Journal of Computers Vol. 32 No. 6, 2021, pp. 195-205
doi:10.53106/199115992021123206017

Expression Recognition in Sparse Principal Component Combine Low-Rank Decomposition Architecture

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Received 1 July 2021; Revised 18 August 2021; Accepted 19 August 2021

Abstract. In order to solve the problem of low face recognition rate in uncontrolled scenes, a face recognition algorithm based on sparse representation of principal components and low rank decomposition in uncontrolled scenes is proposed. Firstly, the basic face database is constructed by the data collected by the core basic information platform, and then the classroom photos are collected and the sampled photos are segmented by principal component sparse representation and low rank decomposition algorithm. Finally, the basic face database is used as a sample for matching recognition, and the results not handled in low rank decomposition are compared with those handled in low rank decomposition. The experimental results show that the recognition effect of superimposed low rank decomposition by sparse representation of principal components in uncontrolled scene is robust to the change of light, and the influence on shelter blocking is relatively obvious. The highest recognition accuracy is 92.4%, which achieves a better face recognition effect in uncontrolled scenes. The algorithm is helpful to the research of face recognition, expression recognition and behavior recognition in common uncontrolled scenes.

Keywords: Uncontrolled scenes, Principal components, Sparse representation, Low rank decomposition, Face recognition

1 Introduction

Face recognition has a very broad application prospect. Because of its non-invasive, covert operation and good interactivity, the research on face recognition has gradually become the mainstream focus in recent years [1]. At present, the research on face recognition in controlled scenes has been mature and achieved good results, even has been popularized in some fields. However, due to the influence of illumination, shelter blocking, expression, posture, image quality and other factors, the face recognition technology in uncontrolled scenes is still in the early stage of development. It is still a difficult problem to be deeply studied and solved in the field of computer vision and pattern recognition. Since the introduction of principal component analysis (PCA) [2] into the field of face recognition twenty years ago, with the continuous development of feature extraction techniques, all kinds of classical methods have been innovated, discriminant analysis [3], sparse error dictionary learning [4], joint aided dictionary learning [5], etc. The methods of identifying sparse maintenance continue to provide various solutions to the problems encountered in face recognition research.

At present, the main idea of face recognition is to extract and train facial recognizable features, and then to obtain classifier samples to further complete the discrimination and classification work. In uncontrolled scenes, the image quality is not good, the illumination is not guaranteed, the shelter blocking is serious, the posture transformation is frequent and so on. The core elements can be summarized as two kinds of problems: (1) how to extract the pure low rank information and sparse interference information of the main features of face. (2) how to reduce the dimension of the extracted high dimensional matrix. In order to further improve the face recognition rate in uncontrolled scenes and reduce the influence of interference factors in uncontrolled scenes, this paper proposes a principal

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component sparse representation method to characterize face features. The low rank decomposition method is used to reduce the influence of various interference factors on the image and reduce the aggregation correlation. In this paper, the image is projected to the low rank subspace and converted to sparse representation, and the noise effect is reduced by low rank decomposition, which increases the robustness and robustness of the recognition effect.

2 Face Recognition in Non-Controlled Scene

General face recognition includes five main stages: face detection, preprocessing, feature extraction, classification recognition and identity recognition. The basic process is shown in Fig. 1 [7]. Face recognition belongs to the category of pattern recognition. The main working steps are as follows: the first step is to preprocess the image of the sample library, extract its key features, reduce the amount of image information, then reduce the dimension of image data. The second step is to repeat the recognition image, and then obtain the feature vector of the image to be recognized. In the third step, the feature vector of the image to be recognized is used to match the feature vector in the sample library to retrieve whether the matching is satisfied. The so-called face recognition in uncontrolled scenes refers to the process of confirming the identity of the object to be detected without deliberate interference. Compared with the face image in the controlled scene, the image quality in the uncontrolled scene is poor, there are different degrees of shelter blocking, the attitude angle changes greatly, the illumination can not be guaranteed, and so on, which results in the face recognition of the uncontrolled scene facing huge obstacles.

