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An Improved Locally Linear Embedding Algorithm for Ear Recognition

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Abstract

In order to improve the recognition rate of ear, a novel ear recognition algorithm is proposed based on improved locally linear embedding algorithm. Firstly, the ear features are extracted by Gabor transform, and then the improved LLE is used to reduce dimensionality of features and select the optimal features of ear recognition, finally support vector machine is used to establish the classifier of human ear recognition, and the simulation experiment is carried out on USTB3 ear images. Compared with the reference methods, the proposed algorithm has obtained higher ear recognition rate, and the experimental results verify the effectiveness.

Keywords: *ear recognition, locally linear embedding, Gabor wavelets, support vector machine, features extraction*

1. Introduction

Ear recognition is a new biometric identification technology in recent years; compared to other biometrics, it is not affected by the expression, age, mentality, makeup and other factors, and the human ear image is relatively small with small amount of calculation, hence becoming focus areas of biometric research [1].

In the course of ear recognition, feature extraction is an important step to identify the human ear; according to the different characteristics extraction methods it can be roughly divided into two categories: Geometry feature-based and algebraic geometry-based [2]. Geometry characteristic features due to the need to extract the edge of the outer ear and the inner ear, the characteristic is vulnerable to shooting angle, and the light intensity, its feature extraction is instable [3-4]. Algebraic method can be used to extract overall characteristics of the human ear, and the representative algorithm are principle component analysis (PCA), independent component analysis (ICA), *etc.*; the using pretext is two algorithms datasets existing in the global linear structure; due to the impact of the light intensity, head posture, and the shooting angle, the human ear images like the face images in high-dimensional space is nonlinear manifold structure, while ear image is clearly not satisfied this premise, thus the PCA and ICA for the human ear recognition has some limitations [5, 6]. Unlike methods based on geometric features, manifold learning method from the perspective of human perception, through the study of high -dimensional data sets inherent geometry and found its intrinsic geometric regularity, constructing topology space to maintain embedding, hence becomes a better solution to the data nonlinear problems [7, 8]. Unlike two algebraic methods -- PCA and KPCA which are based on the overall model, manifold learning method through the establishment of local models, considers partial assumption as a basis of space , making the original nonlinear problem become linear expressions; manifold learning method can better find the structure of high-dimensional data sets, provide a more intuitive understanding of the data [9]. In the year of 2000, Roweis and Saul published article in the Science, proposed LLE (Locally Linear Embedding, LLE) manifold learning method, which can map high-dimensional

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input data point to a global low-dimensional coordinate system, while maintaining the relationship of neighborhood points, hence the intrinsic geometry can be preserved. This algorithm can not only effectively find the nonlinear structure of the data, but also has an invariant feature such as translation, and rotation. In 2008, Xie Zhaoxia *etc.*[10] took LLE algorithm for multi- pose ear recognition under different attitude and made good recognition results, but they did not solve the problem of neighbors points selection number. Gabor wavelet kernel function can well describe simple visual neurons receptive properties of mammalian primary visual system; compared with the Fourier transform , Gabor wavelet transform has good time- frequency localization , not sensitive to light , and can tolerate a certain degree of image rotation and deformation [11].

In order to improve the multi-pose ear recognition rate, focused on LLE algorithm's sensitivity to light changes and insensitivity to neighbor point selection, the author took the advantages of Gabor wavelet, proposed an improved LLE (Improved LLE, ILLE) of ear recognition method (Gabor-ILLE). Firstly, through Gabor transform to extract ear image features, then using LLE to reduce the dimension of the feature, choosing the most beneficial features of ear recognition, finally using support vector machine to build the human ear classifier and conduct simulated experiment on USTB3 ear image library, so as to test Gabor-ILLE ear recognition method effect.

2. Gabor Wavelet and Feature Extraction

Dimensional Gabor filter function expression formula (1) as follows:

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

wherein, $K_{u,v} = \begin{pmatrix} k_x \\ k_y \end{pmatrix} = \begin{pmatrix} k_v \cos \varphi_u \\ k_v \sin \varphi_u \end{pmatrix}$; $k_v = \frac{k_{\max}}{f^v}$; $\varphi_u = \frac{\pi u}{K}$; $k_{\max}$ represents the maximum sampling frequency; f is the sampling step length in frequency domain ; σ determines the width and wavelength ratio of the Gaussian window ; X=[x,y] is a spatial position coordinates of the pixel; ||·|| is modulo arithmetic; u and v indicates the direction and scale of Gabor filter. In the selection of five scales, eight directions of Gabor filter bank, v ∈ {0-4}, u ∈ {0-2... 7} [12].

