A SPARSE REPRESENTATION METHOD WITH MAXIMUM PROBABILITY OF PARTIAL RANKING FOR FACE RECOGNITION

Yi-Haur Shiau[1] and Chaur-Chin Chen[2]

[1]Department of Computer Science, National Tsing Hua University, Hsinchu, Taiwan
[2]Institute of Information Systems and Applications, National Tsing Hua University, Hsinchu, Taiwan

ABSTRACT

Face recognition is a popular topic in computer vision applications. Compressive sensing is a novel sampling technique for finding sparse solutions to underdetermined linear systems. Recently, a sparse representation-based classification (SRC) method based on compressive sensing is presented. It has been shown to be robust for face recognition. In this paper, we proposed a maximum probability of partial ranking method based on the framework of SRC, called SRC-MP. It computes the maximum probability from the largest γ weighting coefficients for the individuals, respectively. Experiments are implemented on Extended Yale B and ORL face databases using eigenfaces, fisherfaces, 2DPCA and 2DLDA for feature extraction. Furthermore, we compare our proposed method with classical projection-based methods such as principal component analysis (PCA), linear discriminant analysis (LDA), 2DPCA and 2DLDA. The experimental results demonstrate our proposed method is able to achieve higher recognition rate than other methods.

Index Terms— Compressive sensing, face recognition, sparse representation classification, principal component analysis, linear discriminant analysis

1. INTRODUCTION

In recent years the research of face recognition has apparently turned into the priority of Biometric Identification. In terms of less intrusion than other biometric systems, face recognition has gradually obtained its popularity. Although many papers reported face recognition methods, researchers have focused primarily on projection-based methods rather than other methods [2]. As to the advantages of the projection-based methods, face images are reconstructed promptly and image features are extracted instantly, such as Principal Component Analysis (PCA) [6] and Linear Discriminant Analysis (LDA) [3]. Besides, the projection-based methods have achieved high recognition rates for several public face image databases. However, one of the major disadvantages of the linear dimensionality reduction algorithms is that the projections are linear combination of all the original features or variables. Meanwhile, all weighting coefficients in the linear combination known as loadings are typically non-zero. Thus, inadequate physical interpretations are revealed in many applications. Fortunately, compressive sensing theorem [1, 5, 11], a novel sampling technique, is proved to overcome the drawback. According to sparsity principle of compressive sensing, it is possible to recover certain signals and images exactly from far fewer samples of measurements beyond Nyquist rates [4]. A sparse representation-based classification (SRC) method based on compressive sensing is presented [7, 10]. It has been shown to be robust for face recognition. In this paper, we propose a maximum probability of partial ranking method based on the framework of SRC, called SRC-MP. PCA (eigenfaces), LDA (fisherfaces), 2DPCA [8] and 2DLDA [9] are used for feature extraction. By applying our proposed method, we enable to gain the higher recognition rate than classical projection-based methods.

The rest of this paper is organized as follows: Section 2 briefly reviews SRC method [7]. Section 3 proposes our method based on the framework of SRC. Section 4 depicts experiment results and the conclusion is drawn in Section 5.

2. SPARSE REPRESENTATION-BASED CLASSIFICATION

2.1. Compressive Sensing

Compressive sensing is a sampling technique for finding sparse solutions to underdetermined linear systems [4, 7]. A K-sparse signal is a signal that owns at most K nonzero coefficients where $K << N$, N is the size of signal. The compressive sensing theorem adopts the sparsity property, and is performed under the following optimization method based on l_1-norm:

$$\min_{\hat{\boldsymbol{a}} \in \mathbf{R}^N} \|\hat{\boldsymbol{a}}\|_1 \text{ subject to } \boldsymbol{b} = \Phi^{\mathrm{T}}\hat{\boldsymbol{a}} \quad (1)$$

Where

$\boldsymbol{b}$: an observed M

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Φ: an NθM sensing matrix.

