An Angular Spatial Linear Dimensionality Reduction Face Recognition Algorithm for Real Scenes

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Abstract: Since the original image sample is small and the feature dimension is high, the effective recognition of the face has always been a difficult point. In order to solve the problem of parameter selection in local projection, and rationally use sample label information to enhance the discriminativeness of sample features after dimensionality reduction, this paper proposes a local Fisher criterion discriminant projection algorithm for angular spatial linear dimension reduction for real scenes. The algorithm adaptively selects the neighbor's neighbor parameter K to make the distribution relationship between samples as true as possible. By constructing the local Fisher criterion to discriminate the projection objective function, the similar samples can be better represented by the same dimension after the dimensionality reduction of the projection, and the samples of the same kind are not significantly different. Finally, the experiment was performed on the Yale face database. The results show that the proposed algorithm can effectively achieve dimensionality reduction and has a higher face recognition rate.

1. Introduction

Face recognition has been widely used and concerned due to the requirements of biometric authentication, monitoring management and human-computer interaction [1]. As an important biological feature, face recognition has not only broad practical value but also important academic value. Face recognition has become a hot research topic.

In a complex environment, the face is susceptible to various unfavorable factors, and the captured image contains many features that are unfavorable for recognition [2]. The noise in the collected data, the non-uniform illumination in the external environment, the partial occlusion of the face and the accessory will have a big difference on the same face, and even the changes caused by these factors are more obvious than the changes in the face sample category [3]. At the same time, different types of face images also have certain similarities. Without judgment, there may be a phenomenon that the intra-class distribution changes more than the inter-class distribution [4]. The early feature extraction research algorithm uses geometric feature algorithms, such as the position and shape of the face, nose and mouth, to describe it briefly [5]. This algorithm is simple and economical in terms of data dimensions, but the features are not reliable, and a lot of face texture features are lost [6]. The other uses a test image to match the library image for model matching [7]. The algorithm based on geometric features is more restricted, and the reliability of image quality and sub-features are higher. The algorithm of template matching has great development. In recent years, the main algorithms of face recognition include subspace analysis dimension reduction algorithm, sparse representation classification algorithm, and automatic feature extraction algorithm through deep learning [8]. Finding the representation of the face image in the low-dimensional manifold space not only reduces the feature dimension, but also extracts the computational complexity and can extract features that are beneficial to the classification. Various subspace algorithms are also reflected in how to efficiently seek this subspace. Each face image can be efficiently represented by a low-dimensional feature vector, which provides more significant and rich information than the feature vector extracted from the feature vector in the original image [9]. The data obtained in the real world is more likely to present a nonlinear structure or a strong correlation of attributes [10]. Feature mining of nonlinear structural data has deep learning, kernel algorithm and manifold learning. It is unreliable to measure the similarity between sample points by Euclidean distance, which leads to the unrealistic distribution of samples in low-dimensional space. When samples are sampled in manifold structures, it is difficult to seek such low-dimensional embedding through global linear mapping. Learning can reveal the essential low-dimensional distribution of the sample.

In this paper, a local Fisher criterion discriminant embedding algorithm is proposed. Based on the local preservation projection, the algorithm solves the problem of adjacency matrix parameter selection. At the same time, the discriminative ability of the discriminant information enhancement weight matrix is introduced to extract the discriminant information which is more conducive to classification. We construct a custom intra-class local divergence matrix and an inter-class local divergence matrix, so that the discriminating ability brought by the sample tag information can be improved while preserving the neighbor relationship between samples. Simulation experiments show that the proposed algorithm has certain advantages.

2. Linear Discriminant Dimensionality Reduction and Local Discriminant Embedding

2.1 Linear Discriminant Analysis

The linear discriminant analysis seeks to make the optimal projection axis with large distribution between the sample classes after projection and small intra-class divergence distribution. As a monitoring technology, LDA has an excellent performance in the field of face recognition.

