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Recognition Based on Metric-optimized Neighborhood Preserving Embedding

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Abstract

Face recognition is a biometric technology with great developable potential. It has a great deal of potential applications in public security and information security. To overcome the problem in the high-dimensional face data processing, the k-nearest neighbors is chose by Linear Discriminate Analysis (LDA). A Metric-optimized is proposed for Neighborhood Preserving Embedding (MONPE). MONPE algorithm, with the dimensions of data reduced by LDA, will be reasonable in NPE algorithm. On the other hand, LDA maximizes the between-class scatter and minimizes the within-class scatter, so the neighbors of a sample will have higher possibility to be picked from the same class. With the ORL face database and the Yale database, the recognition rate and run time is compared among NPE, MONPE and CLMONPE. The simulation results show that CLMONPE has obvious advantage in application.

Keywords*: face recognition, manifold, supervised neighborhood preserving embedding*

1. Introduction

Manifold reaching has been great used in the field of data dinning, machine studying, computer visual recently. The aim of manifold study is to gain the topology structure and its law among the data space, when the collected data perform the manifold structure [1]. When the face and gesture change, the general face recognition method will become less effective. That's why manifold study is chosen in face recognition. When face and gesture changes, the collected data will change in nonlinear way. So the general data dimension decrease way such as PCA [2, 3] and LDA [4] can not perform the true inner structure of image space. But the manifold study can do it well. The typical papers about face recognition is published in Science in the same issue by Tenenbaum [5] and Rowels [6]. They show different manifold study methods as Isometrical Mapping (ISOMAP) [7] and Locally Linear Embedding (LLE) [8].

2. Research Method

ISOMAP is a kind of best whole situation nonlinear dimension decrease method. It can ensure data convergence gradually. The original idea is that: geodesic distance is a good dissimilarity measurement, which need to solve the problem of geodesic distance between non-neighborhood dots. The problem can be solved by computing the distance matrix to construct subspace of the nonlinear manifold distribution. The dimension can be decreased in this way.

Locally Linear Embedding (LLE) aims to construct an weight vector between the sample and its neighborhood, and it also keeps an constant weight value for each neighborhood in decreased dimension space. This means that the embody map is under local linear condition and the reconstruct error seems to be the least. This approach can not only find the nonlinear construct efficiently, but also has the invariance of translation and rotation. Donoho [9] invented the HLLE from LLE. The HLLE can find the latent equal distance parameter in local manifold. Zhang Changsui presented a method which can map from low embody space to high space and the method has been proved in muti-gesture face image reconstruction experiment [10-11]. This approach improved the nonlinear decrease method better.

Recently different kinds of manifold study methods spring up, e.g., Laplacian Eigenmap, local tangent space alignment (LTSA), and so on. Laplacian Eigenmap solve the nonlinear function through Laplacian operator, by which the closed points in high dimension space can be

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mapped to low dimension space with little distance changed. Local tangent space alignment first construct the local low dimension manifold by the tangent space of every sample point, then it get the whole low embody coordinate by the arrangement of tangent space.

Saul and Roweis the LLE algorithm is applied to the face pose image to obtain its distribution. Zhang combinedthe LLE algorithm with the SVR (Support Vector Regression) in the real face pose estimation to get better experimental results. But the manifold learning methods have a common drawback: they did not give an explicit mapping function, so can't extract the characteristics of the new sample. He Xiaofei gives a Laplacian Eigenmap linear approximation method, the Locality Preserving Projections, referred to as "LPP, obtained explicit projection mapping, and apply it to face recognition. Zhang gives the local tangent space alignment algorithm of linear approximation method, linear local tangent space alignment (LLTSA), and applied to face recognition to achieve effective results. Later, PangYanWei et al., on the basis of the locally linear embedding (LLE) proposed an efficient nonlinear subspace learning method, kernel neighborhood keep projection, its main idea is a linear transformation matrix is introduced to approximate the classical local linear embedding, and then by the method of nuclear technique in high dimensional space to solve. Zhang, etc. This paper proposes a face recognition method based on nearest neighbor manifold. The method adopts manifold learning algorithm to calculate the mapping of the high dimension space to low dimension linear manifold, the discriminant analysis based on nearest neighbor rule of manifold. Wu, a discriminant of manifold learning algorithm is proposed, will face data in high-dimensional observation space of nested in low dimensional manifold space. Unlike LLE, ISOMAP algorithm, this method USES the correlation components analysis (RCA) to establish a nonlinear nested discriminant rule in the data. Yang, such as face recognition method based on extended ISOMAP is put forward. The key is to estimate the geodesic distance, the method and geodesic distance as a feature vector, in pairs with FLD finally find the best projection direction.