2.2. Sparse Representation-based Classification

An SRC method based on compressive sensing theorem is provided for face recognition [7]. The basic idea of SRC is to represent a testing image as a sparse linear combination of all training images. In order to obtain a sparse solution, the feature dimensions must be much smaller than the number of all training images.

Suppose there are K individuals in the face database, and let $B = [B_1, B_2, \ldots, B_K]$ be the concatenation of the N training images from all of the K individuals, where $N = n_1+n_2+\ldots+n_K$. $B_i = \left[\boldsymbol{s}_1^{(i)}, \boldsymbol{s}_2^{(i)}, \ldots, \boldsymbol{s}_{n_i}^{(i)}\right] \in \boldsymbol{R}^{m \times n_i}$, is the set of training images of the i^{th} individual, where $\boldsymbol{s}_j^{(i)}$, j = 1, 2, …, n_i, is an m-dimensional vector stretched by the j^{th} image of the i^{th} individual. A new testing image $\boldsymbol{y} \epsilon \boldsymbol{R}^m$ of the i^{th} individual could be represented as a linear combination of the training images in B_i, i.e. $\boldsymbol{y} = \sum_{j=1}^{n_i} \alpha_j^{(i)} s_j^{(i)} = B_i\, \boldsymbol{\alpha}^{(i)}$, where $\boldsymbol{\alpha}^{(i)} = [\alpha_1^{(i)}, \alpha_2^{(i)}, \ldots, \alpha_{n_i}^{(i)}]^T \in \boldsymbol{R}^{n_i}$ are weighting coefficients. Let $\boldsymbol{y} = B\boldsymbol{\alpha}$ represent the testing image $\boldsymbol{y}$ by using B, where $\boldsymbol{\alpha} = [\boldsymbol{\alpha}^{(1)}; \boldsymbol{\alpha}^{(2)};\ldots;\boldsymbol{\alpha}^{(K)}]$. Due to $\boldsymbol{y}$ belongs to the i^{th} individual and $\boldsymbol{y} = B_i\boldsymbol{\alpha}^{(i)}$, only the coefficients in $\boldsymbol{\alpha}^{(i)}$ have significant values in a noiseless case to $\boldsymbol{\alpha}$, and all the coefficients in $\boldsymbol{\alpha}^{(j)}$, j=1,2,…,K and $j \neq i$, are nearly zero. The SRC algorithm is listed as follows [7].

1. Normalize the columns of B to have unit l_2-norm.
2. Solve the following l_1-norm minimization problem:
$$\widehat{\boldsymbol{\alpha}}_1 = \arg\min_{\boldsymbol{\alpha}} \|\boldsymbol{\alpha}\|_1 \text{ subject to } \|B\boldsymbol{\alpha} - \boldsymbol{y}\|_2 \le \varepsilon. \quad (2)$$
3. Compute the residuals
$$r_i(\boldsymbol{y}) = \|\boldsymbol{y} - B\delta_i(\widehat{\boldsymbol{\alpha}}_1)\|_2 \text{ for } i = 1,\ldots,K. \quad (3)$$
4. Get output result by identity($\boldsymbol{y}$) = arg{min $r_i(\boldsymbol{y})$}

3. OUR PROPOSED METHOD

In the noiseless case, all the non-zero coefficients of $\widehat{\boldsymbol{\alpha}}_1$ will completely be associated with the columns in B from a single individual. The testing image $\boldsymbol{y}$ can be easily assigned to that individual. As to the noise case, however, these non-zero coefficients may be associated with multiple subjects. It is difficult to accurately assign $\boldsymbol{y}$. Some classifiers are used to solve this problem. We assign $\boldsymbol{y}$ to the individual with only the largest coefficient of $\widehat{\boldsymbol{\alpha}}_1$ as a simple method (SRC-LV). However, such heuristics do not harness the subspace structure associated with images in face recognition. An SRC method assigns $\boldsymbol{y}$ to the subject that minimizes the residuals. In this paper, we propose a maximum probability of partial ranking method as a classifier, called SRC-MP. It is found by experiments that the largest coefficient may not belong to the exact individual, however, the γ largest coefficients may almost match the correct individual. Thus, we convert and normalize the weight coefficient $v_j^{(i)}$ into the probability value $p_j^{(i)} = \frac{v_j^{(i)}}{\sum_{i=1}^{K}\sum_{j=1}^{n_i} v_j^{(i)}}$, where $v_j^{(i)}$ is the j^{th} non-zero coefficient greater than zero of the i^{th} individual of $\widehat{\boldsymbol{\alpha}}_1$. Then, we assign a partial ranking value γ (first largest coefficients), and sum up these largest γ coefficients to obtain a new probability value for each of the individuals, respectively. Moreover, we employed the new maximum probability as the classifier. For example in Fig. 1, the green box represents the correct individual and the blue box represents the wrong individual for assigning the testing image $\boldsymbol{y}$ which is assigned to the

