Fast face recognition based on KDDA and SRC

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Abstract. Recently, the sparse representation-based classification (SRC) is getting more and more attention in many fields, such as pattern classification, which has been successfully applied to face recognition. However, the essence of SRC, within face recognition, is to use the linear combination in the same level to train and test samples to represent this one. Firstly, the raw data is nonlinear. Using some high resolution images, the sample space will be too big, and "small sample size problem" (SSS) will appear under the high dimension. Secondly, SRC is mainly through an over-completed to obtain the sparse representation of the test sample. On the condition of large data, the computational complexity will seriously affect its performance. To solve these problems, we propose kernel direct discriminant analysis (KDDA), which maps the original nonlinear face subspace into a low-dimensional linear face feature subspace. On this base SRC is performed. Finally, extensive experiments on database are conducted. Experimental results show that our method significantly improves the recognition speed compared with the original SRC, which achieves comparable or even better recognition rates.

Introduction

Face recognition is a classical hot topic of computer vision. With the rapid development of signal processing and machine learning, a lot of face recognition algorithms have been proposed. These methods can achieve relatively high accuracy in controlled environments (e.g. in biometric system), and ameliorate the performance degradation caused by variations (illumination, poses, occlusions etc.) under incoercible situations (e.g. video surveillance system). However, these algorithms are centred on two core issues: 1) choose the face characteristics; 2) classify a new face based on the selected features.

In recent years, sparse representation has aroused extensive attention in pattern recognition, machine vision and machine learning. John Wright et al. [1] applied sparse representation in face recognition, assuming those training samples from the class to which the test sample belongs are enough, the test sample can be linearly represented by all those training samples to convert face recognition problem into sparse representation, apart from zero weight of training samples from the other class. Therefore, this paper put forward the sparse representation-based classification (SRC). Wright pointed out when the SRC was not sensitive to the default data and if the coefficients were sparse enough, the selection of feature space became no longer important, which had made SRC very popular as a classification algorithm. It has been proved that the SRC is better than nearest neighbor (NN) and nearest subspace (NS) based classifiers in various subspaces (e.g. PCA or LDA) now. Following Wright et al.'s work, some extensions based on SRC face recognition had been proposed. Zhou et al. [2] applied a Markov Random Field model to SRC based face recognition for improving performances under severe continuous occlusion. Yang and Zhang [3] used image Gabor-features for SRC in order to reduce the cost in coding occluded faces meanwhile improving accuracy. Yang et al. [4] reviewed five representative L1-minimization methods in the context of SRC based face recognition. However, the existing algorithm will not accurately calculate the zero coefficients during a limited time, which results lots of small non-zero coefficients, so that the SRC will be extremely time-consuming. When the data are large, computational complexity of the algorithm will seriously affect its performance.

To improve the SRC, Li et al. [5] proposed local sparse representation classification, which reduced the computational complexity through just using k adjacent samples of a test sample to compute the sparse representation. However, fewer adjacent samples can't meet the requirements of overcomplete basis. In addition, the adjacent sample set of a test sample don't guarantee these adjacent samples contain all the training samples from the same class of this test sample. So it's not good solution to the SRC computational complexity problem.

Principal component analysis (PCA) and linear discriminant analysis (LDA) are two widely methods applied in the dimensional reduction and feature extraction. Many excellent methods of face recognition were proposed on the basis of the two technologies or derivative methods, such as Eigenface [6] and Fisherfaces [7]. LDA-based algorithms outperform PCA-based ones, because the former optimizes the low-dimensional representation of the objects focusing on the most discriminant feature extraction while the latter achieves simple object reconstruction. While many LDA-based algorithms are limited by linear conditions, the so-called "small sample size problem" (SSS) existing in high-dimensional pattern recognition tasks, namely the number of available samples is smaller than the dimensionality of the samples. To extract the nonlinear principal component, Bernhard Schölkopf et al. [8] put forward the kernel principal component analysis(KPCA), extracting the features with KPCA in function as global features for all the categories which put difficulty in discriminating one from other categories. The traditional solution is to utilize PCA concepts in conjunction with LDA (PCA+LDA) to solve the SSS problem such as Fisherfaces [7]. Recently, more effective direct LDA (D-LDA) method has been presented. It's still limited by linear methods although successful in many cases.

