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Abstract	For face recognition, conventional dictionary learning (DL) methods have disadvantages. In the paper, we propose a novel robust, discriminative and comprehensive DL (RDCDL) model. The proposed model uses sample diversities of the same face image to make the dictionary robust. The model includes class-specific dictionary atoms and disturbance dictionary atoms, which can well represent the data from different classes. Both the dictionary and the representation coefficients of data on the dictionary introduce discriminative information, which improves effectively the discrimination capability of the dictionary. The proposed RDCDL is extensively evaluated on benchmark face image databases, and it shows superior performance to many state-of-the-art sparse representation and dictionary learning methods for face recognition.

Keywords (separated by '-')	Dictionary learning - Face recognition - Sparse representation

Author Proof

Sample Diversity, Discriminative and Comprehensive Dictionary Learning for Face Recognition

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Abstract. For face recognition, conventional dictionary learning (DL) methods have disadvantages. In the paper, we propose a novel robust, discriminative and comprehensive DL (RDCDL) model. The proposed model uses sample diversities of the same face image to make the dictionary robust. The model includes class-specific dictionary atoms and disturbance dictionary atoms, which can well represent the data from different classes. Both the dictionary and the representation coefficients of data on the dictionary introduce discriminative information, which improves effectively the discrimination capability of the dictionary. The proposed RDCDL is extensively evaluated on benchmark face image databases, and it shows superior performance to many state-of-the-art sparse representation and dictionary learning methods for face recognition. AQ1

Keywords: Dictionary learning · Face recognition · Sparse representation

1 Introduction

Recently sparse representation technology has been successfully used in image restoration [1] and image classification [2, 17]. For the success of sparse representation, the dictionary is very important. Dictionary learning (DL) aims to learn the desired dictionary from the training samples. The desired dictionary can well represent or code the given signal. Many latest DL methods learn properly the desired dictionary from the original training data have led to state-of-the-art results in many practical applications, such as face recognition [3, 4, 8, 16, 18].

Though dictionary learning has achieved promising performance in face recognition, previous DL methods suffer from the severe problem for face recognition. First, because face images of the same person vary with facial expressions, illuminations and disguises, conventional DL for face recognition is hard to obtain a very robust dictionary. For face recognition tasks, only if the dictionary is not very sensitive to variations of expressions, illuminations and disguises, it is able to get relatively stable descriptions of the face

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image and obtain a high accuracy. Second, conventional DL methods don't cover important components (e.g., particularity and disturbance) completely, which limit their performance. In order to address the above two problems, in the paper, we propose a novel robust, discriminative and comprehensive DL (RDCDL) model.

The proposed RDCDL uses the training sample diversities of the same face image to get a robust dictionary. For face recognition tasks, RDCDL achieves the robustness by generating virtual face images that convey new possible expressions, illuminations and disguises of the face. The virtual training samples are the alternative training samples, which are obtained by corrupting the original training samples. RDCDL is applied to the original and virtual training samples. The dictionary of RDCDL includes the class-specific dictionary atoms and the disturbance dictionary atoms, which can completely represent the practical data (e.g., the data of the different classes has class-specific component and disturbance component such as noise, outlier and occlusion). Both the comprehensive dictionary and the representation coefficients of data on the dictionary exploit the discriminative information, which improves effectively the discriminative capability of the dictionary.

The rest of this paper is organized as follows. Section 2 briefly introduces related work. Section 3 presents the proposed RDCDL model. Section 4 describes the optimization procedure of RDCDL. Section 5 presents the RDCDL based classification. Section 6 conducts experiments, and Sect. 7 concludes the paper.

2 Related Work

According to the relationship between dictionary atoms and class labels, current supervised dictionary learning can be categorized into three main types: class-shared dictionary learning, class-specific dictionary learning and hybrid dictionary learning.

In the first category, a dictionary whose atoms are shared by all classes of data is learned while the discrimination of coding coefficients is exploited. Based on KSVD [6], Zhang and Li [3] proposed a dictionary learning method called discriminative KSVD (DKSVD). Based on DKSVD [3], Jiang *et al.* [4] added a label consistent term and proposed so-called Label-Consistent KSVD (LCKSVD). Because each class-shared dictionary atom can represent all classes of data, the class-shared dictionary loses the correspondence between the dictionary atoms and the class labels, weakening the classification capability of the class-shared dictionary. Classifiers based on the class-shared dictionary cannot perform classification based on the class-specific representation residuals.