4.1. Extended Yale B Face Image Database

The Extended Yale B database has about 2,500 images of 39 different individuals. We use 34 individuals because there are some images missing. Our database consists of 2,108 face cropped and normalized images of 192 rows and 168 columns in PGM file format. There are 34 persons individually contributed 62 frontal-images by capturing under various laboratory-controlled lighting conditions. The first 10 images of individual 1 are shown in Fig. 2. As for each subject, 31 images for training and the rest 31 images for testing are randomly selected.

Fig. 2. The 10 face images of the 1^{th} individual on the Extended Yale B face database.

We compute the recognition rates with the feature space dimensions d = 20, 30, 60, 120, 150, respectively. For SRC-MP method, we assign the partial ranking value γ = 10. Table 1 shows the recognition rates of all methods: (1) PCA, (2) Eigen + SRC-LV, (3) Eigen + SRC-MP, (4) LDA, (5) Fisher + SRC-LV and (6) Fisher + SRC-MP. The recognition rates of SRC-LV are higher than classical projection-based methods, and SRC-MP obtains higher recognition rates than SRC-LV. In particular, the bold values indicate the best recognition rate accomplished by our proposed method. The curves of recognition rate versus the dimension of features are illustrated in Fig. 3.

Table 1. The recognition rates (%) of all methods on the Extended Yale B database versus the corresponding feature dimensions

	d = 20	d = 30	d = 60	d = 120	d = 150
(1)	51.04	59.58	70.59	76.85	77.61
(2)	79.13	89.47	93.26	94.97	95.73
(3)	80.74	90.99	94.40	95.92	96.20
(4)	92.60	94.50	92.88	88.99	89.66
(5)	93.55	94.59	96.77	96.58	96.68
(6)	**94.59**	**95.16**	**97.25**	**97.25**	**97.34**

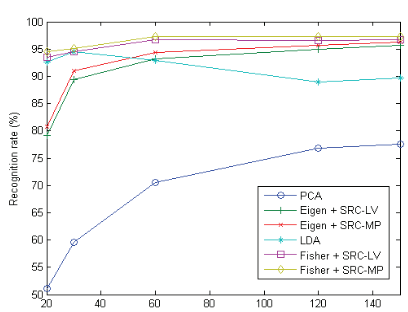

Fig. 3. Recognition rates of all methods versus feature dimension on the Extended Yale B database.

We also compare SRC-MP with 2DPCA and 2DLDA. Due to the feature dimension must be smaller than the number of training samples, we convert the images on the Extended Yale B database into the size of 84x96. We compute the recognition rates with the feature space dimensions 96×d where d = 2, 3, 4, respectively. Table 2 shows the recognition rates of all methods: (1) 2DPCA, (2) 2DLDA, (3) 2DPCA + SRC-MP (γ = 10), (4) 2DLDA + SRC-MP (γ = 10). The curves of recognition rate versus the feature dimensions are illustrated in Fig. 4.