Recognize faces mainly according to the features of a face, that is to say that there is a big difference between different individuals with the same person is more stable measurement, due to the complexity of face changing, so the expression features and feature extraction is very difficult. Due to the dimensions of the original image is quite high, on the basis of the original image is processed directly, will increase the complexity of the algorithm, and the performance is also a challenge to the computer hardware, so the feature extraction to become one of the most basic problem in face recognition, extraction of effective identification features is the key to solve the problem.

It should be pointed out that the characteristics of the choice of good or bad and adopt corresponding classifier has close relationship. For example, under a classifier classification effect good characteristic, under another classifier may get worse classification effect. How to maximize the extraction to the characteristics of the classification, is the ultimate goal of pattern recognition, and it is also the core problem of pattern recognition system.

3. The NPE Algorithm

NPE algorithm and local projection (LLP) there are some similar properties, but their objective function is completely different. NPE is a linear algorithm, so its fast and suitability for practical application.

As stated earlier, NPE methods is the linear approximation of LLE method. And PCA method, PCA method is designed to keep the global structural characteristics, and the method of NPE is to keep the local features. The so-called keep local features is to use the combination of the adjacent point to one point on linear said this.

In has been under the condition of data set, we can choose close neighbors, and the adjacency graph. In some cases, the data point distribution on a nonlinear sub-manifolds, but only under the condition of considering local nearby, assumed to be linear, this approach is likely to be reasonable. In this way, we can through a point by its neighboring the weight coefficient of the linear said local characteristics of adjacent to reflect this point. By minimizing the reconstruction error, the fixed weight coefficient is as follows:

$$\varepsilon(W) = \sum_j \| x_j - \sum_i w_{ij} x_i \|^2 \qquad (1)$$

The reconstruction error is the sum of each point by its neighboring reconstruction error. In order to realize the linear representation in neighboring points, we have to think about the initial point is mapped to a line. If you want to get a good map, should make the following objective function to get the minimum.

$$\Phi(Y)=\sum_i \| y_i-\sum_j w_{ij}y_j \|^2 \tag{2}$$

x_j refers to values for the jth face image and x_{ij} preforms the neighborhood of x_j in k distance.

$$X=\{x_1,x_2,\cdots,x_n\} \tag{3}$$

$$Y=\{y_1,y_2,\cdots,y_m\}^T \tag{4}$$

$$Y^T=A^T X \tag{5}$$

A is a good map which can fit Equation (5) better. Assuming x_i is the i th vector of matrix X, we can define $Z_i=y_i-\sum_j w_{ij}y_j$ and the extend matrix $Z=(I-W)Y$ .Then the following can be simplify as:

$$\begin{aligned}\Phi(Y)&=\sum_i (y_i-\sum_j w_{ij}y_j)^2\\&=\sum_i (Z_i)^2\\&=Z^T Z\\&=Y^T(I-W)^T(I-W)X^T A\\&=A^T X(I-W)^T(I-W)X^T A\\&=A^T XMX^T A\end{aligned} \tag{6}$$

$M=(I-W)^T(I-W)$ .Obviously, to get $A^T XMX^T A$ means to solve the following equation:

$$XMX^T a=\lambda XX^T a \tag{7}$$

$$X=USV^T \tag{8}$$

$$\tilde{X}=U^T X=SV \tag{9}$$

$U=\{U_1,U_2,\cdots,U_l\}$ is the eigenvector of matrix XX^T and $V=\{V_1,V_2,\cdots,V_l\}$ is the eigenvector of matrix $X^T X$. S are diagonal matrix coming from the non-zero eigenvalues of X . S and V are both diagonal matrix. So $\tilde{X}$ is full rank matrix. The problem can be simplify as:

$$\tilde{X}M\tilde{X}^T a=\lambda\tilde{X}\tilde{X}^T a \tag{10}$$

4. The MONPE and CMONPE Algorithm

NPE algorithm can be either unsupervised algorithm also can be supervised algorithm. When a known class label, NPE algorithm be supervised algorithm. Experiments show that: supervised NPE algorithm than unsupervised NPE algorithm has obvious advantages: on the one hand, in the actual face database, the same face data of similar degree is greater than the face data of different people. Data of similar degree is higher, the smaller the reconstruction error of the linear representation should. So the supervision of a neighborhood of embedding algorithm than unsupervised keep neighborhood embedding algorithm reconstruction error is smaller; Keep neighborhood, on the other hand, due to the supervision when selecting neighbor embedding algorithm to distinguish the classification label, makes the range of parameter values than keep supervision much smaller neighborhood embedding algorithm, which greatly reduce the program running time. However, whether NPE algorithm of supervised or unsupervised NPE algorithm, under the Euclidean metric, high dimensional face data may show thin and empty space. To solve this problem we NPE algorithm was put forward. For the purposes of writing, the improved algorithm for MONPE. For the purpose of difference, the original still consider the supervision class label NPE algorithm called NPE algorithm.

On the thoughts of the above, we proposed MONPE algorithm of two situations: First, selecting neighbor consider class label. In order to facilitate the discussion in this article, it is called CLMONPE.Second, selecting neighbor class label. It is still rememberedas MONPE.

MONPE can be done in the following steps:

Step 1: Select the k neighborhood of the original data.

Step 2: Reconstruct the weight coefficient under the constraint of minimum errors.

$$\arg\min \sum_j \| x_j - \sum_i w_{ij} x_i \|^2 \tag{11}$$

x_j is the neighborhood of x_i in the same class $j = 1, 2, 3, \cdots, k$.

Step 3: Take PCA algorithm to deal with X and get X . Compute the following equation to get its minimum value.

$$\arg\min \sum_i \| y_i - \sum_j w_{ij} y_j \|^2 \tag{12}$$

Due to flip, scale transform, such as local geometric structure is relatively unchanged, so in the third step calculation data dimension reduction is in the second step in the right under the premise of coefficient matrix is constant.

Note: due to the need to use LDA algorithm of data processing, so no matter CLMONPE algorithm or MONPE algorithm, are carried out under considering the class label. The difference is: whether to consider when selecting neighbor class label.

5. Experiment and Simulation

5.1. Experiment Designation

(a) The purpose of the experiment

The algorithm is presented in this paper, on the basis of considering the classification of face data information, and combining with the algorithm MONPE algorithm is proposed, therefore, the objective of this paper is to compare and evaluate the supervision of the algorithm, MONPE algorithm and CLMONPE advantages and disadvantages of the algorithm. There are two indicators:

(1) the same condition, different classification accuracy of the algorithm.

(2) the same condition, the length of the different algorithm running time.

According to the above two indicators, in order to accurately reflect the characteristics of the same algorithm and the comparison between the algorithm, the objective of this paper is as follows:

(1) In ORL face database, the different algorithms, under different training for comparison, the change of testing its classification accuracy and program running time.

(2) In the Yale face database, for different algorithms, compare under different training number, test the change of its classification accuracy and program running time.

(b) The steps of the experiment

Both NPE algorithm and MONPE algorithm, in order to get the results of the optimal algorithm of the execution of various parameters to make the final classification accuracy of the highest value. In detail in this paper, the specific test below steps:

Step 1: Prepare test data; In order to compare the results under different dimension face data, this paper experiments on the ORL and Yale face database data.

Step 2: Implementation algorithm of the optimal classification accuracy; In determining the number of training and training mode, select the optimal value of the highest classification accuracy. According to the determination of a large number of experiments, the optimal when testing the neighbor to 1.

Step 3: Determine the results; In ORL and Yale face database, all take 40 different training methods. Then, their average.

Step 4: Discussthe above calculated results, analyze the characteristics of each algorithm and comparing the advantages and disadvantages of the algorithm.

5.2. Face Database Selection for Experiment

It Is by the AT&T Cambridge that ORL face database laboratory with simultaneous speech at Cambridge university, vision and robotics group, made up of 40 different people each of 10 different images is constructed. These images are in different periods, different illumination, under the condition of different facial expression and facial details. Seen as：

Figure 1. Face Image in the Database of ORL

Figure 2. Face Image in the Database of Yale

Yale face database contains 15 165 images of the individual, each person, 11 images containing under different light conditions (e.g., on the left side of the light, the right lighting, central light), different expressions, such as happy, sad, sleep, surprised, blink of an eye) of the face image. Seen as Figure 2：

5.3. The Simulation Result

In order to reduce the influence of randomness and some disturbance, on the premise of all parameter optimal, to consider each training several randomly selected 40 different training methods, and then compare the average. In addition, because of the improved algorithm in time complexity with little change, so the test results only compare the accuracy of classification.