Ear Image I (z) =I(x, y) and the convolution of Gabor filter:

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

Gabor image wavelet transform resulting is composed of the real and imaginary parts of the complex; in the vicinity of the edge of the image, the real and imaginary parts have the oscillation, if the peak response is not smooth, it is not conducive to the subsequent stages of ear recognition feature matching. Amplitude reflects the image of the energy spectrum, which is relatively stable, and will not produce oscillations near the edges of the image, nor produce the rotation varies with the location, hence it is often used to represent the image features. After these Gabor wavelet transform, ear image produces 40 Gabor amplitude spectrums, which is specifically shown in Figure 1.

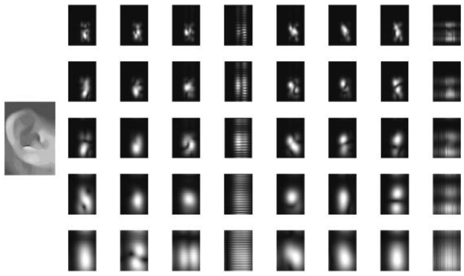


Figure 1. Human Ear Image in Representation of Gabor Amplitude

2. ILLE Algorithm and Support Vector Machine Classification Algorithm

2.1. Locally Linear Embedding (LLE) Algorithm

LLE algorithm through overlapping local structure and overall analysis to provide global geometric information of dimensionality reduction, thus completing the data from the original high-dimensional space mapping into low dimensional space coordinate space in neighbor distance while maintaining the same premise. Provided there are N data samples with X = {xi | xi ∈ RD, i = 1, 2... N}, and they fall in a high-dimensional space. The purpose of LLE algorithm is to find a low-dimensional mapping based on certain criteria Y = {yi | yi∈ Rd, i = 1, 2, N}, where d << D, in order to achieve dimensionality reduction of high-dimensional data. Algorithm steps are as follows:

(1) Search local neighborhood sites. Generally we use K-nearest neighbor method to calculate each sample point xi neighbor points in high-dimensional space; k value has played an important role in ensuring the flow of low-dimensional shape embedding of LLE algorithm reconstruction.

(2) Calculate the partial reconstruction weight matrix of sample point. In order to achieve linear reconstruction purposes, we define a cost function to make the overall reconstruction error be minimized, namely:

$$\varepsilon(W) = \sum_{i=1}^{N} \| x_i - \sum_{j=1}^{k} W_{ij} x_{i,j} \|^2 \qquad (4)$$

Wherein, xi is a sample vector, Wij is the sample weights xi the j-th neighborhood point xij to reconstruction contribution of xi.

To calculate these weights, LLE adds two qualifiers: The first condition is that each data point xi must be reconstructed from the point of its neighborhood, so that when xj not belongs to the xi field, Wij = 0; the second condition is weighted sum of each row of the matrix is 1, namely:

$$\sum_{j=1}^{N} W_{ij} = 1 \qquad (3)$$

(5) In order to solve a partial reconstruction of the weight matrix W, we construct a partial covariance matrix C, to minimize the reconstruction error which can be obtained in:

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

(6) Taking into account the formula (3) shown constraints, we use Lagrange multiplier method, and solve the optimal linear partial reconstruction weight matrix:

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

Normally, C is a singular matrix, and is in need to go through regularization to ensure nonsingular. Introducing a regularization parameter r, and can be obtained: C = C + r · I (I is a unit matrix of k×k).

(3) By feature maps to calculate low-dimensional embedding . All sample points are mapped to low-dimensional space, fixed weights Wij, in order to obtain the minimum objective function, we need to find maps yi：

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

Where, yi is the low-dimensional mapping of the vector xi, yi,j belonging to the set of k point areas of yi , and should be consistent with $\sum_{i=1}^{N} y_i = 0$, $\frac{1}{N}\sum_{i=1}^{N} y_i y_i^T = I$ （I is a unit matrix of D × D）.

