years.

Recently, some nonlinear methods have been developed to discover the nonlinear structure of the manifold, algorithms e.g. Isomap, locally linear embedding (LLE), and Locality Preserving Projections (LPP) [3-4].The first two algorithms are nonlinear but the LPP is a linear dimensionality reduction algorithm. LPP method aims to preserve the local structure of samples. Experiments show that LPP is able to extract nonlinear features in the local and nonlinear manifold and can thus perform better in face recognition [4].

This paper presents a novel, hybrid scheme for face recognition by combining Gabor wavelets and an improved LPP method called Gabor-based improved locality preserving projections. Since LPP represents an image by a vector in high-dimensional space which is often confronted with the difficulty that sometimes the matrix is singular, we improved the LPP method by two-directional 2DPCA [8]-[9] to overcome this problem. In our method, face images are first decomposed into their spatial/frequency domains by Gabor wavelet transforms and then a two-directional 2DPCA algorithm is utilized to reduce the dimension of the Gabor feature vectors. Eventually, LPP is applied to the resultant feature vectors to extract robust and discriminative features for recognition. Experiments on the ORL database also demonstrate the discrimination power of the new algorithm we proposed this paper.

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2. GABOR FEATURE EXTRACTION

2.1. Gabor wavelet transforms

Gabor wavelet representation of face images derives desirable features gained by spatial frequency, spatial locality, and orientation selectivity. These discriminative features extracted from the Gabor filtered images could be more robust to illumination and facial expression changes.

In the spatial domain, the Gabor wavelet is a two-dimensional plane wave with wavelet vector with $\overline{k_j}$ restricted by a Gaussian envelope function with relative width σ that can be defined as follow [5]-[7]:

$$\psi_{\mu,\nu}(\vec{z}) = \frac{\left\|\vec{k}_{\mu,\nu}\right\|^2}{\sigma^2}\exp\left(-\frac{\left\|\vec{k}_{\mu,\nu}\right\|^2\left\|\vec{z}\right\|^2}{2\sigma^2}\right)\left[\exp(i\vec{k}_{\mu,\nu}\vec{z}) - \exp\left(-\frac{\sigma^2}{2}\right)\right] \quad (1)$$

where μ and ν define the orientation and scale of the Gabor kernels, $\vec{z} = (x, y)$, $\|\bullet\|$ denotes the norm operator, and the wave vector $\vec{k}_{\mu,\nu}$ is defined as:

$$\vec{k}_{\mu,\nu} = k_\nu e^{i\phi_\mu} \quad (2)$$

where $k_\nu = k_{\max} / f^\nu$ and $\phi_\mu = \pi\mu/8$. $k_{\max}$ is the maximum frequency, and f is the spacing factor between kernels in the frequency domain [6].In most face recognition cases, parameters of Gabor wavelets $\sigma = 2\pi,\ k_{\max} = \pi/2, f = \sqrt{2}$ are used by most researchers [6][7].

By different scaling and rotation via the wave vector $\vec{k}_{\mu,\nu}$, Gabor kernel is generated from a Gaussian envelop and a complex plane wave. In Eqn.1, the first term in the square brackets determines the oscillatory part of the kernel and the second term makes the wavelets DC-free.

2.2. Gabor Feature Representation

Let $I(z)$ be a gray level face image. The Gabor wavelet representation of I is the convolution of the image with a family of Gabor kernel filters in Eqn.1 and can be defined as:

$$G_{\mu,\nu}(z) = I(z) * \psi_{\mu,\nu}(z) \quad (3)$$

where $z = (x, y)$, $*$ denotes the convolution operator, and $G_{\mu,\nu}(z)$ is the convolution result corresponding to the Gabor filter at orientation μ and scale ν. In this paper, Gabor wavelets of five different scales, $\nu \in \{0,\ldots,4\}$ and eight orientations, $\mu \in \{0,\ldots,7\}$ are used [6] [7]. Therefore, the face image $I(\vec{z})$ is represented by a set of Gabor coefficients $\{G_{\mu,\nu}(z) : \mu \in \{0,\ldots,7\}, \nu \in \{0,\ldots,4\}\}$ and the magnitude of each $G_{\mu,\nu}(z)$ is then downsampled, normalized to zero mean and unit variance.

The discriminative Gabor feature can be derived to represent the image I by using different combination of μ and ν. However, the dimension of the feature is quite high, for example, a 112 × 92 image, the vector dimension is $l = 10304$. Then, an improved LPP is introduced to reduce the feature dimension.

3. IMPROVED LOCALITY PRESERVING PROJECTIONS

When the discriminative features are extracted from the Gabor filtered images, Locality Preserving Projections which is then improved by two-direction 2DPCA is performed for classification and recognition.

