Research on Fast Kernel Subspace Face Recognition Based on Deep Belief Network

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Abstract. Face recognition usually uses different features as input signals. There are many conventional techniques being used and these include technical and fundamental analysis. In this paper, the sample data is mapped from low-dimensional space to high-dimensional space by the kernel method, which makes the classification algorithm have the ability to deal with non-linear data and can solve the small sample problem. At the same time, deep belief network is used as feature transformation and classification to mine feature information of high-dimensional face data. The experimental results show that the optimal recognition rate of the proposed algorithm in a specific face database is up to 96%.

1. Introduction

With the development of economy, security issue has gradually become the focus of attention. Therefore, the demand of society for accurate and efficient automatic identity authentication is growing. There are many existing methods for identity authentication, and face recognition technology can distinguish individuals through biological characteristics of organisms to improve the accuracy of biological identification, therefore, this technology has been widely concerned and respected, making this field become a hot spot in the research of biometric features. Face recognition is a typical application of large data sets with high dimensions based on image pattern recognition. Over the years, researchers have done a lot of work in the research of face recognition, and have made many achievements[1][2]. At present, face recognition technology based on kernel subspace is one of the most widely used technologies in the field of face recognition[3]. However, because all training samples are used for feature representation in kernel subspace, the projection speed of test samples decreases with the increase of the number of training samples, which seriously affects the speed of face recognition, especially in real-time and online systems, this kind of malpractice is more obvious. This paper mainly discusses face recognition method based on subspace.

2. Fast Kernel Subspace Algorithm

2.1. KPCA algorithm

Kernel Principal Component Analysis (KPCA) maps sample data from low-dimensional space to high-dimensional space by kernel method, which makes PC algorithm have the ability to process non-linear data. Therefore, KPCA algorithm can be applied to non-linear separable pattern recognition problems. The core of KPCA algorithm is to perform linear principal component analysis in the kernel space, mapping the linear inseparable sample data in low-dimensional space to high-dimensional space[4]. In this way, the KPCA not only has the advantages of fast classification speed and high accuracy, but also has the processing ability of non-linear data information.

Face recognition algorithm based on KPCA can be summarized as follows:
1. Kernel matrix is calculated for the given M training sets data \( X = [x_1, x_2, \ldots, x_M] \), in which, \( K_{i,j} = (\Phi(x_i) \cdot \Phi(x_j)) \).

2. Centralized matrix \( H \) is constructed to solve the characteristics equation \( HKH = UAU^T \).

3. Calculate vectors \( K_s = [K(x_1, x_1), K(x_1, x_2), \ldots, K(x_M, x_M)]^T \) and \( \bar{K}_s = H(K_s - \frac{1}{M}KI) \).

4. By extracting the former \( k \) principal components whose total contribution rate is more than 90%, to form the characteristic subspace, and obtain the sample data set \( Y \) retained after principal component analysis of face data.

5. For the test data set \( X' \), it is projected into the characteristic subspace of the training set to get the test data set \( Y' \) after feature extraction.

6. Sample \( Y' \) is classified and identified by forming classifiers.

2.2. KFDA algorithm

Kernel Fisher Discriminant Analysis (KFDA) also maps sample data from low-dimensional space to high-dimensional space with the help of kernel method, thus transforming low-dimensional linear inseparability problem into high-dimensional linear separability problem. By mapping sample data in low-dimensional space to high-dimensional kernel space through kernel function, LDA method is used in the kernel space, which makes up for the deficiency of LDA method in dealing with non-linear data, improves the ability of discriminating non-linear features of face, and thus achieves higher accuracy of face recognition[5]. The first problem LDA encounters in face recognition is the singular value problem of the inner covariance matrix, also known as the small sample problem. As a linear generalization of LDA, KFDA also has the problem of small sample size. A classical method to solve KFDA’s small sample problem is to use KFDA to reduce the dimension of training set in kernel space, and then implement LDA in reduced dimension space. This method is called KPCA+LDA algorithm. In this paper, this algorithm is used in KFDA face recognition experiment. The algorithm of face recognition based on KFDA can be summarized as follows:

1. 1-3 steps of KPCA algorithm are carried out firstly.

2. By extracting the former \( k \) principal components whose total contribution rate is more than 90%, to complete the first face feature extraction, and obtain the sample data set \( Y \) retained after principal component analysis of face data.

3. Linear discriminant analysis method is used to do \( Y \)’s second feature extraction. According to the criterion function in \( \max J(\alpha) = \frac{\alpha^T M \alpha}{\alpha^T L \alpha} \), the optimal projection direction \( W \) is calculated, and \( Y \) is projected to the optimal projection direction \( W \) of LDA, then KFDA feature extraction is completed, feature subspace is formed, and training sample data set is obtained.

4. For test data set \( X' \), it is projected into the feature subspace of the training set to get the test data set \( Z' \) after feature extraction.

5. Sample \( Z' \) is classified and identified by forming classifiers.

3. Deep Belief Neural Network

Deep Belief Network (DBN)[5] is a probability graph model that can effectively learn the complex dependencies among variables. DBN contains many hidden variables, which can effectively learn the internal feature representative data, and also can be used as an effective non-linear dimension reduction method[6]. The learned internal feature representations contain more advanced and valuable information of the data, which can be used for classification and regression prediction[7][8]. The structure is shown in the figure.
As can be seen from the figure 1, DBN can be seen as a stack of multiple-Restricted Boltzmann Machine (RBM) from top to bottom. Layer l is the hidden layer of RBM and is the observable layer of RBM of layer l + 1. Further, DBN can be trained quickly by layer-by-layer training, that is, from the bottom layer, only one layer at a time, until the last layer. ‘Layer-by-layer training’ is the earliest way to train depth model effectively.