(a) The results of ORL database

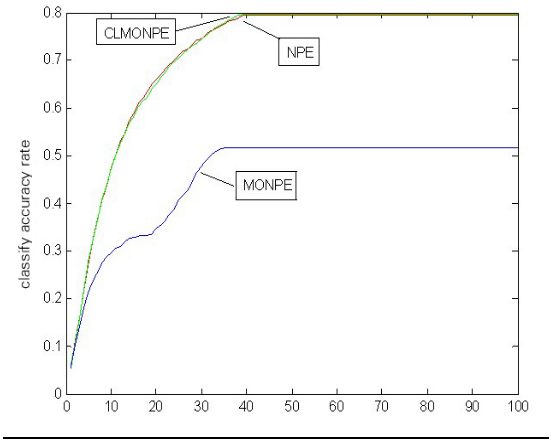

Figure 3. The Result for 2 Training Times

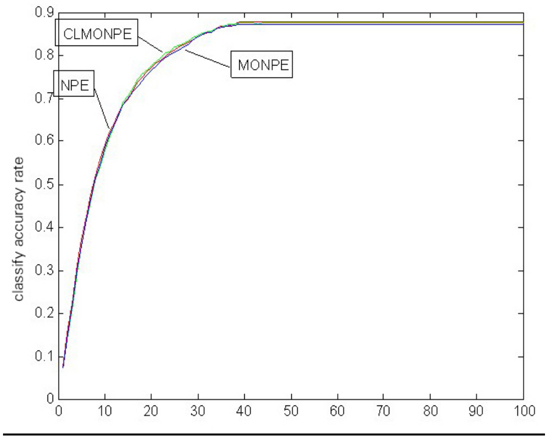

Figure 4. The Result for 3 Training Times

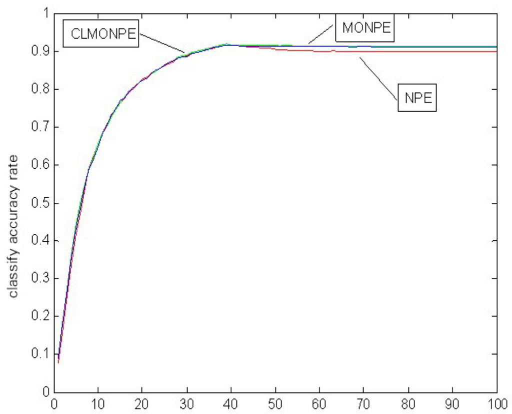

Figure 5. The Result for 4 Training Times

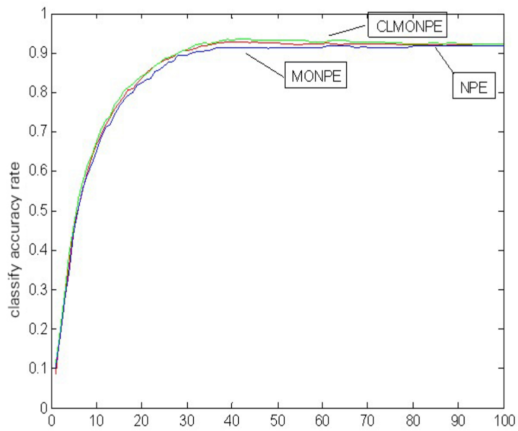

Figure 6. The Result for 5 Training Times

Table. Classification Accuracy for ORL Face Image Database

	Training time 2	Training time 3	Training time 4	Training time 5
NPE	79.45%	87.69%	91.73%	92.83%
CLMONPE	79.70%	87.41%	91.90%	93.30%
MONPE	51.56%	87.18%	91.70%	91.73%

