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Face Recognition Technology Based on Sparse Representation

Dongyan Cui
School of Artificial Intelligence, North China University of Science and Technology, Tangshan, Hebei, China
E-mail: *cdy_xxz@163.com*

Abstract

The basic idea of sparse representation is to represent the signal with a few non-zero elements as possible, reflecting the structure and essential attributes of the image. In the sparse representation classifier for face recognition, the sparse representation coefficients are obtained by solving the problem of coefficient representation, and the test samples are classified into the class of the least reconstruction error constructed from the training samples. In the actual face recognition problem, the dimensions of face images are very large. First, Principal Component Analysis (PCA) is used to reduce the dimension, which not only reduces the computational requirements, but also improves the recognition rate and robustness. This paper proposed a discriminant K-means and Singular Value Decomposition (K-SVD) algorithms in order to ensure that the dictionaries have good representation ability and strong discrimination. An optimized small-scale dictionary is trained as a large-scale training sample set, which reduces the size of the sample space and improves the recognition speed of the algorithm. Finally, the feasibility and validity of the proposed algorithm are verified by using the YALE, ORL, and AR face database by Matlab.

Keywords: Sparse representation, face recognition, principal component analysis, discriminant K-SVD algorithm.

1. Introduction

The processes of face recognition [1] include face detection, face location, feature extraction and feature recognition. At present, face recognition algorithms can be divided into the following categories:

(1) Methods based on local feature extraction [2] such as Gabor wavelet extraction algorithms, Local Binary Pattern(LBP) and local ternary pattern (LTP), which focus on the extraction of facial features. The extracted feature descriptors usually have a better-discriminated degree and are more robust to face recognition of uncontrollable environment;

(2) Methods based on subspace analysis [3] (e.g., GWT, Principal Component Analysis(PCA) [4], Linear Discriminant Analysis(LDA), Independent principal Component Analysis (ICA) and Nonnegative Matrix Factor (NMF)).

The main idea is to map the face image to a subspace with lower dimension and a higher degree of differentiation by spatial transformation. The redundant information of the face image is eliminated and most of the useful information is retained at the same time.

The classical algorithms such as Eigenfaces proposed by Turk and Pentland and the Linear Discriminant Analysis (LDA) algorithm proposed by Belhumeur and YuH, the Independent Component Analysis (ICA) algorithm proposed by Bartlett et al. [5]. In recent years, Yang et al. [6] have proposed a recognition algorithm (2DPCA) based on image matrix analysis. The computational complexity obviously reduced to compare with the traditional PCA method of reducing the recognition rate, and good results have been obtained.

(3) The model-based face recognition method focuses on the design of the overall framework and a set of the classifier, such as using the improved algorithm designed by Hidden Markov Model to apply to face recognition. The artificial neural network used to make the face recognition algorithm self-organizing and adaptive.

In recent years, inspired by the extensive application of compressed sensing theory in signal processing, face recognition technology based on sparse representation has been widely studied [7-8]. After the original image signal is transformed by DCT, only a few elements are non-zero, and most of the elements are equal to zero or close to zero, which is the sparsity of the signal.

Sparse representation theory has been widely used in image processing, such as image restoration, image de-noising, image classification, image recognition and so on. The Sparse Representation Classifier (SRC), which applies sparse representation to face recognition is widely studied and used for reference. In SRC, the test sample is trained to be sparse, and its sparse representation coefficient is obtained by solving the problem of coefficient representation. The test samples are assigned to the class with the minimum reconstruction error with this kind of training samples.

Wright et al. used sparse representation theory to deal with the problem of face recognition of the first time for literature and proposed a sparse representation based classification (Sparse Representation-based Classification, SRC) algorithm [9]. This paper provides a new research perspective and solution for face recognition. Zhou et al. combined sparse representation with Markov random field to identify partially camouflaged human faces [10]. Yang et al. add Gabor features to sparse representation [11]. It was not only improved the ability to distinguish faces but also reduced the dimension of overcomplete dictionaries. Deng et al. proposed a prototype plus variation representation model to solve the single sample face recognition problem [12]. Elad et al. used a K-SVD method to obtain overcomplete dictionaries, which made the complete dictionary RC more representational [13]. Zhang et al. consider that cooperative representation dominates the working mechanism of SRC and that L2 used to replace L1 norm will reduce the computational complexity [14], and the speed of face recognition is improved. However, the sparse representation algorithm is usually based on the whole human face information classification, ignoring the impact on face local features on the recognition effect, in addition, the test samples and training samples should be strictly aligned when there is an expression and pose angle change, the recognition effect obviously decreased.

Therefore, this paper proposes an improved sparse classifier based on PCA [15] and SRC, which uses the discriminant K-SVD algorithm (D-KSVD) to obtain the optimized small-scale dictionary, and realizes the fast and effective classification under the premise of ensuring the classification effect. Finally, different face databases are used to test the effectiveness of the algorithm.