3.1. Two-directional 2DPCA algorithm [11]

The goal of two-directional 2DPCA is to extract features that can well preserve the principal information in a matrix form. Let X denote an n-dimensional unitary column vector and $A_i (i = 1,\ldots,M)$ denote the m×n Gabor feature based image matrix of the *ith* sample, an $\dim 1 \times \dim 2$ projected vector D can be obtained from the following linear transformation:

$$D_i = V^T A_i U = [Y_1^T, \cdots Y_{\dim 2}{}^T] A_i [X_1, \cdots, X_{\dim 1}] \quad (4)$$

where,dim1 and dim2 are the dimensions of the column and row projector, separately.

First, In order to get the optimal projection vector $U = [X_1, \cdots, X_{\dim 1}]$, one directional 2DPCA is performed by maximizing the following criterion function J_x:

$$J_x = X^T S_x X \quad (5)$$

Where $S_x = \frac{1}{M}\sum_{i=1}^{M}(A_i - \overline{A})^T (A_i - \overline{A})$.

Analogous, the projective function and criterion function of the other directional 2DPCA can be defined as:

$$J_x = Y^T S_y Y \quad (6)$$

where $S_y = \frac{1}{M}\sum_{i=1}^{M}(A_i - \overline{A})(A_i - \overline{A})^T = S_x{}^T$.

The optimal vector set $X_1, \cdots, X_{\dim 1}$ and $Y_1, \cdots, Y_{\dim 2}$ should be the eigenvectors of S_x and S_y corresponding to the largest dim1 and dim2 eigenvalues. Thus it can be seen, the feature vector gained by two-directional 2DLDA algorithm dim1 × dim2 image matrix.

3.2. Locality Preserving Projections algorithm improved by the two-directional 2DPCA

Considering, the samples $x_1, x_2, \cdots, x_n$ with zero mean are in a vector form. A linear transformation $y_i = W^T x_i$ is found from the d-dimensional space to a line, where d is obtained by the two-directional 2DLDA algorithm and $d = \dim 1 \times \dim 2$. The objective function of LPP is as follows:

$$\min_y \sum_{ij} (y_i - y_j)^2 S_{ij} \quad (7),$$

where y_i is the one-dimensional representation of x_i and the matrix $\boldsymbol{S}$ is a similarity matrix. The objective functions with the choice of S_{ij} result in a heavy penalty if neighboring points x_i and x_j are mapped far apart. Therefore, minimizing it is an attempt to ensure that if x_i and x_j is 'close' then y_i and y_j is close too.

If node i and j are connected, define the weighted similarity matrix [5]:

$$S_{ij} = \begin{cases} \exp(-\|x_i - x_j\|^2 / t) & , \|x_i - x_j\|^2 < \varepsilon \\ 0 & otherwise \end{cases} \quad (8)$$

where ε is sufficiently small, and ε>0.

Therefore, the objective function can be reduced by the following algebra formulation:

$$\begin{aligned} & \frac{1}{2}\sum_{ij}(y_i - y_j)S_{ij} \\ &= \frac{1}{2}\sum_{ij}(w^T x_i - w^T x_j)^2 S_{ij} \\ &= \sum_{ij} w^T x_i S_{ij} x_i^T w - \sum_{ij} w^T x_i S_{ij} x_j^T w \quad (9), \\ &= \sum_{i} w^T x_i D_{ii} x_i^T w - \sum_{ij} w^T x_i S_{ij} x_j^T w \\ &= w^T X(D-S)X^T w \\ &= w^T XLX^T w \end{aligned}$$

where $X = [x_1, x_2, \cdots x_n]$ and D is a diagonal matrix; its entries are column (or row, since $\boldsymbol{S}$ is symmetric) sums of $\boldsymbol{S}$, $D_{ii} = \sum_j S_{ij}$. **L** = **D – S** is the Laplacian matrix [3]. Besides, a constraint is imposed as follows:

$$y^T Dy = 1 \Rightarrow w^T XDX^T w = 1 \quad (10)$$

Therefore, the minimization problem reduces to finding:

$$\arg\min_{\substack{w \\ w^T XDX^T w}} \quad J(w) = w^T XLX^T w \quad (11)$$

The transformation vector w that minimizes the objective function is obtained by minimizing the generalized eigenvalue problem:

$$\mathrm{XLX^T} w = \lambda XDX^T w \quad (12)$$

Note that the two matrices $\mathrm{XLX^T}$ and $\mathrm{XDX^T}$ are both symmetric and positive semi-definite.

Thus, according to their first k largest eigenvalues, the embedding is as follows:

$$x_i \to y_i = W^T x_i, W = [w_0, w_1, \ldots, w_{k-1}] \quad (13),$$

where y_i is a k-dimensional vector, and $\boldsymbol{W}$ is a N×k matrix.