Then the formula (6) can be written as:

$$\varepsilon(y) = tr(yMy^T) \quad (7)$$

Where, M= (I-W) T (I-W), each column of y is constituted by yi to reach a minimum value of the loss function, Y is taken as the minimum d non-zero Eigen values of M corresponding eigenvectors. In the process, the characteristic value M is arranged in ascending order until the first characteristic value is almost close to zero, discarding the first characteristic value. Take between 2~d+1 eigenvalues corresponding eigenvectors to each row (d coordinate) [13] as each column of Y output.

2.2. Improved LLE Algorithm

The basic idea of the LLE algorithm is to keep each point in low-dimensional space by a linear combination of neighboring points has the same reconstructed weights, namely high-dimensional space neighbor points in low-dimensional space point still are close neighbors, and weights are unchanged; from the basic idea it can be seen that selecting high-dimensional space neighbor point is very important; if neighbor points are not selected properly, it will directly impact dimensionality reduction results . For sparse distribution or noise-affected data sets, LLE algorithm might select points far apart as neighbors' points, which after dimensionality reduction will be mapped to the location of neighboring points. So we need to find a better way to select a neighbor point, making the quality of the selected neighbor points higher, thus improving the accuracy of ear recognition.

In this paper, the original LLE algorithm has been improved, using a layered approach to find the neighbor points, but other processes are the same as LLE algorithm. Using hierarchical LLE algorithm (ILLE) to find the neighbors point of sample points, there are two steps:

(1) calculation of the class center of each category.

(2) calculation of the Euclidean distance of the sample point to the class center of all categories, taking all m class of data points with minimum Euclidean distance as neighbor points.

When using this method, we can exclude some points close to the sample point close, but whose class center point is farther. Under normal circumstances, after the adoption of LLE algorithm to reduce the dimensions, neighbors' points of each sample in low-dimensional space are still its neighbor's points. From the very beginning the exclusion of far points from the class center can improve ear recognition accuracy.

As shown in Figure 2, there are three types of samples in the figure corresponding to the three points in the diagram center, respectively according to the original LLE algorithm to select neighboring points, which will inevitably select other two classes points as neighboring points, not conducive to the identification, because these points are still neighboring points of this sample point in the low-dimensional space and would interfere with the classifier. Using the layered LLE algorithm to select the neighbor points can avoid this situation. Also, assume that the sample points xi and xj belong to the same class, using the traditional LLE algorithm to find neighbor points of xi: if the Euclidean distance between them is greater, then xj most likely will not be selected as neighbors point, while in the layered LLE algorithm, as long as m categories center nearest to xi include xi category, it can select all same categories with xi as its neighbors points.

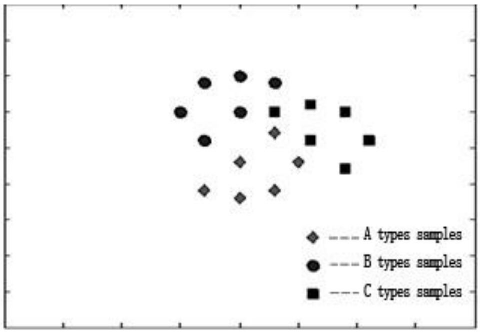


Figure 2. Schematic Diagram of Three Types Samples

2.3. Support Vector Machine Algorithm

Given data set(xi,yi)，xi∈Rn，yi∈{-1,1}，i=1,2,…,n， then, SVM's optimal hyper plane is:

$$y = \omega \cdot \varphi(x) + b \quad (8)$$

Wherein, ω is a normal vector to the hyper plane, b is the offset vector hyper plane.

To make all the training set of data points between the optimal hyper plane vector has the maximum distance from the plane, we convert it into the quadratic optimization problem, that is:

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

Wherein, c is the penalty parameter.

For large sample classification, SVM has slow training speed, low efficiency, which was transformed into the dual problem by introducing Lagrangian multiplier, then solves the dual problem and accelerates classification speed, ultra-flat classification decision function changes:

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

Wherein, sign is the sign function, αi is the Lagrange multiplier [14].

