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Application in Face Recognition Based on Improved Local Linear Embedding Algorithm and Artificial Vector Machine

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Abstract

In order to improve the accuracy of face recognition in a variety of gestures, a face recognition method of improved local linear embedding algorithm is proposed. First, facial features are extracted by Gabor transform and then dimensions of the facial features are reduced according to the local linear embedding algorithm to obtain characteristic vectors of face recognition. Finally, faces are recognized by using supporting vector machine. Simulation experiments have shown that algorithm in this paper can obtain a higher face recognition rate to a certain extent with a certain promotional effect.

Keywords: *face recognition; local linear embedding; Gabor wavelet*

1. Introduction

Currently, face recognition under limited local conditions has been developing quickly, but in practical application, the recognition rate of face images collected has been greatly affected by illumination, expression and other uncontrollable factors. Therefore, it is an urgent problem to be solved as how to improve facial recognition rate under complex conditions [1].

In the process of face recognition, it is an important step as how to extract features, and currently, feature extraction methods are mainly divided into those based on geometric features and those based on algebraic features [2]. Geometric features are susceptible to shooting angle, light intensity and other factors, resulting in an unstable feature extraction [3-4]. Algebraic feature method can be used to extract the overall features of a human face on the whole, and it mainly includes principal component analysis (PCA) and independent component analysis (ICA), etc. But there is a premise in using these two algorithms, that is, the data must be stored in the global linear structure. In high-dimensional space, face image is nonlinear. Therefore, there are some limitations in applying PCA and ICA to face recognition [5, 6]. Manifold learning method researches into the geometric structure in high-dimensional data set from the perspective of human perception and construct an embedding space to maintain topology, thus better solving the nonlinear problem of data [7-9].

In order to improve the recognition rate of faces with different gestures, an improved local linear embedding manifold learning algorithm is proposed in this paper by using the advantages of Gabor wavelet and aiming at the deficiency of local linear embedding manifold learning method's being sensitive to illumination and the choice of neighboring points. Firstly, features of face images are extracted by Gabor transform, and then dimensions are reduced to select facial features effectively. Finally, supporting vector machine is used to classify facial features. Experiments have shown that algorithm in this paper has a higher recognition rate to a certain extent.

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2. Gabor Wavelet and Feature Extraction

Extract the multi-angle, multi-scale and multi-direction space frequency feature in the image's characteristic region with Gabor wavelet, and function expression of two-dimensional Gabor filter is as shown in Figure (1):

$$\psi_{u,v}(z)=\frac{\left\|k_{u,v}\right\|^2}{\sigma^2}e^{-\frac{\left\|k_{u,v}\right\|^2(x^2+y^2)}{2\sigma^2}}(e^{ik_{u,v}\square z}-e^{-\frac{\sigma^2}{2}}) \tag{1}$$

In the formula, $K_{u,v}=\begin{pmatrix}k_x\\k_y\end{pmatrix}=\begin{pmatrix}k_v\cos\varphi_u\\k_v\sin\varphi_u\end{pmatrix}$, $k_v=\frac{k_{\max}}{f^v}$, $\varphi_u=\frac{\pi u}{K}$ and $k_{\max}$ refers to the maximum sampling frequency, f refers to sampling step length in the frequency domain, σ determines the bandwidth of wavelet filter, X=[x,y] refers to pixel location coordinates within the spatial domain, ‖·‖is modular arithmetic and u and v refer to the direction and scale of Gabor filter.

Convolution of face image I(z)=I(x,y) and Gabor filter is:

$$G_{u,v}(z)=I(z)*\psi_{u,v}(z) \tag{2}$$

Gabor wavelet transform of the image is pluralized by real part and imaginary part, which will oscillate with each other. Unsmooth peak response will not be conducive to feature matching at the face recognition stage. However, amplitude can reflect the energy of image, and will not cause oscillations at the edge of image, so it can be used to represent the image feature.

3. Local Linear Embedding Algorithm & Supporting Vector Machine Classification Algorithm

3.1 Local Linear Embedding Algorithm

In local linear embedding algorithm, the research objects are analyzed mainly by the partial overlapping structure so as to provide information for the follow-up dimension reduction and reflect data in the high-dimension space to the coordinates of a low dimension space as possible as it can be under the premise of maintaining the distance between neighboring nodes. Algorithm steps are as follows:

(1) Searching local neighboring points. Generally, k neighboring method is adopted to calculate the neighboring point of each sample point xi in the high dimension space and the choice of k value plays an important role in ensuring the restructure of local linear embedding algorithm.