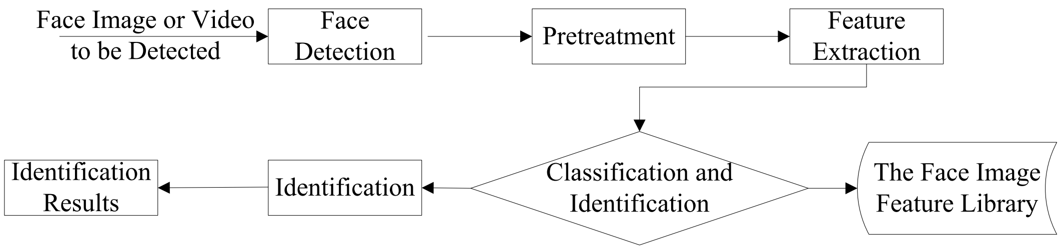

Fig. 1. Frame flow chart of the main phase of face recognition

At present, there are four main methods for face recognition under uncontrolled conditions: (1) shelter blocking face recognition algorithm based on image repair method. (2) shelter blocking face recognition algorithm based on local feature analysis method. (3) shelter blocking face recognition algorithm based on robust estimation method. (4) shelter blocking face recognition algorithm based on sparse representation method [8]. The principle of the first kind of method is to extract gray value from the shelter blocking area, and then to repair the neighborhood shelter blocking area. The recognition rate of this method is high in the case of small range shelter blocking, but the success rate of recognition will be greatly attenuated in the case of large shelter blocking. The principle of the second kind of method is to extract the features of each region and set different weights, but because the weighting process itself is random, it is difficult to achieve the desired recognition effect. The third kind of method principle is to use machine learning method, based on the unshielded area, to estimate the occluded area in the neighborhood. Because of its strong noise sensitivity and high requirement for training samples, the application feasibility is poor. The principle of the fourth method is to distinguish and classify the images according to the sparse representation results. The method has a good effect on the shelter blocking recognition of spatial correlation, but the recognition effect of continuous shelter blocking is poor.

Because of the influence of illumination, shelter blocking and pose, the effect of face recognition can not be guaranteed in uncontrolled scenes, which are also the three main factors leading to the poor recognition effect in uncontrolled scenes. These three factors are usually treated separately in order to achieve the effect of integrated processing. Because the face image acquisition scene is affected by the illumination condition, even the same person, the imaging effect will be different under different lighting conditions. Generally, the processing methods of illumination effect are to improve the recognition rate of image face by illumination compensation preprocessing. The main methods of illumination compensation preprocessing are as follows: (1) Based on image re-processing techniques, such as histogram equalization, histogram regularization, and Gamma grayscale correction [9]. (2) Based on illumination model modification, such as single-scale or multi-scale self-quotient image illumination preprocessing [10]. (3) Subspace analysis correction. The influence of shelter blocking and attitude change is generally solved by image synthesis and reconstruction. The common methods are Mulit-View integration method [11] and 3D modeling and reconstruction method [12].

The basic method of face image representation is to extract all pixels of the image and to characterize the column and column cascaded vectors according to the gray value. However, for images in uncontrolled scenes, illumination, shelter blocking and attitude make the gray value of the image change very much. If the pixel column and column cascade are directly displayed, the recognition accuracy will decay rapidly and be extremely unstable. As a result, the features based on frequency domain or wavelet domain are usually used to represent faces in uncontrolled scenes. The important ones are Fourier transform [13], discrete cosine transform [14], discrete wavelet transform [15] and Gabor wavelet transform [16]. The most important foundation of face recognition is the extraction of face features. In face recognition under uncontrolled conditions, the excellent feature representation method should be able to distinguish the essential differences between individuals to be detected under the background of great influence and change of external environment. Only robust and robust representation can meet the changeable needs of uncontrolled scenarios.