Let the inter-class divergence matrix and the intra-class divergence matrix be expressed as S_b and S_w, respectively. The calculation methods of S_b and S_w are:

$$S_b = \sum_{i=1}^{c} n_i (u_i - \overline{u})(u_i - \overline{u})^T \tag{1}$$

$$S_w = \sum_{i=1}^{c} \sum_{j=1}^{n_i} (x_j^i - \overline{u})(x_j^i - \overline{u})^T \tag{2}$$

The LDA algorithm finds the projection direction so that the inter-class divergence matrix S_b and the intra-class divergence matrix S_w of the sample have the largest ratio in the direction. The objective function of the LDA can be expressed as:

$$J(w_i) = \arg\max\left(\frac{w_i^T S_b w_i}{w_i^T S_w w_i}\right) \tag{3}$$

This is a generalized Rayleigh quotient of physics. The objective function can be derived from w_i to obtain a high optimal projection direction:

$$\frac{\partial J}{\partial w_i} = \frac{(w_i^T S_w w_i) S_b w_i - (w_i^T S_b w_i) S_w w_i}{(w_i^T S_w w_i)^2} = 0 \tag{4}$$

Fisherface first uses PCA dimensionality reduction to ensure that the intra-class divergence matrix S_w constructed in the dimensionality reduction subspace is non-singular, and then uses the Fisher linear discriminant criterion to find the optimal projection discriminant matrix W. First, PCA is used to extract the optimal discriminant projection matrix by LDA, and it is easy to lose the sub-component space that may contain the authentication information in the process of PCA.

The discriminant linear subspace feature extraction algorithm can extract the connotation features favorable to classification in the sample of the ideal database.

2.2 Local Discriminant Embedding

The main purpose of LPP is to ensure that the sample maintains the local similarity of the original samples in the low-dimensional manifold subspace. This idea is important in information retrieval and clustering. In the classification task, information that can distinguish different classes as much as possible can be added on the basis of LPP. The local discrimination keeps the characteristics of local similarity retention in the projection retention manifold hypothesis, and at the same time separates the sub-manifold structures of different classes. The local discriminative projection also considers the sample label information when applying the K-nearest neighbor Laplacian graph.

The eigenvector G and the penalty graph G' are constructed with n nodes. The local discriminant embedding seeks the projection matrix so that the similar neighbors are projected to be close to each other, and the neighboring points of different types are prevented from being close to each other after projection. The objective function is expressed as:

$$s.t.\sum_{i,j}^{n}\left\|y_i - y_j\right\|_2^2 s_{ij} = 1 \tag{5}$$

Where y_i represents the low-dimensional representation of the sample x_i after projection, simplification of the objective function is:

$$J(y) = J^{'}(W) = 2tr(W^T X(D^{'} - S^{'})X^T W) \tag{6}$$

3. Simulation Experiments and Results Analysis

In order to verify the effectiveness of the proposed algorithm, this paper mainly conducts experiments on the Yale public face database. The Yale database consists of 165 frontal images of 15 people, 11 per person. These images were collected under different lighting conditions, facial expression changes, and wearing glasses. In this experiment, each image was cropped to a size of 32×32 and the gray level of the pixel was normalized. Each person randomly selected l (l=3, 4, 5, 6) images for training, and the remaining 11-l images were used for testing.

In order to compare the distribution of the new sample after the dimensional reduction of the original sample, from the perspective of visualization, this part of the experiment draws the first two dimensions of the sample features after the subspace reduction of the sample on the graph. Taking Yale as an example, each person randomly selects half or 32 images for training, and the remaining images are used for testing. Figure 1 shows the subspace distribution of a randomly selected class 5 test sample after linear dimensionality reduction.

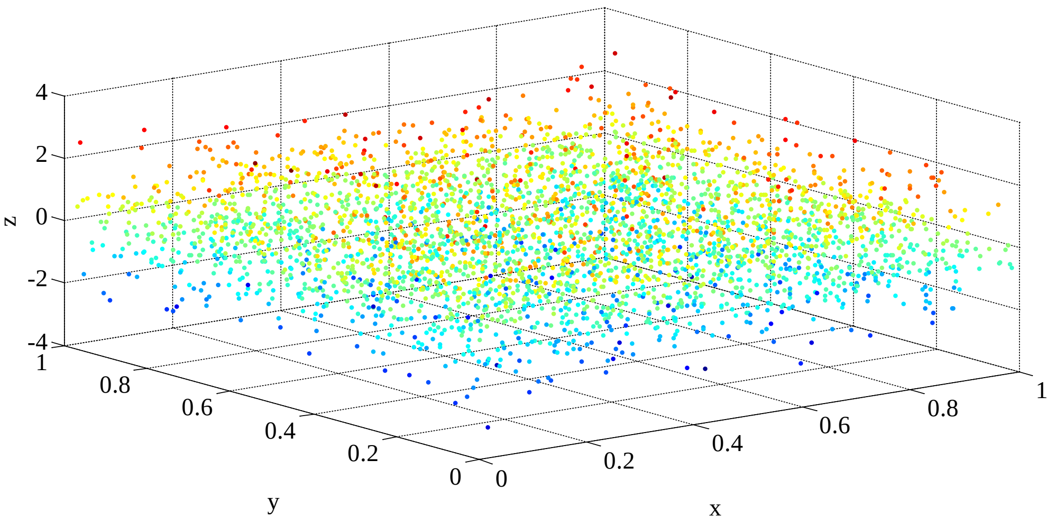

Figure 1. Distribution of face data by linear dimensionality reduction to three-dimensional subspace