(2) Establishing local reconstruction weights matrix of sample points. Error function is defined to ensure the minimum over reconstruction error, namely:

$$f(W)=\sum_{i=1}^{N}\|x_i-\sum_{j=1}^{k}W_{ij}x_{i,j}\|^2 \tag{3}$$

Herein, x_i refers to the function of sample point, and the reconstruction contribution of the j neighboring point x_{ij} around the sample point x_i to is defined as W_{ij}. The data point x_i must be reconstructed by its neighboring points, and if x_j does not belong to the neighboring points of x_i, then $W_{ij}=0$.

(3) In order to solve the local reconstruction weight matrix W, local covariance matrix C is constructed. And usually, the minimum error is reconstructed by minimization, and then there is：

$$C_{jk}=(x_i-x_{i,j})^T(x_i-x_{i,k}) \tag{4}$$

(4) Considering the constraint condition as shown in formula (3), Lagrange multiplier method is used so as to get the local optimal linear reconstruction weight matrix:

$$W_{ij} = \frac{\sum_{m=1}^{k} C_{jm}^{-1}}{\sum_{p=1}^{k} \sum_{q=1}^{k} C_{pq}^{-1}} \tag{5}$$

Generally, C is a singular matrix. A regularization parameter r in introduced and then get $C=C+r\cdot I$ (I is a $k\times k$ unit matrix).

(5) Calculate the low dimension by feature reflection. All the samples are reflected into the low-dimension space and fixed weight W_{ij}. In order to get the minimum target function, reflection y_i is needed to be found:

$$f(Y) = \sum_{i=1}^{N} \| y_i - \sum_{j=1}^{k} W_{ij} y_{i,j} \|^2 \tag{6}$$

Herein, y_i is the low-dimension reflection vector of x_i and $y_{i,j}$ belongs to the k field points of y_i and complies with $\sum_{i=1}^{N} y_i = 0$, $\frac{1}{N}\sum_{i=1}^{N} y_i y_i^T = I$ (I is the unit matrix of $D\times D$).

Then formula (6) can be written as:

$$f(y) = tr(yMy^T) \tag{7}$$

Herein, M=(I-W)T(I-W), and each column of y is composed of yi.

In order to make the value of loss function minimum, take the corresponding characteristic vector of d minimum non-zero characteristic value with Y as M. In the process, arrange the characteristic value of M from small to big until the first characteristic value is almost close to zero, and eliminate the first characteristic value.

3.2 Supporting Vector Machine

For the given data set (x_i, y_i), there is $x_i \in R^n$ and $y_i \in \{-1,1\}$, suppose i=1,2,…,n, so the optimal classification hyper-plane of the supporting vector machine is:

$$y = \omega \cdot \varphi(x) + b \tag{8}$$

In formula (8), ω is the normal vector of hyper-plane and b is the offset vector.

In order to maintain the maximum data point vector in the training set and the maximum hyper-plane to the maximum extent, it is converted into a two optimization problem, and then there is:

$$\min J(w,\xi) = \frac{1}{2}\|w\|^2 + c\sum_{i=1}^{n} \xi_i \tag{9}$$

In the formula, c refers to penalty parameter.

When the sample is relatively large, the speed of supporting vector machine becomes slow, thus causing low efficiency. It can be turned into a dual problem by introducing Lagrange multiplier, and then transformed into a dual problem to get the solution, accelerating the speed of classification. Function changes are as follows:

$$f(x) = sign\left(\sum_{i=1}^{n} \alpha_i y_i (\varphi(x, x_i)) + b\right) \tag{10}$$

In the formula, sign refers to the sign function and α_i refers to Lagrange multiplier [12].

If the classification is not a linear problem, the dot product $\varphi(x, x_i)$ can be replaced by kernel function $K(x, x_i)$ in supporting vector machine, so the classification decision function is as follows:

$$f(x) = sign\left(\sum_{i=1}^{n} \alpha_i y_i k(x_i, x) + b\right) \tag{11}$$

There is few parameters needed to be optimized in the radial basis kernel function, so classification function of the supporting vector machine can be established, so there is:

$$f(x) = sgn(\alpha_i y_i \exp\left(-\frac{\|x - x_i\|}{\sigma^2}\right) + b) \tag{12}$$

In the formula, σ refers to the width of radial basis kernel function.

3.3 Algorithm in this Paper

As can be seen from the basic thought of local linear embedding algorithm, in high-dimensional space, the choice of neighboring points is very important because the improper choice will affect the follow-up effect of dimension reduction. In local linear embedding algorithm, distant points may be chosen as the neighboring points and after dimension reduction, these points will be reflected to the locations of neighboring points.