2. Methods and algorithm steps

2.1. Sparse representation classifier (SRC) for face recognition

The basic idea of sparse representation is to represent the signal with a few non-zero elements as possible, which makes the signal processing simple and reflects the structure and essential attributes of the image [16]. In this paper, the sparse non-zero elements in the training sample are used to represent the test samples linearly to achieve the purpose of recognition. In the sparse representation classifier (SRC) [17] for face recognition, the test samples are trained to be sparse, and the sparse representation coefficients are obtained by solving the problem of coefficient representation. The test samples are assigned to the SRC classification process of the category with the smallest reconstruction error from this type of training sample, as shown in Fig.1.

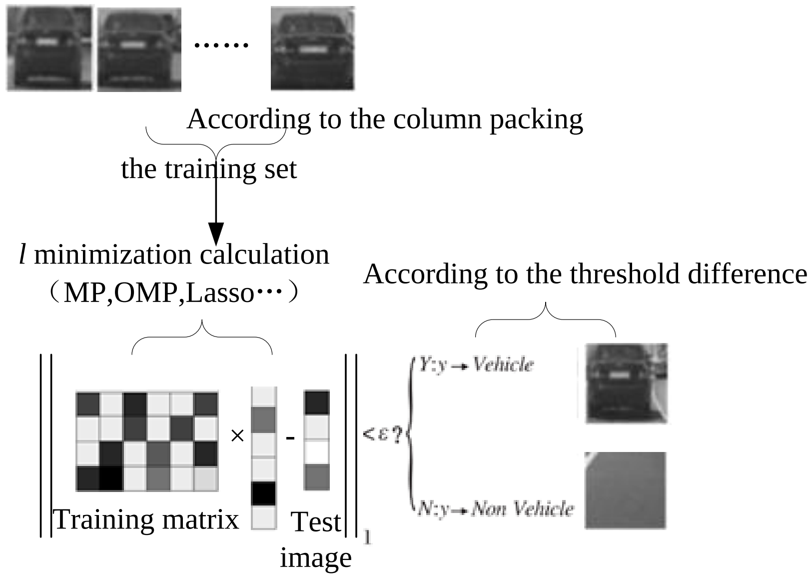


Fig. 1. Sparse Representation Classification Process

The principle of sparse representation is as follows:

Assuming that the training set has a total of k class images and each class ha n_i s training samples, the $k \times n_i$ training samples can be arranged into a matrix in columns:

$$A = \left[A_1, A_2, \cdots A_k\right] = \left\lfloor v_{1,1}, v_{1,2}, \cdots v_{k,n_k} \right\rfloor \tag{1}$$

Where A_i is the class i training image. For the test image y, according to the principle of linear subspace, it can generally be expressed by a linear combination of a certain class of elements in A:

$$y = A\alpha \in R^m$$

$$s.t.\ \alpha \in \left\lfloor 0, \cdots 0, \alpha_{i,1}, \alpha_{i,2}, \cdots, \alpha_{i,n_i}, 0, \cdots 0 \right\rfloor \tag{2}$$

Where α denotes that y is only related to the class i, and the corresponding coefficient of the other class is zero, and then y is independent of this class. Obviously, if $m > n_i$, then the linear equations $y = A\alpha$ is over determined, that is, the number of equations is larger than the number of nonzero unknown numbers, so α can generally obtain a unique solution. However, in the case of general recognition, the number of equations $y = A\alpha$ is less than the number of nonzero unknown. Therefore, the mathematical knowledge shows that the linear equations are undetermined and the solutions to the equations are not unique. In general, it can be solved by selecting the minimum $l_1 - norm$ solution:

$$\hat{\boldsymbol{\alpha}} = \arg\min_{\alpha} \| \mathbf{y} - \mathbf{A}\boldsymbol{\alpha} \|_2^2 + \lambda \| \boldsymbol{\alpha} \|_1, \lambda > 0 \tag{3}$$

λ is the parameter of equilibrium reconstruction error and sparsity, then

$$\mathbf{y} = \arg\min_{i} \| y - \mathbf{A}_i \boldsymbol{\alpha} \|_2 \tag{4}$$

In this way, the linear expression closest to the test image y is obtained by iteration, which is the final recognition result.

Given a sufficient number of the class c trained face images, $A_k^i \in R^m$ is used as a column to construct a matrix $A_i = \left[A_1^i, A_2^i, \cdots, A_{n_i}^i \right] \in R^{m \times n_i}$, $A_k^i \in R^m$ represents the n_i training images of the class i. Then a training matrix $A = \left[A_1, A_2, ..., A_c \right] \in R^{m \times n}$ is formed, where $n = \sum n_i$. The test image $y \in R^m$ belonging to the class i should be able to be approximately linearly represented by the class i training image, that is,

$$y \approx A_i \alpha_i, \alpha_i \in R^{n_i} \tag{5}$$

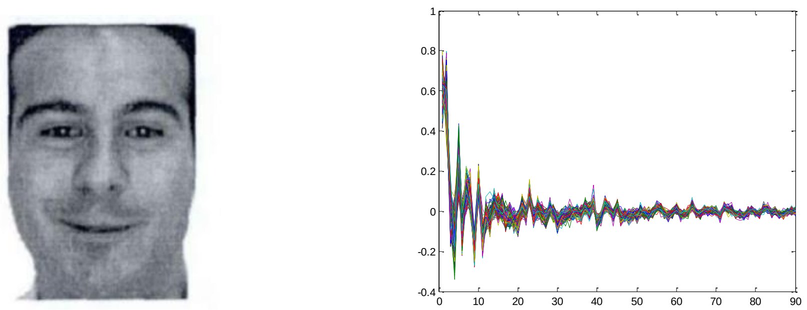
Because the class of the $y \in R^m$ test face image is unknown, all training samples can be linearly represented as:

$$y \approx A\alpha, \alpha = \left[\alpha_1, \cdots \alpha_i, \cdots \alpha_c \right] \in R^{n_i} \tag{6}$$

