Face Recognition Based on Joint Sparse Representation of Multiple Features for Public Safety

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Abstract. A face recognition method based on joint sparse representation of multiple features is proposed in this paper. First, principle component analysis (PCA), kernel PCA (KPCA), and non-negative matrix factorization (NMF) are used to extract feature vectors of face images. The three features could provide complementary descriptions for face images. Then, in the classification stage, joint sparse representation is employed to classify the three features thus considering their correlations. Finally, the total reconstruction errors of the three features on different kinds of training classes are calculated to determine the label of test sample. Experiments are conducted on AR and Yale-B databases to validate the effectiveness of the proposed method.

1. Introduction

Face recognition is a classical problem in pattern recognition filed, which has been intensively studied. Generally, a face recognition algorithm is comprised of two parts: feature extraction and classifier. There are many feature extraction methods used in face recognition such as principal component analysis (PCA) [1], kernel PCA (KPCA) [2], non-negative matrix factorization (NMF) [3], etc. These features could reflect the properties of face images from different aspects. During the classification stage, classifiers are designed to classify the extracted features thus determining the labels of test samples. Typical classifiers used in face recognition include K-nearest neighbour (KNN) [4], support vector machine (SVM) [5], sparse representation-based classification (SRC) [6], etc. Recently, the deep learning algorithms are validated to be notably effective for face recognition problems [7][8].

In this study, a face recognition method is proposed via joint sparse representation (JSR) [9][10] of multiple features. PCA, KPCA, and KPCA are used to extract feature vectors from face images. The three kinds of features could provide more discriminative information for the following classification. Afterwards, JSR is employed to classify the three feature vectors jointly, which could consider their inner correlations. Finally, based on the total reconstruction of the three features, the label of a test sample can be determined. In the experiments, the famous AR and Yale-B face image databases are used to test the proposed method and the results show its validity.

2. Method Description

2.1 JSR of Multiple Features
The features extracted by PCA, KPCA, and NMF are adopted as the multiple features in this paper. For a test sample $y$, its three corresponding feature vectors are denoted as $[y^{(1)} y^{(2)} y^{(3)}]$. And three linear representation problems can be formulated as:

$$y^{(k)} = A^{(k)} \alpha^{(k)} + e^{(k)} \quad (k = 1, 2, 3)$$  \hspace{1cm} (1)

In equation (1), $A^{(k)}$ is the global dictionary established by all the training classes; $\alpha^{(k)}$ denotes the sparse coefficient vector. The JSR problem of the three features is:

$$\min_{\beta} \left\{ g(\beta) = \sum_{k=1}^{3} \| y^{(k)} - A^{(k)} \alpha^{(k)} \| \right\}$$  \hspace{1cm} (2)

where $\beta = [\alpha^{(1)} \alpha^{(2)} \alpha^{(3)}]$ denotes the coefficient matrix. To properly consider the correlations between the three features, the $\ell_1 / \ell_2$ norm is imposed on the coefficient matrix to get the new optimization task as:

$$\min_{\beta} g(\beta) + \lambda \| \beta \|_{1,1}$$  \hspace{1cm} (3)

To solve the problem in equation (3), several traditional algorithms can be used such as Bayesian compressive sensing (BCS) [9] or simultaneous orthogonal matching pursuit (SOMP) [10]. Then, based on the solved coefficient matrix, the label of the test sample can be determined according to equation (4).

$$\text{identity}(y) = \min_{i} \sum_{k=1}^{3} \| y^{(k)} - A^{(k)} \alpha^{(k)} \|$$  \hspace{1cm} (4)

### 2.2 Procedure of Face Recognition

According to the former analysis, the basic procedure of the face recognition algorithm proposed in this study can be seen in Fig. 1, which can be summarized as following steps.

- **Step 1**: Extract the features of all the training samples by PCA, KPCA and NMF to build three independent dictionaries;
- **Step 2**: Extract the three features of the test samples using the same way in Step 1;
- **Step 3**: Jointly represent the three features from test sample based on the three dictionaries using JSR;
- **Step 4**: Calculate the reconstruction errors of different training classes based on equation (4) to determine the label of the test sample.

![Fig. 1 Basic procedure of the proposed face recognition method.](image-url)
3. Experiments

3.1 Data for Experiments
In the experiments, AR and Yale-B face images databases are used to test the proposed method. In the AR database, there are 120 face images for each of 26 people, respectively, which are collected under different illumination conditions and facial expressions. The sizes of these images are 40 pixels \times 50 pixels. In the Yale-B database, there are 45 face images for each of 10 people with the sizes of 32 pixels \times 32 pixels.

For AR database, the first 13 images are used for training and the remaining ones are classified. In the Yale-B database, the first 20 images for each person are trained to classify the remaining images. During the examination of the proposed method, several traditional face recognition algorithms are used for comparison such as KNN [4], SVM [5], and SRC [6].

3.2 Results and Analysis
First, the proposed method is tested on the original AR and Yale-B databases. And the average recognition rates of different methods are listed in Table 1. It clearly shows that the proposed method could achieve the highest recognition rates in both databases, which validate its superior effectiveness. In comparison with Yale-B database, the performance of different methods on AR database is relatively lower mainly because the complex illumination conditions and facial expressions in AR database.

Furtherly, the performance of different methods under noise corruption is tested. The original test samples in both databases are added with different levels of noises. Fig. 2 shows the average recognition rates of different methods at different signal-to-noise (SNR) levels on both databases. With the highest recognition rates at each SNR, the proposed method has the best robustness to noise corruption.

Table 1. Average recognition rates of different methods on AR and Yale-B databases.

| Method | AR database (%) | Yale-B database (%) |
|--------|-----------------|---------------------|
| Proposed | 70.26 | 92.67 |
| KNN | 64.55 | 87.09 |
| SVM | 67.36 | 90.85 |
| SRC | 66.52 | 90.16 |

Fig. 2 The average recognition rates of different methods under noise corruption on AR and Yale-B databases.
4. Conclusion
This study proposes a face recognition method based on JSR of feature vectors extracted by PCA, KPCA, and NMF. The three features could provide more descriptions for the face object. Then, in the classification stage, JSR is used to jointly represent the three features and calculate the total reconstruction errors of different training classes. Finally, the label of a test sample can be determined according to the minimum reconstruction error. According to the experimental results on AR and Yale-B databases, the proposed method could achieve high effectiveness and robustness for face recognition problems.

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