If the classification problem belongs to non-linear problem, SVM by introducing kernel function K (xi,x) to replace dot product φ (xi, x), and therefore the final SVM classification decision function is:

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

Since the radial basis kernel function has less optimization parameter, we choose it to create SVM classification function, therefore:

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

Where, σ is the width of radial basis kernel function [15].

2.4. Gabor-ILLE Ear Recognition

(1) ear image acquisition, and image preprocessing.

(2) extraction of ear image feature by Gabor wavelet vector to get the ear of the image.

(3) using ILLE to conduct feature reduction algorithm, selecting the optimal characteristics of the human ear, mapping high-dimensional Gabor features to low-dimensional differential space.

(4) According to the optimal characteristics, processing the training set and test set samples, and selecting their Gabor features.

(5) Input the training set to support vector machine for learning; the establishment of optimal human ear classifier, and identification of test sample sets, hence getting ear recognition results.

3. Simulation

3.1. Ear Image Library

Data comes from USTB3 ear library of Beijing Science and Technology University; the library contains a total of 79 individuals, each of 10 images, the image size is 30 × 20 pixels; Figure 3 shows an example of a sample of individuals.

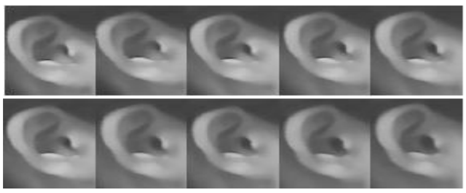


Figure 3. A Person's 10 Ear Images

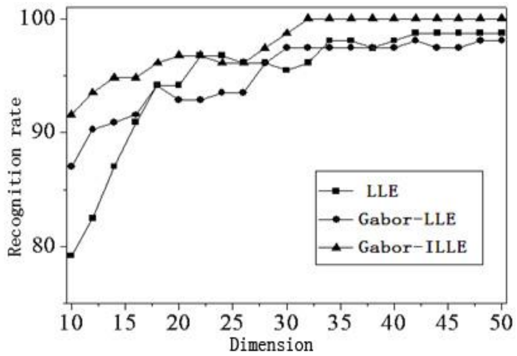
3.2. Comparison and Evaluation of Methods

On Core2 Intel 3.0GHZ CPU, RAM 4.0G, Windows 7 platforms, using Matlab 2012 for simulation experiments. To verify the Gabor-ILLE human ear recognition performance, using PCA algorithm, LLE algorithm, Gabor-LLE (LEE classic algorithm) for comparison experiments, using recognition rate and time as the performance evaluation.

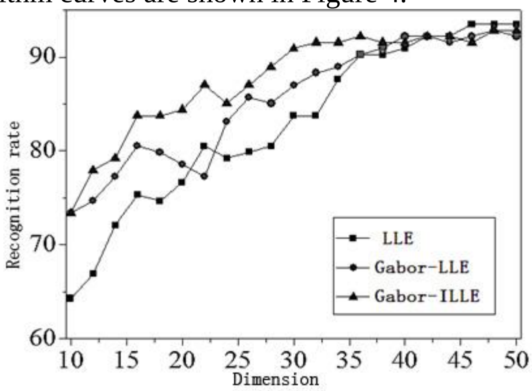
4. Results and Analysis

4.1. Multi-Pose Ear Recognition

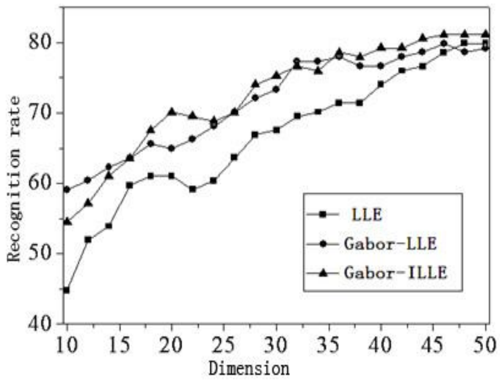
Each person selects 0 °image for the training , and respectively selects 5 °, 10 °, 15 °, 20 ° ear images for testing, randomly selects three images for the test sample; select the category number m as 3, the number of neighbors k = 8, support vector machines using radial basis function, using genetic algorithm to optimize the parameters C ∈ [1 10000] and σ∈ [0.1 100], it gets optimal parameters C = 165.25, σ = 1.75; at last we establish the optimal parameters ear classifier. With characteristic dimension changes, ear recognition rate LLE, Gabor-LLE and Gabor-ILLE algorithm curves are shown in Figure 4.