Where: α_i is a subvector corresponding to A_i, and when y belongs to the class i, only the component of α_i is very large and the value of $\alpha_k \left(k \neq i \right)$ other subvectors is very small. Thus, to find the classification coefficient of the test image y of an overcomplete dictionary, we can express it with the following mathematical model:

$$\hat{\alpha} = \arg\min \left\| \alpha \right\|_0 \quad s.t. \ y = A\alpha \tag{7}$$

The sparse representation coefficient $\hat{a}$ obtained by solving the model (7) can well reflect the class of the test image y. For example, in Fig .2, figure (a) is an image of the first person in the AR face database, and figure (b)is a distributed image of the coefficients obtained by the formula (7). Obviously, the value of each component of the coefficient vector for one person is very large, while the value corresponding to the others is very small.



(A) (B)

Fig. 2. Classification baesed on sparse representation

(A) Test Pattern (B) Classification of Sparse Representation Coefficients

Thus, if $\hat{\alpha} = \left[\hat{\alpha}_1, \cdots \hat{\alpha}_i, \cdots \hat{\alpha}_c \right] \in R^n$, is made, the final classification can be completed according to the representation residual of each class.

$$r_i = \left\| y - A_i \hat{\alpha}_i \right\|_2^2 \tag{8}$$

2.2. Design of face recognition algorithm based on PCA and SRC

The main process of extracting face features by PCA [18] is shown in Fig.3, which mainly includes the following stages: training samples, feature extraction [19], feature space construction, projection calculation.

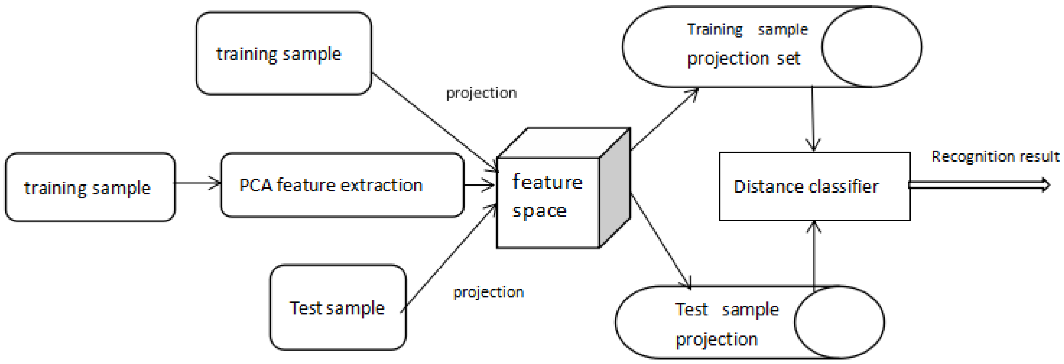


Fig. 3. Face feature flow chart for PCA face extraction

200 face images were randomly selected from ORL database as experimental objects of constructing feature face space by PCA algorithm. According to the PCA algorithm, the face image is transformed into a matrix, the covariance matrix of the matrix is obtained, and the main information of 80% of the face image is extracted. It is necessary to select the eigenvector corresponding to the first 30 eigenvalues with the largest contribution to form the feature face space. The result is shown in Fig.4.

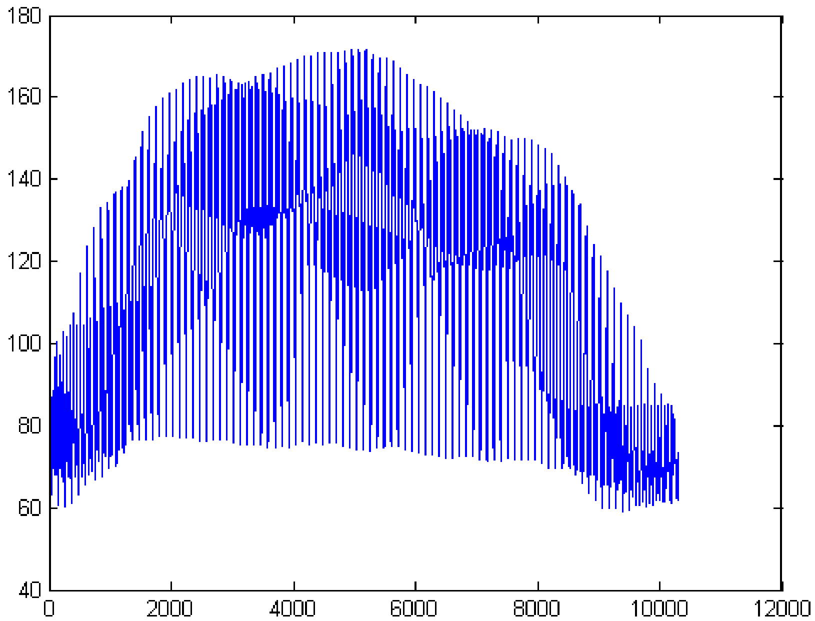


Fig. 4. Percentage contribution to the number of eigenvalues

From Fig.4 we know that the first 30 Eigenvectors of the covariance matrix are normalized orthogonal to form the feature face space which contains the main features of the face image and obtains the feature face image. A set of one-dimensional vectors is obtained by projecting the face image into the space. The essence of the vector is the position of the image in the feature face space, because different images have different positions in the feature face space. Therefore, the projection vector can be used to represent the face.