In the second category, class-specific dictionary learning requires that each dictionary atom should be corresponded to a single class label. Inspired by SRC [2], the class-specific dictionary is widely applied to the design of classifiers. Based on the KSVD [6] model, Mairal *et al.* [9] introduced a discriminative reconstruction penalty term. Ramirez *et al.* [7] proposed DLSI which minimized the coherence term of the dictionary to improve the discriminative capability of the dictionary. Yang *et al.* [8, 16] proposed Fisher discrimination dictionary learning (FDDL), where both the representation residual and the representation coefficients achieved the discriminative information. Although class-specific dictionary learning can achieve better performance, the coherence among the different class-specific dictionaries is inevitable. The number of the dictionary is usually large.

In the third category, hybrid dictionary is the dictionary which combines the class-specific dictionary atoms with the class-shared dictionary atoms. Recently, some hybrid DL methods are proposed. Deng *et al.* [10] proposed extended sparse representation based classification (ESRC) which constructed an intra-class variation dictionary as a shared dictionary. Kong *et al.* [5] proposed dictionary learning with commonality and particularity (COPAR) which learned a hybrid dictionary by introducing an incoherence penalty term to the class-specific sub-dictionaries. However, these hybrid DL methods cannot well describe the disturbance such as noise, outlier and occlusion. In addition, these methods don't introduce the discriminative information to both the dictionary and the representation coefficients.

3 Robust, Discriminative and Comprehensive Dictionary Learning

In order to improve the performance of previous DL methods, we propose a new robust, discriminative and comprehensive dictionary learning (RDCDL) model. Suppose that we have N classes of subjects, the comprehensive dictionary $\boldsymbol{D}$ includes a class-specific dictionaries $\boldsymbol{D}_i(i = 1, 2, \cdots, N)$ and a disturbance dictionary $\boldsymbol{D}_b$. The class-specific dictionaries represent the particularity of different class data, and the high-performance class-specific representation residual can be used. While the disturbance dictionary can represent other components not related to the identity of data (e.g., noise, outlier and occlusion).

Denote by $\boldsymbol{Y} = [\boldsymbol{Y}_1, \boldsymbol{Y}_2, \cdots, \boldsymbol{Y}_N]$ a set of training samples, where $\boldsymbol{Y}_i$ is the training samples of class i. Denote by $\boldsymbol{Z} = [\boldsymbol{Z}_1, \boldsymbol{Z}_2, \cdots, \boldsymbol{Z}_N]$ a set of alternative training samples. $\boldsymbol{Z}_i$ has the same size and structure as the original training samples $\boldsymbol{Y}_i$ ($i = 1, 2, \cdots, N$). Let $\boldsymbol{X} = [\boldsymbol{X}_1, \boldsymbol{X}_2, \cdots, \boldsymbol{X}_N]$, $\boldsymbol{B} = [\boldsymbol{B}_1, \boldsymbol{B}_2, \cdots, \boldsymbol{B}_N]$, where $\boldsymbol{X}_i$ is the coding coefficient matrix of $\boldsymbol{Y}_i$ over the dictionary $[\boldsymbol{D}_1, \boldsymbol{D}_2, \cdots, \boldsymbol{D}_N]$. $\boldsymbol{B}_i$ is the coding coefficient matrix of $\boldsymbol{Z}_i - \boldsymbol{D}_i\boldsymbol{X}_i^i$ over the dictionary $\boldsymbol{D}_b$. In order to make the learned dictionary robust to variations of facial expressions, illuminations and disguises of the same person, we can obtain alternative training samples using a special scheme. For the comprehensive dictionary $\boldsymbol{D} = [\boldsymbol{D}_1, \boldsymbol{D}_2, \cdots, \boldsymbol{D}_N, \boldsymbol{D}_b]$, we propose the followed RDCDL model:

$$J_{(\boldsymbol{D},\boldsymbol{X},\boldsymbol{B})} = \arg\min_{\boldsymbol{D},\boldsymbol{X},\boldsymbol{B}} \sum_{i=1}^{N} \left[\begin{array}{l} \left\| \boldsymbol{Y}_i - \boldsymbol{D}_i\boldsymbol{X}_i^i - \sum_{j\neq i} \boldsymbol{D}_j\boldsymbol{X}_i^j \right\|_F^2 + \lambda_1 \left\| \boldsymbol{Z}_i - \boldsymbol{D}_i\boldsymbol{X}_i^i - \boldsymbol{D}_b\boldsymbol{B}_i \right\|_F^2 \\ + \lambda_2 \left(\|\boldsymbol{X}_i\|_1 + \|\boldsymbol{B}_i\|_1 \right) + \lambda_3 \phi(\boldsymbol{X}_i) + \lambda_4 \varphi(\boldsymbol{D}) \end{array} \right] \quad (1)$$

where λ_1, λ_2, λ_3 and λ_4 are scalar parameters, $\boldsymbol{X}_i^i$ is the coding coefficient matrix of $\boldsymbol{Y}_i$ over the dictionary $\boldsymbol{D}_i$, $\boldsymbol{X}_i^j$ is the coding coefficient matrix of $\boldsymbol{Y}_i$ over the dictionary $\boldsymbol{D}_j$. $\phi(\boldsymbol{X}_i)$ is the representation coefficient discrimination constraint term and $\varphi(\boldsymbol{D})$ is the dictionary discrimination constraint term.

The proposed model obtains alternative training samples using a special scheme. In this paper, we use two methods to generate the alternative training samples, the procedures to generate alternative training samples are presented as follows:

(1) We use the corrupted images of original training samples as alternative training samples. Figure 1 shows alternative training samples by corrupting the original face images by using the Salt & Pepper noise.

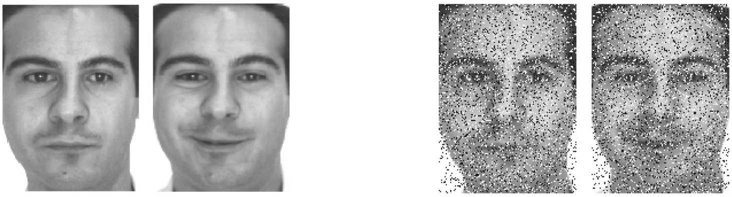

Fig. 1. The left two images are original training samples, the right two images are alternative training samples by corrupting the left two images.

(2) We use the original training samples with random block occlusion as alternative training samples. Figure 2 shows the original training samples and the alternative training samples.

Fig. 2. The left two images are original training samples, the right two images are alternative training samples by occluding the left two images by the random block.

$\boldsymbol{X}_i = \left[\boldsymbol{X}_i^1, \boldsymbol{X}_i^2, \cdots, \boldsymbol{X}_i^N\right]$ is the coding coefficients of $\boldsymbol{Y}_i$ over the dictionary $[\boldsymbol{D}_1, \boldsymbol{D}_2, \cdots, \boldsymbol{D}_N]$. In order to improve classification capability of the spare, we require that $\boldsymbol{Y}_i$ should be only represented on $\boldsymbol{D}_i$ and not be represented on the other class-special dictionaries, i.e., $\boldsymbol{X}_i^j = 0$. At the same time, we also require that the within-class scatter of the representation coefficient $\boldsymbol{X}_i^i$ of $\boldsymbol{Y}_i$ over $\boldsymbol{D}_i$ is small, i.e., the representation coefficients of the same class data over the class-special dictionary are similar. Thus, the discrimination constraint of $\boldsymbol{X}_i$ is defined as:

$$\phi(\boldsymbol{X}_i) = \left\|\boldsymbol{X}_i^i - \boldsymbol{M}_i\right\|_F^2 \tag{2}$$

where $\boldsymbol{M}_i$ is the coefficient mean value matrix, each column of $\boldsymbol{M}_i$ is the mean vector of $\boldsymbol{X}_i^i$. Because the sparse constraint on $\boldsymbol{X}_i^j$ results in $\boldsymbol{X}_i^j = 0$, here, we do not show $\boldsymbol{X}_i^j = 0$.