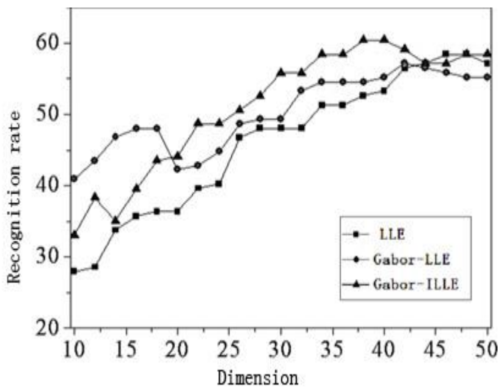
(a) θ=5°



(b) *θ*=10°



（c） θ=15°



(d) θ=20°

Figure 4 Different algorithms of multi-pose ear recognition rate curve after the analysis on Figure 4, we know the Gabor-ILLE has optimal performance, and get the following conclusions:

(1) In each angle, Gabor-LLE recognition rate is generally higher than LLE algorithm, which is due to the Gabor-LLE introducing Gabor wavelet transform which decreases the deflection angle's affection to the human ear recognition.

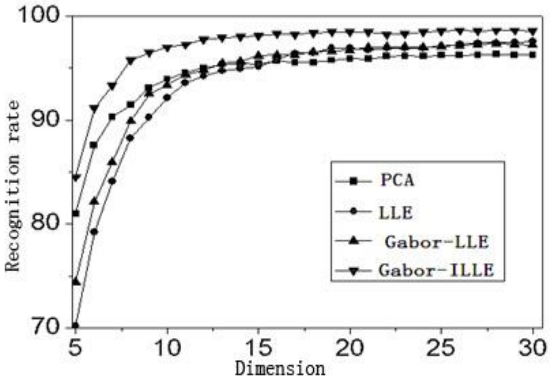
(2) Gabor-ILLE ratio can obtain higher recognition rate than that of Gabor-LLE LLE , because Gabor-ILLE hierarchical algorithm selects the optimal nearest neighboring points k = 8 ; using the category information of samples could better able to reduce the dimensionality of the data, while the introduction of a Gabor wavelet transform is more robust.

(3) when the deflection angle = 5 °, LLE, Gabor-LLE and Gabor-ILLE could obtain a higher recognition rate of human ear: the recognition rate is greater than 80%; with the deflection angle increasing, the recognition rate of all algorithms decreased; when the deflection angle = 20, the recognition rate of all the algorithms are less than 60%, which

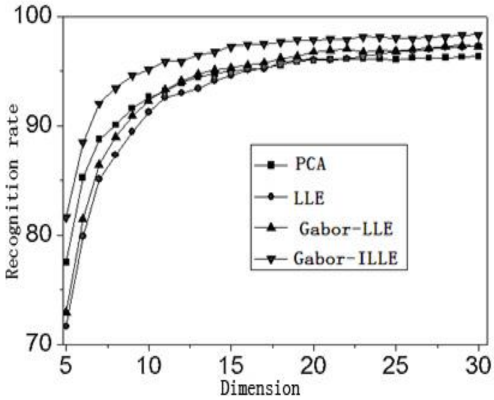
is mainly due to the rotation angle has lost larger amount of sample information, only helix information and parts of the outer ear information left; internal ear ditch texture information could not be seen for the lack of information, hence it is difficult to accurately identify the human ear.