After dimensionality reduction by PCA, the projection matrix of primitive human face image from m dimension high dimension space to $m^{'}$ low dimension space is used as observation matrix, that is, $\Phi=\omega^{T}, \Phi \in R^{m \times m}$ and $m^{'}<N<m$, the complete redundant dictionary is constructed as follows:

$$A=\left[x_{1,1}, x_{1,2}, \cdots, x_{1,k}, \cdots x_{c,1}, x_{c,2}, \cdots, x_{c,k}\right] \in R^{m \times N} \tag{9}$$

Then the sparse face model is constructed, that is,

$$x=A\alpha=\alpha_{i,1} x_{i,1}+\alpha_{i,2} x_{i,2}+\cdots+\alpha_{i,k} x_{i,k} \tag{10}$$

Then the observation matrix Φ is used to project the training data of all human faces, namely:

$$Y=\Phi X \tag{11}$$

Through sparse representation and observation projection, the training process of face image is completed, that is, the training stage is completed. When a test image x is input, the system uses the observation matrix Φ to project the sample x to obtain:

$$y=\Phi x \tag{12}$$

From the above formula (10)-(12), we can know the optimized objective function, that is $Y\alpha=y$, which is solved by using the least l_1 norm method, that is:

$$\langle D, W, \alpha\rangle=\underset{D, W, \alpha}{\arg\min}\left\|\begin{bmatrix} X \\ \sqrt{\gamma} * H \end{bmatrix}-\begin{bmatrix} D \\ \sqrt{\gamma} * W \end{bmatrix} * \alpha\right\|_{2}^{2}$$

$$s.t.\ Y\alpha=y \tag{13}$$

The sparse vector $\hat{\alpha}$ is obtained, and the reconstruction error on each class is used to determine the class to which the test image x belongs. The reconstruction error of $e_i=\left\|y-Y_i r_i\right\|$, is the objective function of sparse recovery, that is:

$$Y\alpha=y \quad s.t.\ e_i=\left\|y-Y_i r_i\right\| \tag{14}$$

Then,

$$\hat{\alpha}=\left[r_1, r_2, \cdots, r_c\right]^{T} \tag{15}$$

The input of face recognition algorithm based on sparse representation includes two parts: the training sample set and the test sample set. The size of each image is the same, order $m=w \times h$. Each image resize is a $m \times 1$ column vector. The column vectors of all pictures are combined into a matrix $A=\left[A_1, A_2, \cdots, A_k\right]=\left\lfloor v_{1,1}, v_{1,2}, \cdots v_{k,n_k}\right\rfloor$, total k class, the class i image set is A_i, for the jth image of the class i as a training sample: $y \in IR^{m}$, y is the column vector of $m \times 1$ as the test sample. The framework of face recognition system based on sparse representation classification is shown in Fig .5.

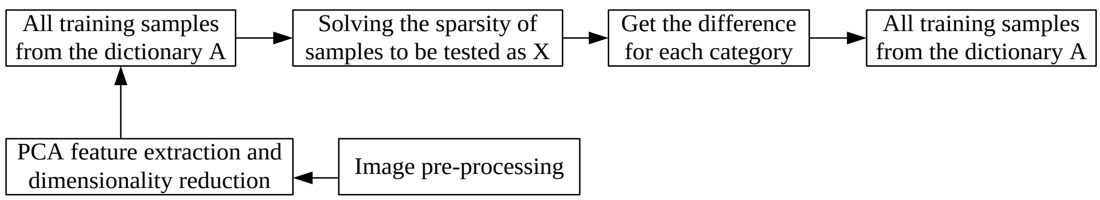


Fig. 5. Framework of face recognition system based on sparse representation classification

The face recognition algorithm based on sparse representation includes the following steps:

Step 1: Normalized each column of A to a unit vector: for column i, calculate the sum of squared elements of this column, sq, and then each element of this column becomes its squared divided by sq;

Step 2: To enhance the robustness to occlusion, extends the equation: $y = y_0 + e_0 = Ax_0 + e_0$ $y = [A, I]\begin{bmatrix} x_0 \\ e_0 \end{bmatrix} = B\omega_0$

Where, A matrix is extended to B matrix , X to ω , I is the unit matrix, ω_0 to be solved.

The solution of the 1-norm minimization problem is: (l_e^1): $\hat{\omega}_1 = \arg\min \| \omega \|_1$ subject to $B\omega = y$. We get the solution: $\hat{\omega}_1 = [\hat{x}_1, \hat{e}_1]$ to restore the unshaded face image: $y_r = y - \hat{e}_1$.