Therefore, the original local linear algorithm has been improved in this paper. Hierarchical method combining the size is used to find the neighboring points, and hierarchical local linear embedding algorithm is used to find the neighboring points of samples. There are two steps:

(1) Calculate the category center of each category.
(2) Calculate the Euclidean distance between this sample point and all the category centers and take all the data points of n-type with the nearest Euclidean distance as the neighboring points.

In choosing neighboring points, some points near the sample points but far from the category centers they belong can be excluded in this method. Generally, the neighboring point of each sample is still its neighboring point. Therefore, points far from the category center can be excluded to improve the accuracy of face recognition.

Suppose there are three kinds of face recognition samples, and if the original linear algorithm is used to obtain the neighboring points, points of the other categories will be chosen as the neighboring points, which cannot bring the possibility to the follow-up low-dimension recognition because in low-dimension space, they are still the neighboring points of the sample point. This situation will be avoided well to choose neighboring points with hierarchical local linear embedding algorithm combining with sizes. Suppose sample point xi and xj belong to the same category and the Euclidean distance is relatively long, xj will probably not be chosen as the neighboring point in finding neighboring points by using local linear embedding algorithm. However, by using the algorithm in this paper, as long as there is at least one category xi belongs to among the nearest n categories to xi, it will be Ok. Therefore, points will the same category with xi can be chosen as the neighboring points.

3.4 Algorithm Steps

Step 1: Make pre-treatment of collected images about facial features

Step2: Extract features of face images with Gabor wavelet and obtain feature vector of face images

Step3: Reduce dimension of features with the algorithm in this paper, select the optimal face feature and reflect the high-dimension Gabor features to low-dimensional differential space.

Step 4: Process the training sample set and testing sample set according to the optimal characteristics and select their Gabor features respectively.

Step 5: Put the training sample set into the supporting vector machine for learning, establish the optimal classifier, and identify the testing sample set to obtain the results of face recognition.

4. Simulation Experiment

4.1 Face Image Database

(1) Yale B Face Image Database

Yale B face image database are made up of the images of 10 people and each people has 9 gestures. Since this paper mainly researches the problem of face recognition with illumination changes, 12 gestures of face image in positive light are chosen, and the specific information is as shown in Figure 1.

Figure 1. Yale B Face Subset in 12 Kinds of Lighting Conditions

(2) CMU-PIE Face Image Database

In this paper, the images of 65 people are selected at random, and the images of one people include a set of images in 21 kinds of lighting conditions. The images of the same people in 15-21 kinds of lighting conditions are selected in this paper, and the images are shown as in Figure 2.

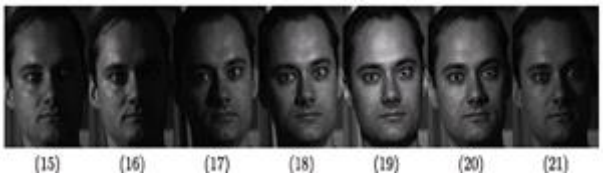


Figure 2. CMU-PIE Images of the Same People in 15-21 Kinds of Lighting Conditions

(3) AR Face Image Database

The AR face image database contains more than 4,000 kinds of color images and a variety of facial expressions deviating from the ideal conditions. In this paper, four kinds of expressions of the same person are selected, and they are shown in Figure 3.

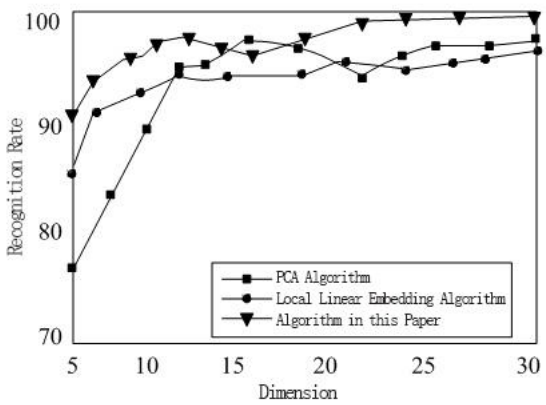
Fig. 3 AR Image of the Same People in Four Kinds of Lighting Conditions