According to the problems above, we propose a more useful approach to combine kernel direct discriminant analysis (KDDA) with SRC for face recognition. Firstly, we nonlinearly map the original input space to an implicit high-dimensional feature space, when the distribution of face pattern is linearized and simplified. Then the D-LDA method is introduced to effectively solve the SSS problem and derive a set of optimal discriminant basis vectors in the feature space. Finally we utilize SRC to classify the test samples in the lower dimensional and linear separable feature space.

2 Fast face recognition based on KDDA and SRC

In this paper, we propose a fast face recognition algorithm based on KDDA and SRC. At first, we utilize KDDA to preprocess face images to get a lower dimensional linear separable distribution region; then use SRC to classify the test samples.

2.1 The KDDA algorithm As the data of face image is nonlinear, it is difficult to directly calculate the characteristics of different categories from the original input space. KDDA algorithm defines a nonlinear mapping from the original input space to a high-dimensional feature space; we can obtain a linear separable distribution region in the high-dimensional feature space. In order to overcome the SSS problem, D-LDA is used for extracting significant discriminant features. However, as the calculation is difficult in the high dimension, we do transformation from the feature space to input space by a kernel function so that it's convenient to perform calculations in the input space., as shown in Fig. 1.

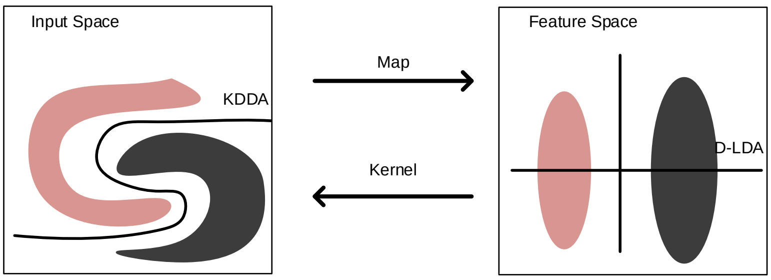

Fig. 1 The KDDA algorithm flow

In other words, KDDA applies kernel technology to improve the D-LDA performance in high-dimensional feature space. The main advantages are as follows:

1) KDDA defines a nonlinear mapping from the input space to an implicit high-dimensional feature space and obtains a linear separable distribution region so that the D-LDA algorithm can be applied. Therefore, D-LDA can be regarded as a special case of KDDA.
2) The KDDA effectively solves the SSS problem in high-dimensional feature space.

There are 200 face images in database and each subject has 5 images whose size is 92*112. The nonlinear original features matrix [10304*200] is mapped to a linear features matrix [39*200] by KDDA. As shown in Fig. 2, KDDA successfully implements a mapping from the original nonlinear face subspace to a low-dimensional and linear separable subspace.

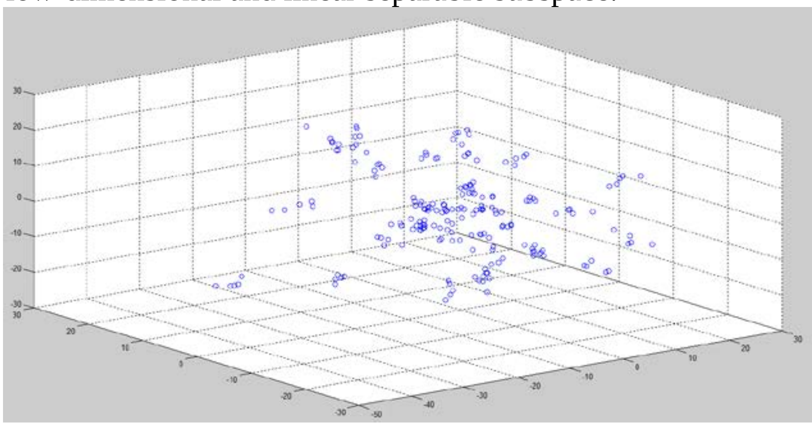

Fig. 2 the result of KDDA classification

2.2 SRC algorithm Sparse representation shows testing sample on linear combination of the training set, which converts face recognition problem into classification problems of a linear regression model. Firstly, we convert face images into a column vector $v \in \mathbf{R}^m$, where m denotes the dimension of feature vector, and assume that the i th class training set contains n_i images, $v_{(i,j)}$ indicates the i th class of the j th image, $A_i = [v_{(i,1)}, \cdots, v_{(i,n_i)}]$ denotes the i th class training set, so all the training samples can be combined into a dictionary A, that is