Step 3: calculates $\delta_i(\hat{x}_1)$: the dimensions are the same to $\hat{x}_1$, leaving only the elements corresponding to the class $\hat{x}_1$ and the class i , while the other elements are 0. Calculate the residuals for each class: $r_i(y) = \| y_r - A\delta_i(\hat{x}_1) \|_2 = \| y - \hat{e}_1 - A\delta_i(\hat{x}_1) \|_2, i = 1,2,3,\ldots,k$ For the smallest residual i , i is the final classification of y .

Step 4: Definition 1(sparsity concentration index(SCI)).The SCI of a coefficient vector $x \in IR^n$ is defined as $SCI(x) = \frac{k \cdot \max_i \| \delta_i(x) \|_1 / \| x \|_1 - 1}{k - 1} \in [0,1]$ .Calculate the SCI of $\hat{x}_1$, if $SCI(\hat{x}) \geq \tau$, output the classification result i , otherwise think the picture is invalid, prompt "invalid picture". The threshold τ is manually input at the beginning, the range is $(0.5,1)$, the recommended value is 0.85. A stranger face that is not in the database or a picture that is not a human face is outputted as an" invalid image".

3. Design of discriminant K-SVD (D-KSVD) algorithm

3.1. Principle of the proposed algorithm

In the algorithm of combining PCA and SRC, some samples are selected to form redundant dictionaries, and face recognition is carried out according to the sparse representation of test samples on redundant dictionaries. After using PCA to reduce the dimension of the training samples, the obtained data is linearly inseparable. Moreover, the algorithm requires a large number of training samples to ensure the over-completeness of redundant dictionaries. Because of the large size of dictionaries, greedy algorithms or iterative search algorithms are required to solve sparse solutions, which results in slow recognition speed. The problem of face recognition based on sparse representation hopes that dictionaries have good representation ability and strong discrimination at the same time. Therefore, in order to make the trained dictionary represent the whole training set well, a discriminant K-SVD algorithm is proposed to train an optimized small dictionary from a large scale training sample set to reduce the size of the sample space. The recognition speed of the algorithm is improved.

The K-SVD algorithm is described as $\langle D, \alpha \rangle = \arg\min_{D,\alpha} \| X - D * \alpha \|_2^2 \quad s.t. \quad \|\alpha\|_0 \leq T$, where, X is the data to be trained and D is the training dictionary and T is the iterative termination of price adjustment. The dictionaries trained by this algorithm lack discrimination and are not suitable for classification problems [20-22].

In order to obtain training dictionaries which satisfy both sparsity and discriminability, a discriminant K-SVD algorithm, D-KSVD, is proposed in this paper. By learning a linear classifier W , it can be classified according to sparse solution α of sparse dictionaries. The mathematical representation is as follows: $\langle W \rangle = \arg\min_{W,\alpha} \| H - W * \alpha \|_2^2$

Where, $H=[h_1,h_2,\cdots,h_k]$ is the class information of the data to be trained, such as $h_3=[0,0,1,0,0,\cdots,0]$,the position of the non-zero element represents the class information of the data to be trained. Combine classifier learning and training dictionaries shown as:

$$\langle D,W,\alpha\rangle=\arg\min_{D,W,\alpha}\|X-D*\alpha\|_2^2+\gamma*\|H-W*\alpha\|_2^2$$

$$s.t.\quad \|\alpha\|_0\le T \tag{16}$$

To solve this problem, we need to solve the training dictionary D and linear classifier W step by step. In order to solve the problem of local optimization, an ideal discriminant dictionary and classifier are obtained, and the algorithm is further improved as follows:

$$\langle D,W,\alpha\rangle=\arg\min_{D,W,\alpha}\left\|\begin{bmatrix}X\\ \sqrt{\gamma}*H\end{bmatrix}-\begin{bmatrix}D\\ \sqrt{\gamma}*W\end{bmatrix}*\alpha\right\|_2^2$$

$$s.t.\quad \|\alpha\|_0\le T \tag{17}$$

Where, X is the data to be trained, H is the class information of the data to be trained, D is the training dictionary and W is the training linear classifier, D and W need to be initialized before the training begins, γ is usually chosen as 1.

After the training dictionary is finished, the matrix $\begin{pmatrix}D\\W\end{pmatrix}$ is obtained. Because the dictionary D and the linear classifier W are concatenated together and normalized by column, so the matrix is split and the dictionary D is normalized, and the corresponding linear classifier of the dictionary also needs W conversion. As shown in formula (18) and (19):

$$D^{'}=\{d_1^{'},d_2^{'},\cdots,d_k^{'}\}=\left\{\frac{d_1}{\|d_1\|_2},\frac{d_2}{\|d_2\|_2},\cdots,\frac{d_k}{\|d_k\|_2}\right\} \tag{18}$$

$$W^{'}=\{w_1^{'},w_2^{'},\cdots,w_k^{'}\}=\left\{\frac{w_1}{\|d_1\|_2},\frac{w_2}{\|d_2\|_2},\cdots,\frac{w_k}{\|d_k\|_2}\right\} \tag{19}$$