(b) The results of Yale database

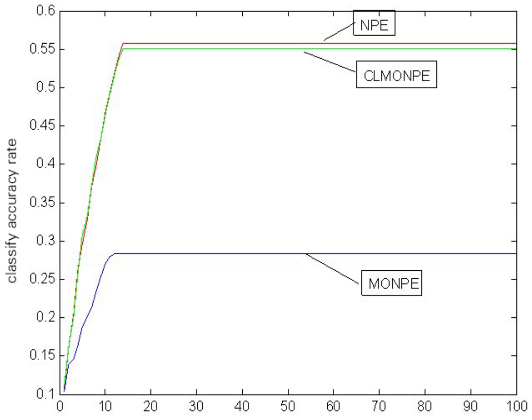

Figure 7. The Result for 2 Training Times

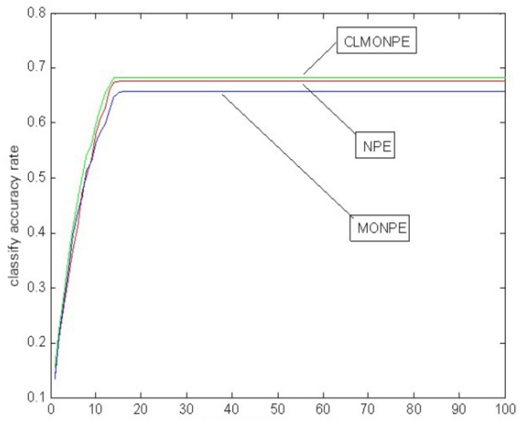

Figure 8. The Result for 3 Training Times

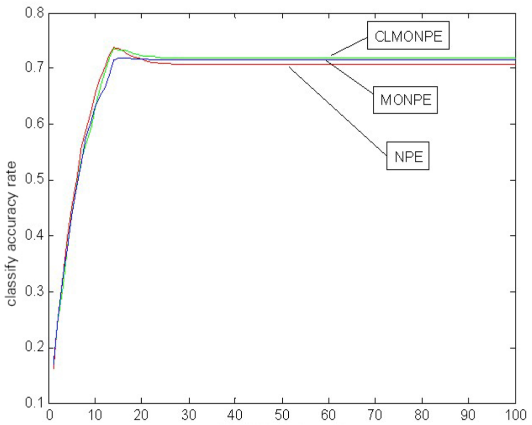

Figure 9. The Result for 4 Training Times

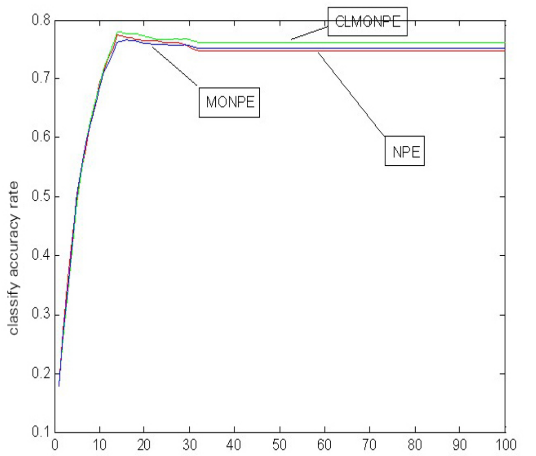

Figure 10. The Result for 5 Training Times

Table 2. Classification Accuracy for Yale Face Image Database

	Training time 2	Training time 3	Training time 4	Training time 5
NPE	55.87%	67.58%	73.83%	77.36%
CLMONPE	55.07%	68.33%	73.48%	77.89%
MONPE	28.35%	65.69%	72.00%	76.64%

6. Conclusion

It can be included that: (1) CLMONPE algorithm is compared with the NPE algorithm and MONPE algorithm, in took the optimal parameters, CLMONPE algorithm are superior to NPE algorithm, less MONPE algorithm in training for poor performance. (2) CLMONPE algorithm is compared with the NPE algorithm, the increase of decline in dimension, in their respective reaches a steady state, steady CLMONPE algorithm is superior to the NPE algorithm. MONPE algorithm and CLMONPE algorithm. (3) The comparison results show that the LDA algorithm is relatively close to the distance between points in class, and the discrete points of the distance between the class this paper puts forward measures to optimize the neighborhood embedding algorithm.This algorithm adopts linear discriminant analysis data dimension reduction algorithm using the selected k neighbor, to some extent, improves the reliability of the Euclidean metric. Further work is that high dimensional face data comparison CLMONPE algorithm and NPE algorithmwill promote the optimization of the measure to other dimension reduction method.

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