4. EXPERIMENTAL RESULTS

The performance of the proposed Gabor-based improved locality preserving projection method is analyzed using the ORL face database. The ORL database (http://www.cam-orl.co.uk) contains images from 40 individuals, each providing 10 different images. For some subjects, the images were taken at different times with different expressions and decorations.

4.1. Comparison with other subspace methods

In the following section, the Gabor-based improved locality preserving projection algorithm is first compared to PCA, LDA and LPP under different feature dimensions. The experiments are performed using the first five images samples per class for training, while the remaining five images for testing. Fig.1 shows the comparative results.

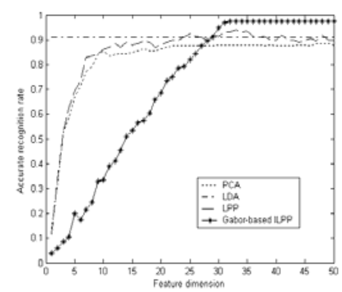

Fig.1. Comparison of recognition rates with four different algorithm under different dimension.

It can be seen that the Gabor-based improved locality preserving projections is more competitive than the other three subspace methods. The accurate recognition rate reaches its top of 97.5% and becomes stable when the number of feature dimension is 32.

To emphasize the discriminating power of the extracted Gabor feature vector, the comparative performance of LPP, Gabor-based LPP, improved LPP and Gabor-based improved LPP are also shown in Fig.2.

From the figure below, it is apparent that the performance of the LPP and Improved LPP is increased by using Gabor feature vector. The highest accurate recognition rate of the four algorithms is 94.00%, 96.00%, 96.5%, 97.5% separately. The Gabor-based LPP method achieves 2% higher accuracy than LPP, while 1% increase is observed for improved LPP when Gabor wavelets are applied.

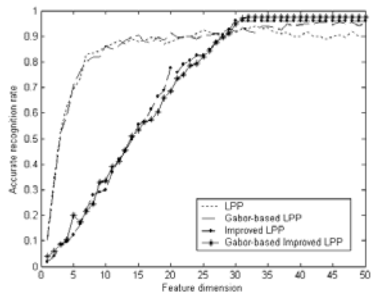

Fig.2. Comparison of recognition rates with LPP, Gabor-based LPP, improved LPP and Gabor-based improved LPP under different dimensions.

4.2. Comparison using different sets of training samples

In the second part of the experiments, for each individual, the first 2,3,4,5,6 face images are selected respectively for training and the rest are used for testing. For each given sets of training samples, we choose the best dimensions of the dimension parameters. Fig.3. shows the plots of recognition rate versus different training samples for LPP, improved LPP and Gabor-based improved LPP methods.

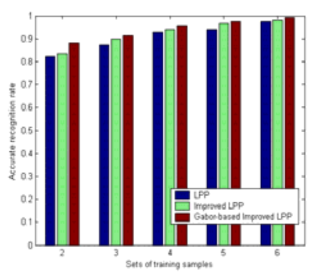

Fig.3. Comparison of recognition rates with the three methods using different sets of training samples

From the diagram above, we can see that the new algorithm present in this paper achieves the highest recognition rate in the three methods when different sets of samples are used for training. Further more, a detail of the experiment is shown in Table.1.

It is found that the new method proposed in this paper outperforms the other two methods with different numbers of training samples (the first 2,3,4,5,6 face images) per individual. The LPP method performs the worst. Extraordinary, when the first 6 images are used for training, the new method achieves the highest accurate recognition rate of nearly 100%.

5. CONCLUSIONS

In this paper, we proposed Gabor-based improved locality preserving projection algorithm to preserve the nonlinear structure of the manifold. For most of traditional face recognition methods (i.e. PCA, LDA, and LPP) consider an image as a vector in high dimensional space, in our method the Gabor filtered images is firstly represented as a matrix. Then a two-directional 2DPCA is utilized before LPP for image matrix compression to removes the inherent redundancy among Gabor features. Important intra-person variations among the Gabor feature space can be captured well and experiments on the ORL database show the new method is more effective and competitive. On the ORL database with six training samples per individual, the Gabor-based improved LPP proposed achieves an accurate recognition rate of nearly 100.00%.

Table1. Comparison of recognition rates with different algorithm Note that the best choices of the number of the components for the top recognition accuracy depend on the test data

	Sets of training samples				
	2	3	4	5	6
LPP	82.19%	87.14%	92.92%	94.00%	97.50%
Improved LPP	83.44%	90.00%	94.00%	96.50%	98.12%
Gabor-based Improved LPP	88.12%	91.43%	95.83%	97.50%	99.38%

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