After normalization, the test sample y is sparse to $\boldsymbol{\alpha}^{'}$ on the training dictionary $D^{'}$, as shown in the following expression:

$$\langle\alpha^{'}\rangle=\arg\min_{\alpha^{'}}\|y-D^{'}*\alpha^{'}\|_2^2\qquad s.t.\quad \|\alpha^{'}\|_0\le T \tag{20}$$

Finally, the linear classifier $W^{'}$, as an evaluation tool of sparse solution $\alpha^{'}$, determines the classification result, as shown above. Vector $l=[l_1,l_2,\cdots l_m]$ can be used as class similarity of test samples, and the class corresponding to the maximum value is the final classification result: $I=W^{'}*\alpha^{'}$

3.2. Process Design

The above analysis can be solved by using the K-SVD algorithm to obtain the discriminant training dictionary D and the linear classifier W .The flow chart of the initialization dictionary is shown in Fig.6 and the flow chart of the training dictionary is shown in Fig.7.

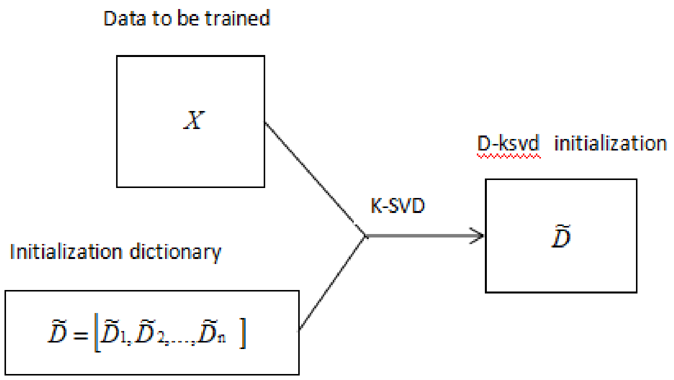


Fig. 6. Flow chart of D-KSVD algorithm initialization dictionary

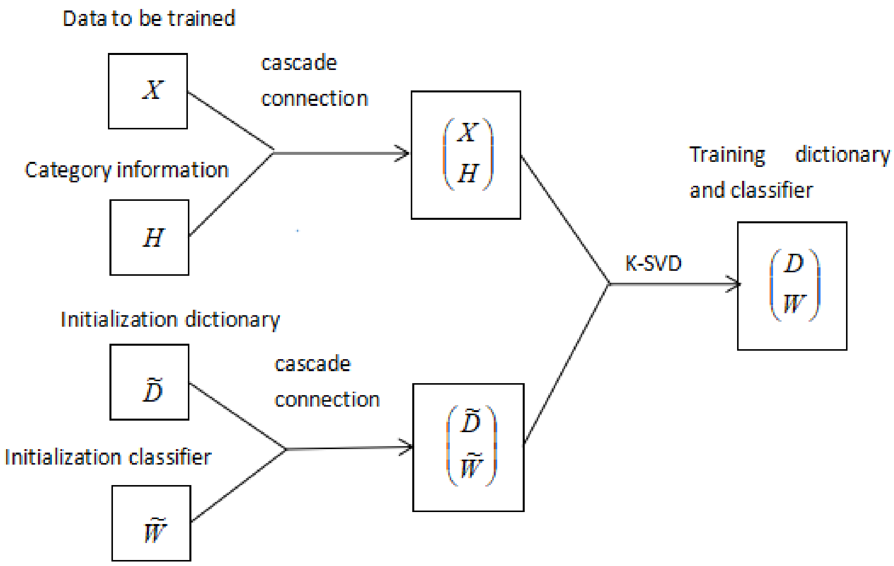


Fig. 7. Flow chart of D-KSVD algorithm training dictionary

The algorithm steps are as follows:

Step1: Firstly, uses a given original dictionary $D^{'}$ to sparse representation sample y to obtain sparse representation coefficient vector $\alpha : \min\left\{\left\|y - D^{'}\alpha\right\|_2^2\right\}, s.t. \forall i, \left\|\alpha_i\right\|_1 \leq \delta$

Step2: The sparse representation coefficient matrix α of y on $D^{'}$ is obtained by using OMP and other classical iterative methods.

Step3: Iterates and updates the matrix to find the best dictionary D.

Step4: To normalize the dictionary D, the corresponding linear classifier W also needs to be converted.

Step5: After normalization is completed, the sparse representation of the test sample y of the training dictionary $D^{'}$ is $\alpha^{'}$. The linear classifier W is used as the evaluation tool of a sparse solution $\alpha^{'}$ to determine the classification result, and the class corresponding to the maximum value is the final classification result: $I = W^{'} * \alpha^{'}$

4. Experiment simulation and result analysis

4.1. Experimental simulation and data source

All the algorithms are used on the PC computer with Matlab2016 software at Intel (R) Core (TM) i7-6700 CPU @ 3.40GHz 3.41 GHz, memory 8 GG / Windows 2010. In order to reduce the experimental error, the average value of each experiment result is obtained several times.