4.1.2. Performance Comparison of Different Samples under Conditions of Training Algorithm

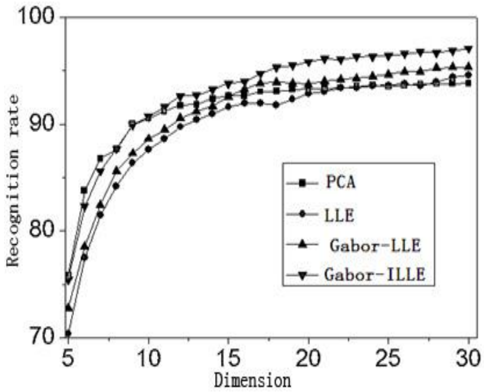
Each chooses randomly j (j = 3-6) images as training images, the remaining images as test images, the number of classes m = 3, the number of neighbor k = 8. To reduce the impact of the classification on the algorithm, all the algorithm were carried out 10 times of experiments, taking the average value as the final result. Under different J values, PCA, LLE, Gabor-LLE and Gabor-ILLE algorithm change with characteristic dimension changes and their average recognition rate curve of the human ear have been shown in Figure 5; all of maximum average recognition rate and the variance are shown in Table 1, the figures in brackets represent its characteristic dimension taken when the maximum average recognition rate is taken.



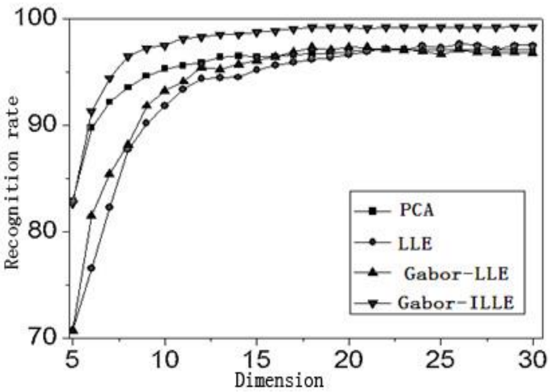
(a) *J*=3



(b) j=4



(c) J=5



(d) j=6

Table 1. Highest Recognition Rate Comparison of Several Algorithms

Number of training samples	PCA	LLE	Gabor-LLE	Gabor-ILLE
j=3	93.80±0.67(30)	94.58±1.18(30)	95.32±0.80(30)	**97.06**±0.51(30)
j=4	96.32±0.76(30)	97.31±0.93(30)	97.31±0.90(29)	**98.31**±0.85(30)
j=5	96.31±0.59(28)	97.50±1.12(30)	97.35±1.31(28)	**98.59**±1.04(26)
j=6	97.07±0.60(22)	97.59±0.78(26)	97.33±0.70(20)	**99.22**±0.29(22)

From Table 1 we could get the following conclusions:

(1) Whether the number of training images j takes what value, recognition rate of Gabor-ILLE is much higher than LLE, PCA, Gabor-LLE, and the Gabor-LLE recognition rate is slightly higher than the LLE, PCA algorithm.

(2) With the increase of the number of training samples, the algorithm identification rate curves gradually increase, which is mainly because each person's more training images help the perfection of recognition system, able to identify more cases.

(3) With the increase of the number of feature dimensions, the recognition rate of all algorithms gradually increases, and slowly becomes more balanced, which is mainly due to the more characteristic dimension the more information of feature is available; one could obtain a higher recognition rate, but when the feature information is rich enough, the recognition rate will tend to balance.

(4) When the number of training samples is 3,4,5,6, the highest recognition rate of Gabor-ILLE compared to Gabor-LLE were raised by 1.74%, 1%, 1.24%, 1.89%, respectively, compared to LLE improved 2.48% , 1%, 1.09%, 1.63%, respectively, compared to PCA improved by 3.26%, 1.99%, 2.28%, 2.15%, and the variance is smaller than the LLE, all indicate that Gabor-ILLE than LLE has better robustness.

5. Conclusion

In LLE algorithm, due to the deflection angle and neighbor point selection effects, the algorithm cannot well reduce the dimensionality to known sample data of class information. This paper combines Gabor wavelet and ILLE algorithm to present Gabor-ILLE ear image recognition method, which takes full advantage of multiscale and multi-directional characterization of Gabor wavelet, and also LLE algorithm can find intrinsic geometry embedded in high-dimensional data with higher feature extraction capabilities. Experiments on USTB3 ear library show that: the algorithm can effectively reduce the dimensionality of high dimensional data, while maintaining topology of the data, thereby reducing the impact of LLE algorithm selected by the deflection angle and neighboring points, and ultimately improve identification ability. Gabor-ILLE compared to LLE algorithm, its highest recognition rate has increased 2.48%, and 1.89%compared with Gabor-LLE algorithm, 3.26% compared with PCA.

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