4.2 Experimental Hardware Platform

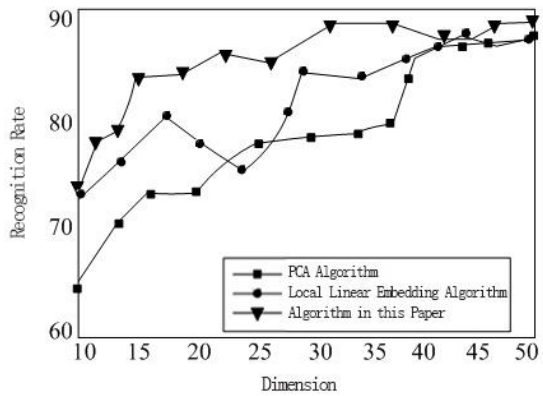
On the platform of Core 2 Intel 3.0GHZ CPU, RAM4.0G and Windows 7, simulation experiment is realized by using Matlab 2012. In order to verify the face recognition function of algorithm in this paper, contrast experiment is carried out between PCA algorithm, local linear embedding algorithm and algorithm in this paper with recognition rate and recognition time as the performance evaluation indexes.

4.3 Results and Analysis

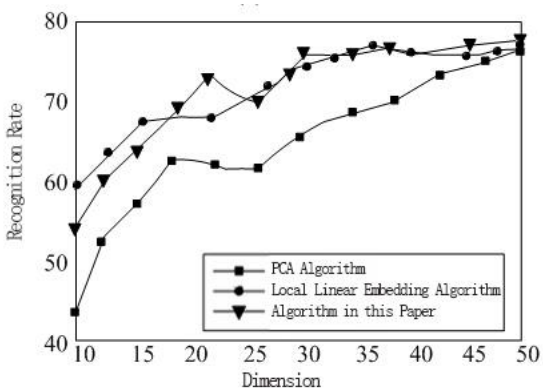
Everyone is required to choose the 0° image for training and 10°, 20°, 30° and 40° face images are selected for testing respectively with 3 randomly selected images as the testing samples. Category number m is selected as 3 and neighboring number k=8. Radial basis kernel function is used in supporting vector machine and genetic algorithm is used to optimize the parameter $C\in$ [1 10000] and $\sigma\in$ [0.1 100], and then optimal parameters are C=165.25 and σ=1.75. Finally, human ear classifier is established by the optimal parameter. With the changes of characteristic dimension, the curve of changes in recognition rates of PCA algorithm, local linear embedding algorithm and algorithm are shown in Figure 4.



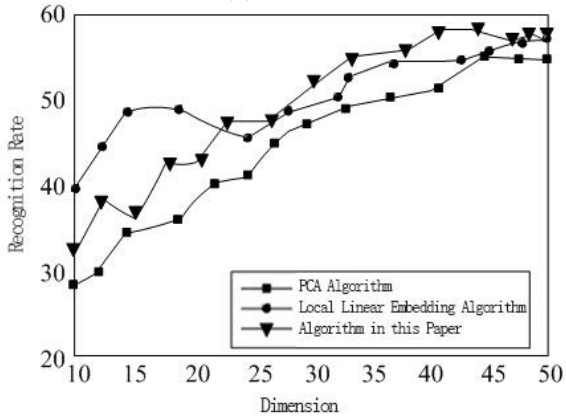
(a) θ=10°



(b) θ=20°



(c) θ=30°



(d) θ=40°

Figure 4. Curve of Changes in Recognition Rate of Faces with Different Gestures

As can be seen from the analysis of Figure 4, generally, algorithm in this paper has higher recognition rate than local linear embedding algorithm and PCA algorithm in each angle, mainly because of the introduction of Gabor wavelet transform, which has reduced the influence of defection angle to face recognition. Second, algorithm in this paper can get higher recognition rate than local linear embedding algorithm and PCA algorithm, mainly because hierarchical method is used by the algorithm in this paper to select the optimal neighboring point with k=8, and category information of samples is used to reduce the dimensions of data better. Meanwhile, Gabor wavelet transform is introduced and it is stronger than robustness. In the process of deflection angle changing from 10° to 40°, the recognition rate of all the algorithm has declined, and when the deflection angle θ=40°, the recognition rate of all the algorithms is below 60%, which is mainly because when the deflection angle reaches to a certain angle, much of the sample information has been lost with only the basic contour information remained. The texture information of face is not very clear, so it is difficult to recognize faces accurately.

5. Conclusion

In face recognition algorithm, due to the influence of deflection angle and the choice of neighboring points, some face recognition algorithm cannot reduce the dimensions of data of the existing samples well. In this paper, face recognition method is proposed combining Gabor wavelet and local linear embedding algorithm. This algorithm can not only reduce the dimensions of high-dimensional data effectively, but also maintain the topological structure of data so as to reduce the influence of defection angle and the

choice of neighboring points to the algorithm and finally improve its identification ability. Simulation experiments have shown that algorithm in this paper can obtain a higher face recognition rate to a certain extent with a certain promotional effect.

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