In the Yale face database, the recognition rates of these subspace algorithms under different training sets and different dimensionality reduction dimensions are tested. The two-dimensional image expansion in image space is represented as a 1024-dimensional vector in order to train to obtain the feature. Space, PCA is used to preprocess the data before implementing other subspace algorithms to extract features, and the nearest neighbor classifier is used to identify the classification.

The general subspace algorithm exhibits different performance depending on the dimension of the extracted features. In order to analyze the influence of dimensionality reduction dimension on face recognition rate, this experiment trains 6 images per person on Yale database, and selects dimension reduction of 89 in PCA stage. The curve of the face recognition rate of each subspace algorithm as a function of dimension is shown in Figure 2.

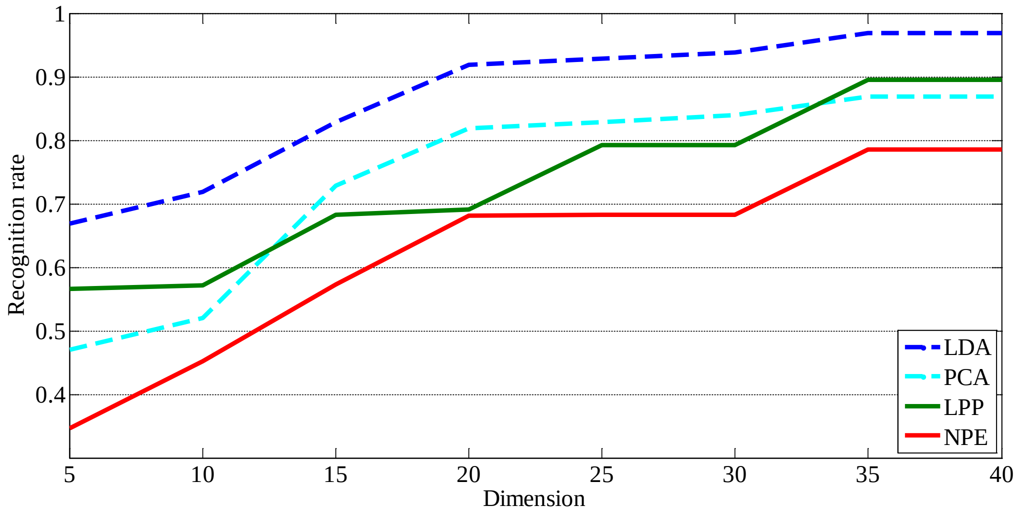

Figure 2. Yale database recognition rate under different dimensions

Linear subspace algorithms generally exhibit different performance under different training samples. In this paper, in the Yale database, each person randomly selects l (l=2, 3, 4, 5, 6) images for training, and the remaining 11-l images for testing. We repeat the experiment 20 times and take the average result of the experiment.

Experiments on the influence of the number of different training samples on the final recognition rate were performed on the Yale database. The results are shown in Table 1.

Table 1. Comparison of algorithm identification performance

Method	2 train	3 train	4 train	5 train	6 train
Baseline	43.4	49.4	52.4	56.3	58.9
PCA	43.5	49.7	52.5	56.7	59.0
LDA	45.6	51.3	54.9	58.8	62.3
LPP	44.2	49.9	53.4	57.1	60.1
NPE	45.2	50.3	54.5	58.0	61.2

4. Conclusion

In this paper, an angular space linear dimensionality reduction face recognition algorithm for real scenes is studied, and experiments on the international common face database are carried out to verify the effectiveness of the proposed algorithm. In addition, the classifier uses the simplest nearest neighbor classifier. By the sparse representation of the sample under the overall sample, the neighbor parameter K of the sample is adaptively selected so that the distribution relationship between the samples is as close as possible to the real situation. By constructing the local Fisher criterion to discriminate the projection objective function, the similar samples can be better represented by the same dimension after the dimensionality reduction of the projection, and the samples of the same kind are not significantly different. Experiments on the Yale public face database show that the face recognition rate of the algorithm is improved. However, the rigid body structure of the face is quite complicated, and the captured face image is affected by many factors, and the sample may be distributed in the nonlinear space. Therefore, the combination of feature extraction algorithm and kernel function is the future research direction.

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