The database uses the international YALE, ORL and AR face databases. The YALE face database contains 165 images of 15 people, and the YALE face database contains 400 images of 40 people, each containing 10 images with different illumination intensity. The facial expressions and images taken at different angles. AR face database contains 2600 images of 100 people, 26 each, divided into two parts, 13 each. The first seven images in the first part are unoccluded images. The tenth image is a sunglass image, and the last three are scarves. The resolution of all images is normalized to 165 * 120. All images of the same person in the face database belong to the same class, the class contained in these three human faces are incremented in turn. But the AR face database is more challenging than the YALE and ORL face databases, because it has far more class than the other two, and it can be used as a training image without occlusion. Fig .8 is an example of one person from each of the three face banks.

(A)

(B)

Fig. 8. An example of a face image in a face database (A) ORL Face Database Example(B) YALE Face Database Example

To evaluate recognition performance more intuitively, the recognition rate (Recognition Rate, RR) is defined as:

$$RR = \frac{Correct \quad classification \quad quantity}{Total \quad number \quad of \quad images \quad tested} \tag{21}$$

4.2. Face recognition experiments without occlusion

For unoccluded data classification, 10% of randomly selected data from each data set is a test sample before classification, and the rest is a training sample. In order to ensure the accuracy and validity of the data, 30 experiments were carried out on each group of data, and the average value was taken. When the training sample number N is 5,6,7,8,9,10, the recognition rate of this design is shown in Tab. 1 under different dimensions. The recognition rates in ORL datasets under different dimensions are shown in Fig .9.

Tab. 1. Recognition rates in ORL datasets with different dimensions

Sample number Dimension	40	50	60	70	80	90	100	110
5	92.5	93.0	94.5	94.5	95.0	95.0	94.5	94.5
6	94.4	93.8	95.0	94.4	95.0	95.0	95.0	95.0
7	967	95.8	95.0	95.0	96.7	96.7	96.7	96.7
8	95.0	96.3	97.5	97.5	96.3	96.3	96.3	97.5
9	95.0	95.0	95.0	95.0	95.0	95.0	95.0	95.0

Tab. 2. Recognition rates in YALE datasets with different dimensions

Sample number Dimension	15	26	37	48	59
5	85.56	91.11	92.22	91.11	93.33
6	85.33	84.00	88.00	85.33	85.33
7	95.00	96.67	98.33	96.67	96.67
8	95.56	97.78	97.78	95.56	95.56
9	90.00	90.00	96.67	93.33	93.33
10	93.33	86.67	86.67	86.67	86.67

At the same time, the general idea of the experiment is to select a certain proportion of data from the training samples randomly as the test samples. Therefore, in the case of different proportions of test sample data, the algorithm is designed to carry out a comparative experiment in YALE. The experimental data are shown in Tab. 2. The recognition rates in YALE datasets under different dimensions are shown in Fig.10.

Analysis of Tab. 2 and Fig.10 shows that the comparison method has better recognition effect for unoccluded data. The experiment proves that the design algorithm has the following advantages: through PCA dimensionality reduction and K-SVD dictionary training, the computation is greatly reduced, thus the recognition time is reduced, and the recognition rate of this design method is a little higher, which fully proves the feasibility and effectiveness of the design method.