$$A = [A_1, \cdots, A_i, \cdots, A_k] = [v_{1,1}, \cdots, v_{(1,n_1)}, v_{(i,1)}, \cdots, v_{(i,n_i)}, \cdots, v_{(k,n_k)}] \in \mathbf{R}^{m*n} \quad (2\text{-}1)$$

where n_k, the number of training set belongs to the k th class and $N = n_1 + n_2 + ... + n_k$ is the total number of training samples. Therefore, the i th class testing sample y can be linearly expressed by all training samples.

$$y = Ax \in \mathbf{R}^m \quad (2\text{-}2)$$

Ideally, the coefficient $x = [0, \cdots, 0, \alpha_{(i,1)}, \alpha_{(i,2)}, \cdots, \alpha_{(i,n_i)}, 0, \cdots, 0]^T \in \mathbf{R}^N$, where the nonzero term of x only corresponds with the i th class of the training set, that is to say, x contains the category of the test sample information. Therefore, the problem of classification of the testing sample can be transformed into the solution of the sparse coefficients. It's more conducive to accurately predict the class of the testing samples, if the solutions are more sparse. Then we consider the influence of image noises, the solution of the sparse coefficients can be transformed into a optimization problem:

$$\hat{x}_1 = \arg\min \|x\|_1 \qquad s.t. \quad \|y - Ax\|_2 \le \varepsilon \quad (2\text{-}3)$$

where $\|\cdot\|_1$ denotes L_1-norm and ε is noise error. For the problem of L_1-norm [4, 9, 10, 11, 12], there are many ways to solve, such as Gradient Projection Sparse Representation (GPSR)，Homotopy [10]，Iterative Shrikage-Thresholding(IST), Truncated Newton Interior-point Method (TNIPM) and Augmented Lagrange Multiplier(ALM).This paper uses Homotopy to solve the problem of L_1-norm, SRC algorithm steps are as follows.

1) Input: a dictionary $A=[A_1,\cdots,A_i,\cdots,A_k]$, a test sample y.

2) Solve the minimizing of L_1-norm: $\hat{x}_1=\arg\min_x\|x\|_1 \quad s.t. \quad \|y-Ax\|_2\le\varepsilon$

3) Compute the residuals $r(y)$: $r(y)=\|y-A\delta_i(\hat{x}_1)\|, \quad i=1,\cdots,k$

where $\delta_i(\hat{x}_1)=[0,\cdots,0,\alpha_{i,1},\alpha_{i,2},\cdots,\alpha_{i,n_i},0,\cdots,0]^{\mathrm{T}}$

4) Output: $l(y)=\arg\min_i r(y)$

where $r(y)$ denotes the class of y.

2.3 KDDA+SRC algorithm Face representation based KDDA and SRC have been discussed. This section mainly focuses on the new algorithm, which includes two main parts: face representation and classifier designing. Face representation extracts a series of features from primitive face image to effectively express the test face. At first we extract the face feature by KDDA. Secondly, we use sparse representation as facial recognition classifier. Fig. 3 shows the flow chart of face recognition based on KDDA + SRC.