In order to improve the discrimination capability of the dictionary, the correlation among the different dictionaries should be very small, i.e., $\left\|\boldsymbol{D}_i^T\boldsymbol{D}_j\right\|_F^2$ is small for $i \neq j$, and $\left\|\boldsymbol{D}_b^T\boldsymbol{D}_i\right\|_F^2$ is small. Therefore, the dictionary discrimination constraint term is designed as:

$$\varphi(\boldsymbol{D}) = \sum\nolimits_{j \neq i} \left\|\boldsymbol{D}_j^T\boldsymbol{D}_i\right\|_F^2 + \sum\nolimits_i \left\|\boldsymbol{D}_b^T\boldsymbol{D}_i\right\|_F^2 \tag{3}$$

By incorporating Eqs. (2) and (3) into Eq. (1) and the discrimination representation coefficient constraint $\boldsymbol{X}_i^j = 0$, $\forall j \neq i$, we have the following RDCDL model:

$$J_{(\boldsymbol{D},\boldsymbol{X},\boldsymbol{B})} = \arg\min_{\boldsymbol{D},\boldsymbol{X},\boldsymbol{B}} \sum_{i=1}^{N} \left[\begin{array}{l} \left\|\boldsymbol{Y}_i - \boldsymbol{D}_i\boldsymbol{X}_i^i\right\|_F^2 + \lambda_1\left\|\boldsymbol{Z}_i - \boldsymbol{D}_i\boldsymbol{X}_i^i - \boldsymbol{D}_b\boldsymbol{B}_i\right\|_F^2 + \lambda_2\left(\left\|\boldsymbol{X}_i^i\right\|_1 + \left\|\boldsymbol{B}_i\right\|_1\right) \\ + \lambda_3\left\|\boldsymbol{X}_i^i - \boldsymbol{M}_i\right\|_F^2 + \lambda_4\left(\sum\nolimits_{j \neq i}\left\|\boldsymbol{D}_j^T\boldsymbol{D}_i\right\|_F^2 + \sum\nolimits_i \left\|\boldsymbol{D}_b^T\boldsymbol{D}_i\right\|_F^2\right) \end{array} \right] \tag{4}$$

We require that l_2-norm of the atoms of the dictionary $\boldsymbol{D}$ should be less than or equal to 1 (i.e., $\|\boldsymbol{d}\|_2^2 \leq 1$) to avoid the trivial solution. Although the objective function $\boldsymbol{J}$ in Eq. (4) is not jointly convex to ($\boldsymbol{D}$, $\boldsymbol{X}$, $\boldsymbol{B}$), it is convex with respect to each of $\boldsymbol{D}$ and ($\boldsymbol{X}$, $\boldsymbol{B}$) when the other is fixed. Equation (4) can be solved by alternatively optimizing $\boldsymbol{D}$ and ($\boldsymbol{X}$, $\boldsymbol{B}$). Optimization procedures are presented in Sect. 4.

4 Optimization of RDCDL

We can solve Eq. (4) by alternatively optimizing $\boldsymbol{D}$ and ($\boldsymbol{X}$, $\boldsymbol{B}$): Updating ($\boldsymbol{X}$, $\boldsymbol{B}$) by fixing $\boldsymbol{D}$; Updating $\boldsymbol{D}$ by fixing ($\boldsymbol{X}$, $\boldsymbol{B}$).

When $\boldsymbol{D}$, $\boldsymbol{B}$ and all $\boldsymbol{X}_j^j$ $(j = 1, \cdots, N, j \neq i)$ are fixed, we can compute $\boldsymbol{X}_i^i$ one by one; When $\boldsymbol{D}$, $\boldsymbol{X}$ and all $\boldsymbol{B}_j$ $(j = 1, \cdots, N, j \neq i)$ are fixed, we can compute $\boldsymbol{B}_i$ one by one. Thus the objective function $\boldsymbol{J}$ in Eq. (4) is respectively reduced to:

$$J_{\left(\boldsymbol{X}_i^i\right)} = \arg\min_{\left(\boldsymbol{X}_i^i\right)}\left\{Q_1\left(\boldsymbol{X}_i^i\right) + 2\tau\left\|\boldsymbol{X}_i^i\right\|_1\right\} \tag{5}$$

$$J_{(\boldsymbol{B}_i)} = \arg\min_{(\boldsymbol{B}_i)}\left\{Q_2(\boldsymbol{B}_i) + 2\tau\|\boldsymbol{B}_i\|_1\right\} \tag{6}$$

where $Q_1\left(\boldsymbol{X}_i^i\right) = \left\|\boldsymbol{Y}_i - \boldsymbol{D}_i\boldsymbol{X}_i^i\right\|_F^2 + \lambda_1\left\|\boldsymbol{Z}_i - \boldsymbol{D}_i\boldsymbol{X}_i^i - \boldsymbol{D}_b\boldsymbol{B}_i\right\|_F^2 + \lambda_2\left\|\boldsymbol{X}_i^i - \boldsymbol{M}_i\right\|_F^2$, $\tau = \frac{\lambda_1}{2}$, $Q_2(\boldsymbol{B}_i) = \lambda_1\left\|\boldsymbol{Z}_i - \boldsymbol{D}_i\boldsymbol{X}_i^i - \boldsymbol{D}_b\boldsymbol{B}_i\right\|_F^2$. The iterative projection method (IPM) [11] can be used to solve Eqs. (5) and (6).

When $\boldsymbol{X}$, $\boldsymbol{B}$, $\boldsymbol{D}_b$ and all $\boldsymbol{D}_j$ $(j = 1, \cdots, N, j \neq i)$ are fixed, we can update $\boldsymbol{D}_i$ atom by atom. When $\boldsymbol{X}$, $\boldsymbol{B}$ and $[\boldsymbol{D}_1, \boldsymbol{D}_2, \cdots, \boldsymbol{D}_N]$ are fixed, we can update $\boldsymbol{D}_b$ atom by atom. Thus the objective function $\boldsymbol{J}$ in Eq. (4) is respectively reduced to:

$$\boldsymbol{D}_i = \arg\min_{\boldsymbol{D}_i}\left[\left\|\boldsymbol{Y}_i - \boldsymbol{D}_i\boldsymbol{X}_i^i\right\|_F^2 + \lambda_1\left\|\boldsymbol{Z}_i - \boldsymbol{D}_i\boldsymbol{X}_i^i - \boldsymbol{D}_b\boldsymbol{B}_i\right\|_F^2\right] + \lambda_4\left[\sum\nolimits_{j\neq i}\left\|\boldsymbol{D}_j^T\boldsymbol{D}_i\right\|_F^2 + \left\|\boldsymbol{D}_b^T\boldsymbol{D}_i\right\|_F^2\right] \tag{7}$$

$$\boldsymbol{D}_b = \arg\min_{\boldsymbol{D}_b}\sum_{i=1}^{N}\lambda_1\left\|\boldsymbol{Z}_i - \boldsymbol{D}_i\boldsymbol{X}_i^i - \boldsymbol{D}_b\boldsymbol{B}_i\right\|_F^2 + \lambda_4\sum\nolimits_i\left\|\boldsymbol{D}_b^T\boldsymbol{D}_i\right\|_F^2 \tag{8}$$

The COPAR [5] can be used to solve Eqs. (7) and (8). The algorithm of DCDL is summarized in Table 1.

Table 1. Algorithm of robust, discriminative and comprehensive dictionary learning