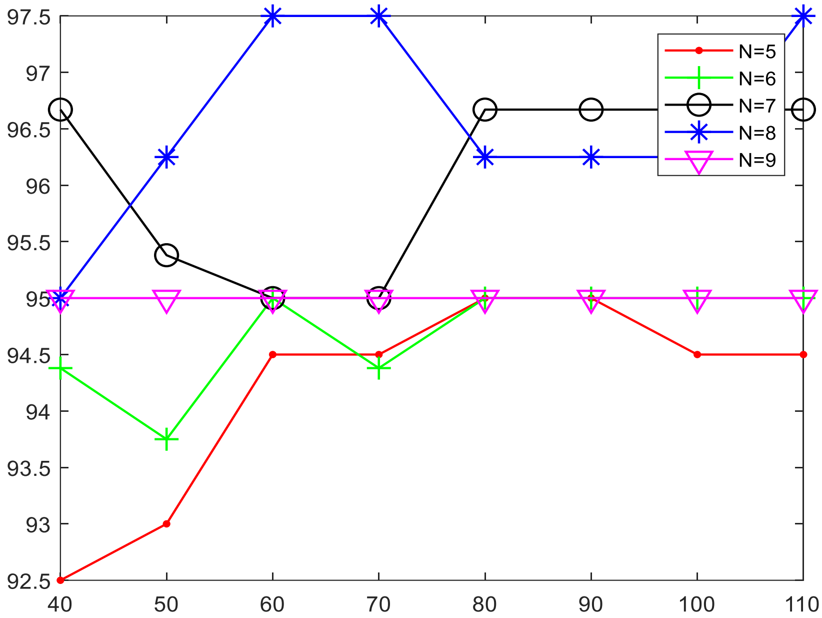


Fig. 9. Recognition rates in ORL datasets under different dimensions

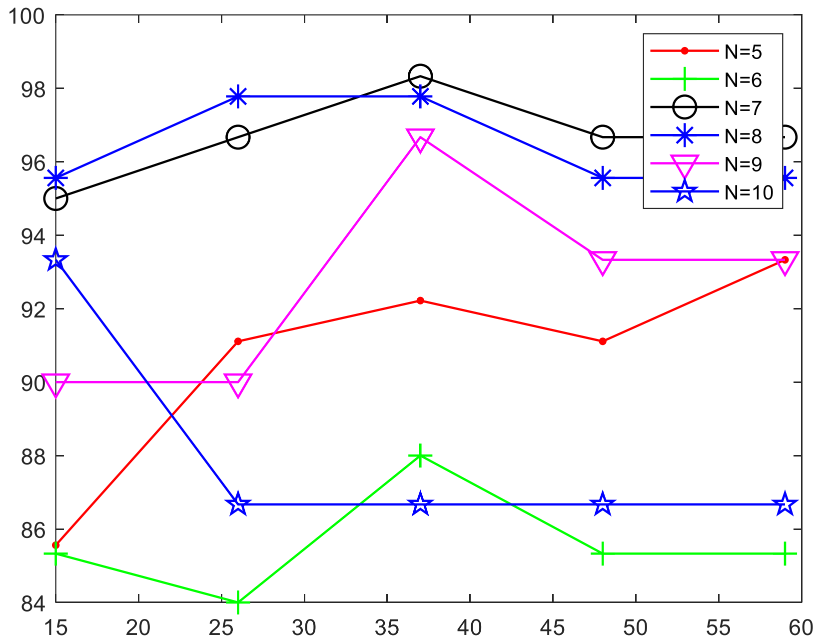


Fig. 10. The Recognition rates in YALE datasets under different dimensions

4.3. Face recognition experiments with occlusion

To verify the robustness of the algorithm, shaded face recognition experiments are only performed on the AR face database, because 14 of the 26 face images of each person are unoccluded. The remaining 12 are shaded by 6 sunglasses and 6 scarves, so the first 7 unoccluded images and the first 2 occluded images are used as training samples, and the remaining ones are used as test samples. The experimental results of the three algorithms are shown in Tab. 3.

Tab. 3. The average recognition rate of occulusion on AR

Algorithm	*PCA*	*SRC*	*PCA+SRC*
Sunglasses occlusion	0.313	0.935	0.953
Scarf occlusion	0.910	0.940	0.943

4.4. Improved D-KSVD algorithm

We use SRC K-SVD method and D-KSVD method to carry out four groups of experiments on Extended Yale B faces database. All the results are the average values of the four experiments. There are two methods in the reference of SRC algorithm: one is to use all training samples to form redundant dictionaries, the other is to select 15 images randomly from each type of training samples to form dictionaries of the same size as the training dictionaries. It is represented by SRC and SRC (15). The D-KSVD algorithm designed in this paper selects 15 images randomly from each kind of training samples to form an initialization dictionary and obtains a training dictionary with the size of 504*650. The four groups of experiments used orthogonal matching tracing (OMP, Orthogonal Matching Pursuit) to solve the sparse solution. The face recognition rate of the four groups of experiments is shown in Tab. 4.

Tab. 4. The face recognition rate and average recognition time based on SRC, K-SVD AND D-KSVD

Method	Dictionary size	Dictionary type	Discrimination (%)	Recognition time (ms)	Training dictionary error
SRC	504*1216	Untrained	93.74	4.834	
SRC（15）	504*650	Untrained	79.47	2.518	
K-SVD	504*650	Untrained in class	92.82	2.435	4.895
D-KSVD	504*650	Untrained in class	93.74	2.441	4.724

Tab. 5. The face recognition rate of K-SVD and D-KSVD alogrithm under different dictionary sizes

Number of selected samples per category	Dictionary size	Recognition rate of K-SVD method(%)	Recognition rate of D-KSVD method(%)
20	504*760	84.43	87.92
15	504*650	92.82	93.74
10	504*380	90.71	91.12

The experimental results show that the recognition rate of D-KSVD is the same as that of SRC, and the recognition rate of D-KSVD is 93.74. The D-KSVD algorithm can solve all the parameters simultaneously in one step, more perfect sparse representation of the test samples, and better classification of the trained separators. Thus, the recognition rate is improved and the fast average speed is guaranteed at the same time.

In Tab. 5, we discuss the recognition rate of the two methods under the condition of randomly selecting a different number of samples and training different dictionary sizes. The experimental results show that the recognition rate of D-KSVD algorithm is always higher than that of the K-SVD algorithm. Experiments show that the algorithm is correct and efficient.

5. Conclusion

In this paper, an improved face recognition algorithm based on sparse representation classification is proposed, which is mainly improved on two aspects. On the one hand, the existing sparse representation classifier (SRC) is combined with PCA to improve the recognition rate and robustness, and in order to ensure that dictionaries have good representation ability and strong discrimination, a discriminant K-SVD algorithm is proposed to train an optimized small-scale dictionary from a large-scale training sample set to reduce the size of sample space. The recognition speed of the algorithm is improved. Finally, the comparative experiments are carried out on the three open face databases of ORL, YALE, and AR. The experimental results show that the proposed algorithm can improve the recognition rate and reduce the computational complexity to a certain extent, especially for occlusion images.

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