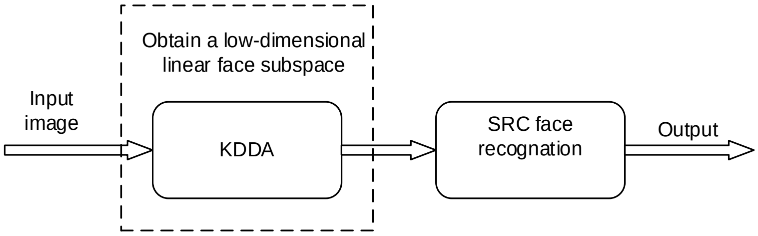

Fig. 3 The flow chart of face recognition based on KDDA + SRC

Firstly, we nonlinearly map the original input image to an implicit high-dimensional feature space, where the distribution of face pattern is linearized and simplified. While the D-LDA method is introduced to effectively solve the SSS problem and extract the effective features in the high-dimensional feature space. However, it will increase the complexity of the calculation in the high dimension, so we apply a kernel function to transform high-dimensional space to low-dimensional space. In other words, KDDA reduces the dimensionality of the raw input data and extracts the effective features, which provides a low-dimensional input data and decreases the complexity calculation for SRC algorithm.

After the transformation of KDDA, the projection from the original image space to feature space can be represented as the matrix $R\in\mathbf{R}^{d*m}$, where $d<<m$. Applying R to both sides of equation (2-2) yields：

$$\tilde{y}=Ry=RAx\in\mathbf{R}^d \tag{2-4}$$

where x is sparse and the dimension d of the feature space is much smaller than n_k, which is the number of training images. Hence, it can be converted into an optimization problem:

$$\hat{x}_1=\arg\min\|x\|_1 \qquad s.t. \quad \|\tilde{y}-RAx\|_2\le\varepsilon \tag{2-5}$$

for a given error tolerance $\varepsilon>0$. Compared with SRC algorithm, we can find that the training sample matrix A is replaced by feature matrix RA, and test sample y is replaced by test sample feature $\tilde{y}$. Therefore, we can eventually get the classification result of the test sample feature $\tilde{y}$, which is the classification results of the test sample.

3 Experimental Results and Analysis

To guarantee the effectiveness of the algorithm, it will be evaluated by two public face databases: ORL and JAFFE. We compare our results with SRC and KDDA + SRC. Experimental environment: Intel Pentium CPU G3250, 3.20GHz, RAM 4GB.

The ORL face database consists of ten different images of each of 40 distinct subjects, and image size is 92*112. These images were taken at different times, varying lighting, facial expressions (open/closed eyes, smiling / not smiling), facial details (glasses / no glasses) and frontal position (with tolerance for some side movement). We randomly select 38 subjects from the database and 7 images from each subject together as the training samples, while the rest are regarded as test samples. Table 1 shows the recognition accuracy and time consuming of the two methods on the ORL database.

Table 1 Comparison of experimental results on ORL database

Method	Recognition Accuracy	Time (s)
SRC	97%	16.97
KDDA+SRC	98%	8.67

The JAFFE database contains 213 images of 7 facial expressions (6 basic facial expressions + 1 neutral) posed by 10 Japanese female models. We randomly select 2 models from the database and 1 image from each expression together as the test samples, the rest of the 2 models are regarded as the training samples. After many experiments, we find that the results of two algorithms identification are obviously different. Table 2 shows the recognition accuracy and time consuming of the two methods on the JAFFE database.

Table 2 Comparison of experimental results on JAFFE database

Method	Recognition Accuracy	Time (s)
SRC	100%	1.43
KDDA+SRC	100%	0.74

From the two tables, we can find that the new proposed method significantly improves the recognition speed compared with the original SRC, while achieving comparable or even better recognition rates on the two databases. This shows the new approach plays a promoting role in the practical application of face recognition.

4 Summary and Forecasts

A new face recognition method introduced in this paper aims to solve the computation complexity of SRC. This method first utilizes KDDA to preprocess face images from high-dimensional input patterns without suffering from the SSS problem, and obtain a lower dimensional and linear separable feature subspace. Then SRC is performed in the feature subspace to greatly reduce the computational complexity. The experiments confirmed the validity of the algorithm on the ORL and JAFFE face database.

Before performing the SRC, however, we extract the effective features by KDDA. which might make influence on its robust performance to occlusions and illumination; Therefore, we will further research the robust of the algorithm for different variables, and hoping it can be applied in practice in the future.

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