The training process of DBN can be divided into two stages: pre-training and fine-tuning. Firstly, the parameters of the model are initialized to a better value by layer-by-layer pre-training, and then the parameters are fine-tuned by traditional learning methods.

In the pre-training stage, the training of DBN is simplified to the training of multiple-RBM by using layer-by-layer training method. The figure 2 shows the layered pre-training process of DBN. After pre-training, combined with specific tasks (supervised learning or unsupervised learning), the network is carried out fine-tuning by the traditional global learning algorithm, so that the model converges to a better local optimum.

4. Kernel Subspace Face Recognition Based on DBN

In the process of face recognition, the test sample should be projected not to the features of characteristic subspace composed of all training samples, but to the reduced approximate subspace, so as to improve the speed of face recognition [7]. In this paper, a fast kernel subspace algorithm model based on DBN is proposed, which uses the training sample data and a set of features extracted from the kernel space by the kernel subspace algorithm to form input-output sample pairs of the training neural network. So that the test set image feature extraction results can be output quickly after the test set data is input into the neural network. The algorithm flow is shown in the figure 3.
The algorithm is described as follows:
Step 1: Import the training image set, preprocess the number of faces in the training set, and generate the initial data.
Step 2: KPCA algorithm is used to extract the features of training samples in the original input space, to form training set sample Y.
Step 3: Training sample set Y is extracted LDA feature to form training sample set Z.
Step 4: A DBN is trained by using training set bitmap data and training sample set Z after feature extraction.
Step 5: Import the images of the test set, and repeat steps 2~3 for the face data of the test set.
Step 6: DBN classifier model is used to classify and recognize the test set images.

5. Experimental Results and Analysis

5.1. Experiment setup
In order to prove the effectiveness of the proposed algorithm, ORL, a classical face recognition database, is selected for experiment. ORL face database, created by AT&T Laboratory of Cambridge University, contains 400 facial images of 40 people. Some of the volunteers’ images include changes in posture, expression and facial ornaments. This database was often used in the early stage of face recognition research.

In the process of experiment using ORL face database, the first m pictures of each person are selected as training images, the last 10-m pictures of each person are selected as test images, and the original 92*112 bmp pictures are used. In the process of storing bitmaps, each picture is transformed from two-dimensional array to one-dimensional array. Finally, the training image set and the test image set are stored into m*40*10304 arrays respectively. The experiment of this paper is based on Matlab2018 under Windows 7 operating system.

5.2. Results analysis
Firstly, different training samples, i.e. the influence of m value on the experimental results, are tested. KFDA uses kernel function to extract 40-dimensional features. DBN uses pre-training and discriminant methods. DBN is a deep structure composed of two RBM classifiers. The number of nodes in each layer is 40,100,100, 40, in which, the 40 nodes in the first layer correspond to 40-dimensional feature vectors. The number of pre-training cycles is 100, and the last layer is set to 40, corresponding to different speakers.

As can be seen from the figure 4, for ORL database, when the number of training samples per person is 7, the recognition rate of training set and test set reaches 100% and 95% respectively. Then, with the increase of the number of training samples, the matching occurs, resulting in a decline in the recognition rate.
Figure 4. Effect of Different Training Samples on Recognition Results.

Next, the influence of DBN network structure on recognition rate is discussed. In this experiment, the training sample is set to a fixed value of 7, the feature is extracted to 40 dimensions, the number of hidden layer nodes is adjusted separately, and different recognition rates are obtained as shown in the table. It can be seen from the table that when the number of nodes is 50 and 60, the recognition rate reaches the best 95.83. Overall, the number of nodes has a certain impact on the recognition performance. The increase of the number of nodes can improve the recognition rate limited, but not the higher the better. It needs to be measured in combination with number and duration of training.

| Number of Hidden Layer Nodes | 10  | 20  | 30  | 40  | 50  | 60  | 70  | 80  | 90  | 100 | 110 | 120 |
|-----------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Recognition Rate            | 79.17 | 56.67 | 95 | 93.3 | 95.83 | 95.83 | 88.3 | 79.17 | 83.73 | 95 | 75 | 75 |

Comparing the influence of different feature dimension extracted by KFDA on recognition rate, as shown in the figure, it can be seen that the increase of dimension can also improve the recognition rate. When the feature dimension is 40, the recognition rate is the highest. Similarly, the selection of feature dimension also needs to be measured in combination with other factors.

6. Conclusion

In this paper, a fast kernel subspace algorithm model based on DBN is proposed, which uses the training sample data and a set of features extracted from the kernel space by the kernel subspace algorithm to form input-output sample pairs of the training DBN, so that the representation of kernel feature subspace can be reduced by using hidden layer units of DBN. Experiment on ORL face database proves that the proposed algorithm in this paper is effective and universal, and the recognition rate can reach 96%. Compared with traditional face recognition algorithm, it shows higher superiority.

At the same time, in the process of face recognition, this paper also verifies the influence of a series of parameters on the recognition rate. Experiment shows that when the number of training samples is 7, the number of hidden layer nodes is 60 and the dimension of feature extraction is 40, the performance is optimal. In the future, this algorithm needs to be applied to different training and testing objects, and the robustness of the system is constantly improved.

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