Table 2. The recognition rates (%) of all methods versus the corresponding feature dimensions

	d = 2	d = 3	d = 4
(1)	59.01	64.52	66.89
(2)	83.02	81.97	81.02
(3)	95.45	95.54	95.16
(4)	**95.83**	**95.92**	**96.02**

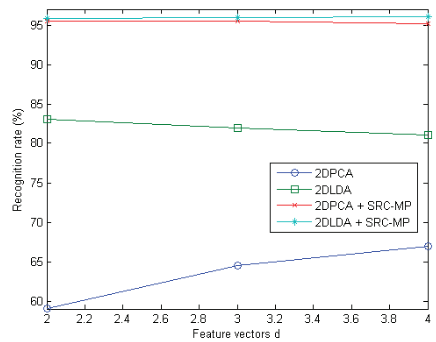

Fig. 4. The recognition rates of all methods versus feature dimension on the Extended Yale B database.

SRC-MP assigns a partial ranking value γ to compute the new maximum probability value. We compare the recognition rates with different parameters γ. The curves of recognition rate versus the different γ values are illustrated in Fig. 5. It shows that the larger the parameter γ, the higher the recognition rate when γ is in a certain range.

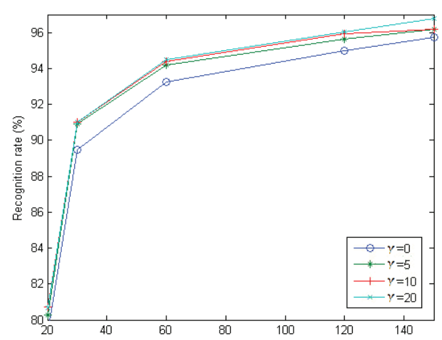

Fig. 5. The recognition rates with different parameters γ on the Extended Yale B face database.

4.2. ORL Face Image Database

The ORL face database contains 400 8-bit gray level images of 112 rows and 92 columns in PGM file format. There are 40 persons individually contributed 10 images at different times, lightings, facial expressions, and some details on face. The 10 images of individual 17 are shown in Fig. 6. As for each individual, the first 5 images for training and the next 5 images for testing were selected.

Fig. 6. The face images of the 17th individual on the ORL face database.

We compute the recognition rates with the feature space dimensions d = 16, 30, 60, respectively. Table 3 shows the recognition rates of all methods: (1) PCA, (2) Eigen + SRC-MP (γ = 10), (3) LDA and (4) Fisher + SRC-MP (γ = 10). The bold values indicate the best recognition rate accomplished by our proposed method. The curves of recognition rate versus the dimension of features are illustrated in Fig. 7. $\frac{1}{2}$

Table 3. The recognition rates (%) of all methods on the ORL versus the corresponding feature dimensions

	d = 16	d = 30	d = 60
(1)	83.0	87.5	89.0
(2)	87.0	89.0	**90.0**
(3)	88.0	86.0	89.5
(4)	**90.0**	**91.5**	**90.0**

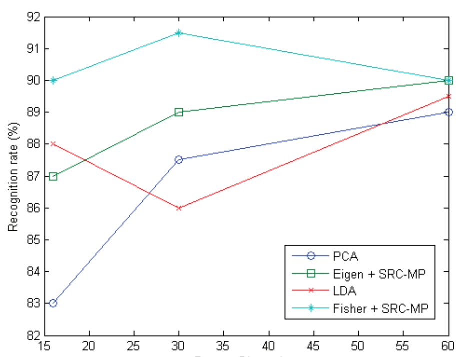

Fig. 7. Recognition rates by different methods versus feature dimension on the ORL database.

5. CONCLUSION

In this paper, we presented a maximum probability of partial ranking method (SRC-MP) based on the framework of sparse representation-based classification (SRC). PCA (eigenfaces), LDA (fisherfaces), 2DPCA and 2DLDA are utilized for feature extraction. We compared our proposed method with classical projection-based approaches such as PCA, LDA, 2DPCA and 2DLDA. Our experiments on Extended Yale B and ORL face databases demonstrated that our proposed method can achieve higher recognition rate under the same dimensionality than classical projection-based methods. The experimental result showed that SRC-MP can obtain higher recognition rate than SRC-LV. It also demonstrated that the larger the parameter γ, the higher the recognition rate when γ is in a certain range.

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