Robust, Discriminative and Comprehensive Dictionary Learning
1. **Initialization** $\boldsymbol{D} = [\boldsymbol{D}_c, \boldsymbol{D}_1, \boldsymbol{D}_2, \hbar, \boldsymbol{D}_N, \boldsymbol{D}_b]$.
We use PCA to initialize the atoms of $\boldsymbol{D}_i$ by $\boldsymbol{Y}_i$ ($i = 1, 2, \hbar, N$) and the atoms of $\boldsymbol{D}_b$ by $\boldsymbol{Z}_i - \boldsymbol{Y}_i$.
2. **Update the representation coefficient** $\boldsymbol{X}$ **and** $\boldsymbol{B}$**.**
Fix $\boldsymbol{D}$ and $\boldsymbol{B}$ and update $\boldsymbol{X}_i^i$ ($i = 1, 2, \hbar, N$) one by one.
Fix $\boldsymbol{D}$ and $\boldsymbol{X}$ and update $\boldsymbol{B}_i$ ($i = 1, 2, \hbar, N$) one by one.
3. **Update the dictionary** $\boldsymbol{D}$**.**
Fix $\boldsymbol{X}$, $\boldsymbol{B}$ and $\boldsymbol{D}_b$ and update $\boldsymbol{D}_i$ ($i = 1, 2, \hbar, N$) one by one.
Fix $\boldsymbol{X}$, $\boldsymbol{B}$ and $[\boldsymbol{D}_1, \boldsymbol{D}_2, \hbar, \boldsymbol{D}_N]$ and update $\boldsymbol{D}_b$ one by one.
4. **Output.**
Return to step 2 until the values of $J_{(\boldsymbol{D},\boldsymbol{X},\boldsymbol{B})}$ in adjacent iterations are closed enough, or the maximum of iterations is reached. Output $\boldsymbol{D}$, $\boldsymbol{X}$ and $\boldsymbol{B}$.

5 The Classification Scheme

After the comprehensive dictionary $\boldsymbol{D} = [\boldsymbol{D}_1, \boldsymbol{D}_2, \cdots, \boldsymbol{D}_N, \boldsymbol{D}_b]$ is got, we can code a testing sample $\boldsymbol{y}$ over the dictionary $\boldsymbol{D}$. In this case, the coding coefficient can be got by solving:

$$\hat{\boldsymbol{\alpha}} = \arg\min_{\boldsymbol{\alpha}}\left\{\|\boldsymbol{y} - [\boldsymbol{D}_1, \cdots, \boldsymbol{D}_N, \boldsymbol{D}_b][\boldsymbol{\alpha}_1; \cdots; \boldsymbol{\alpha}_N; \boldsymbol{\alpha}_b]\|_2^2 + \lambda\|[\boldsymbol{\alpha}_1; \cdots; \boldsymbol{\alpha}_N; \boldsymbol{\alpha}_b]\|_1\right\} \tag{9}$$

where λ is a constant. Denoted by $\hat{\boldsymbol{\alpha}} = [\hat{\boldsymbol{\alpha}}_1; \cdots; \hat{\boldsymbol{\alpha}}_N; \hat{\boldsymbol{\alpha}}_b]$. The reconstruction error of each class is represented as:

$$e_i = \|\boldsymbol{y} - \boldsymbol{D}_i\hat{\boldsymbol{\alpha}}_i - \boldsymbol{D}_b\hat{\boldsymbol{\alpha}}_b\|_2 \tag{10}$$

where $\hat{\boldsymbol{\alpha}}_i$ is the coefficient vector associated with class i. The classification is defined as:

$$\text{identity}(\boldsymbol{y}) = \arg\ \min_i\{e_i\} \tag{11}$$

6 Experimental Results and Analysis

In order to well show the advantage of RDCDL, we compare it with NN, SVM, LCKSVD [4], DLSI [7], FDDL [8], SRC [2], and COPAR [5] algorithms by experiments on the Extended Yale B [12,13], AR [14] and Multi-PIE [15].

6.1 Experimental Setting

In this section, we give the experimental details. For Extended Yale B database, the alternative training images are produced by occluding the original images by the random block, whose level is 0.3, $\lambda_1 = 0.001$, $\lambda_2 = 0.01$, $\lambda_3 = 0.01$, $\lambda_4 = 0.001$ and $\lambda = 0.001$. For AR database, the alternative training images are produced by occluding the original images by the random block, whose level is 0.2, $\lambda_1 = 0.001$, $\lambda_2 = 0.01$, $\lambda_3 = 0.001$, $\lambda_4 = 0.0001$ and $\lambda = 0.001$. For Multi-PIE database, the alternative training images are produced by corrupting the original images by the salt & pepper noise, whose density is 0.5, $\lambda_1 = 0.001$, $\lambda_2 = 0.0005$, $\lambda_3 = 0.1$, $\lambda_4 = 0.0005$ and $\lambda = 0.001$.

6.2 Experimental Results on the Extended Yale B Database

The Extended Yale B database consists of 2414 frontal face images from 38 individuals (about 64 images per subject) captured under various laboratory controlled lighting conditions. In the experiment, the size of the original face images is 96×84, we select the former 2 images per subject from subset 1 for training and the subjects from subset 3 for testing. Then we use PCA to reduce the image dimension to 70. The results of RDCDL, SRC, NN, SVM, LCKSVD, DLSI, FDDL and COPAR are listed in Table 2. It can be seen that RDCDL achieves higher recognition rates than the other compared methods.

Table 2. The recognition rates (%) of competing methods on the Extended Yale B database

Methods	Accuracy (%)	Methods	Accuracy (%)
SRC	83.5	COPAR	77.8
NN	55.4	FDDL	84.2
SVM	47.7	DLSI	83.9
LCKSVD	78.9	**RDCDL**	**91.0**

6.3 Experimental Results on the AR Database

The AR database consists of over 4,000 frontal images from 126 individuals. For each individual, 26 pictures were taken in two separated sessions. As in [2], we chose a subset consisting of 50 male subjects and 50 female subjects in the experiment. The size of the original face images is 165×120. For each subject, the 7 images with illumination and expression changes from session 1 are used for training, and the 13 images (with illumination, expression changes, sunglasses and scarf) from session 2 are used for testing. Then we use PCA to reduce the image dimension to 300. The results of competing methods are shown in Table 3. It can be seen that RDCDL achieves the best recognition rates.

Table 3. The recognition rates (%) of competing methods on the AR database

Methods	Accuracy (%)	Methods	Accuracy (%)
SRC	69.2	COPAR	65.6
NN	48.2	FDDL	69.5
SVM	58.6	DLSI	68.4
LCKSVD	65.5	**RDCDL**	**75.3**

6.4 Experimental Results on the CMU Multi-PIE Database

The CMU Multi-PIE face database is a large scale database of 337 subjects including four sessions with simultaneous variations of pose, expression and illumination. Among the 337 subjects, we chose the former 60 subjects from session 1 as the training set, and the same subjects from session 3 as the testing set. For each subject, we chose the 3 frontal images with illumination {0, 1, 3} and smile expression from session 1 for training, and the 10 frontal images with illumination {0, 2, 4, 6, 8, 10, 12, 14, 16, 18} and smile expression from session 3 for testing. Then we use PCA to reduce the image dimension to 170. Table 4 shows the results of competing methods. It can be seen that RDCDL improves at least 3 % over the other compared methods.

Table 4. The recognition rates (%) of competing methods on the Multi-PIE database

Methods	Accuracy (%)	Methods	Accuracy (%)
SRC	85.3	COPAR	83.5
NN	69.3	FDDL	87.7
SVM	72.2	DLSI	86.5
LCKSVD	82.3	**RDCDL**	**90.8**

6.5 Experimental Analysis

The above experiments show that the proposed RDCDL achieves higher recognition rates than SRC, NN and SVM, which directly use original training samples to perform face recognition. It demonstrates that the obtained dictionaries have more discriminative ability than the original training samples. The experiments also show that the recognition rates of the proposed RDCDL are higher than those of LCKSVD, COPAR, FDDL and DLSI, which are DL methods. It demonstrates that the proposed RDCDL has more power discriminative ability than them.

7 Conclusion

In the paper, we propose a new robust, discriminative and comprehensive DL (RDCDL) model. The proposed model uses sample diversities of the same face image to make the dictionary robust. The model includes class-specific dictionary atoms and disturbance dictionary atoms, which can well represent the data from different classes. Both the dictionary and the representation coefficients of data on the dictionary introduce discriminative information, which improves effectively the discrimination capability of the dictionary. The experiments on face recognition demonstrated the effectiveness of RDCDL to those state-of-the-art methods. Face recognition with a single sample per person is very important in the practical application. In the future, we will apply RDCDL to face recognition with a single sample per person.

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