3 Principal Component Sparse Representation

Principal component analysis is a statistical method. A set of variables that may have correlation are converted into a set of linear uncorrelated variables by orthogonal transformation. The transformed variables are called principal components. Sparse representation, that is, how to describe the energy of the signal as much as possible through a minimum set of coefficients, can also be regarded as the capacity of the information [17]. Different types of signals have different coefficients in different transformation modes [18]. Because the object of principal component analysis, is a linear combination of data variables, when it is further necessary to analyze and explain the principal component, it is impossible to represent the specific characteristics corresponding to each principal component. The sparse representation of principal components is an algorithm evolved to solve this problem. It will sparse the principal component coefficient, identify a large number of interference coefficients and zero them. Through this treatment, the core part of the principal component is expressed explicitly. In the field of image recognition, especially for face detection, a set of column vectors will be composed of multiple images of the same object to be tested:

$$R_i = \left[k_{i,1}, k_{i,2}, \cdots, k_{i,n_i}\right] \in K^{m\times n_i}$$

The m represents the feature vector dimension of the picture, the k represents the sample column vector set of the training set, and the global vector set of the training sample to be detected can be follows:

$$R = \left[R_1, R_2, \cdots, R_T\right] = \left[k_{1,1}, k_{1,2}, \cdots, k_{T,n_T}\right] \in K^{m\times M}$$

The $M = \sum_{i=1}^{T} n_i$ represents the size of the training set and the T represents the category of the image to be detected. For purely theoretical space categories, the above vector sets generally follow the low-rank representation, but in uncontrolled scenarios, limited by various complex interference factors, the general training set can be represented by R' . $R' = S \vee D$ is standard low rank matrix $S \in K^{m\times M}$, and error $D \in R^{m\times M}$ composition under interference. Once the matrix D obeys the Poisson distribution, the optimal solution S the principal component low rank matrix is calculated, in fact, it evolves into the solution of the $\underset{S,D}{Min}\left\|S\right\| sequence(S) \le s, R = S \wedge D$ equation, in which s is the rank number of the low rank matrix S . In the objective function upper, sequence is used to represent the matrix optimal solution sequence.

Using the traditional principal component analysis method to solve the R analysis, the optimal solution can be obtained in theory, but the actual situation is more complex, the matrix D usually does not satisfy the Poisson distribution, and the results obtained by the traditional principal component analysis method will have a large deviation. For the object to be tested, this deviation or error can be represented by sparse matrix, and then the problem is evolved into the optimal solution of double objective:

$$\underset{S,D}{Min}\left(\text{sequence}(\mathrm{S}),\|D\|_0\right), R = S \wedge D$$

However, the direct consequence of binocular standardization will be high dimensional complexity and steep drop of efficiency curve. To solve this problem, it is necessary to set the optimal weight between the targets with different relations of low rank quality and sparse error, and the weight parameters are represented by λ. The process evolved as:

$$\underset{S,D}{Min}\, sequence(S) + \lambda \bullet \|D\|_0, R = S \wedge D$$

The optimal solution is obtained by iterative calculation. The best projection matrix of sparse representation is measured by the inline tightness of vectors and the degree of outreach evacuation. The training sample set S consists of n individual samples. The column vector of each sample in the sample set is expressed as s_i, hypothesis s_i belongs to the S category of x, and the sample size in this category is t_x. Inline tightness can be defined as:

$$Min\left\|u_i^k\right\|_1 sequence\left\|s_i - S_x u_i^k\right\| < \varphi$$

The following two set sequences:

$$S_x = \left[s_{x,1}, s_{x,2}, \cdots, s_{x,n_x}\right] \in K^{m\times n_x},\ u_i^k = \left[u_{i,1}^k, u_{i,2}^k, \cdots, u_{i,n_x}^k\right]^T \in K^{m\times n_x}$$

For inline sparse density, k represents inline mode. Inline tightness is expressed as:

$$\sum_{i=1}^{n}\left\|U^T s_i - \sum_{j=1}^{n} P_{ij}^k U^T s_j\right\|^2 = U^T\left[\sum_{i=1}^{n}(s_i - SP_i^k)(s_i - SP_i^k)^T\right]U$$

Where the P_i^k is the i column vector of the P^k and the $P^k = (P_{ij}^k)$ is the inline weighting matrix. The outreach evacuation degree is represented by the single sample and the exclusive sample set of the sample, the s_i is reconstructed S_x the exclusive sample set excluding the s_i. Outreach evacuation can be expressed as:

$$Min\left\|u_i^v\right\|_1 sequence\left\|s_i - S^x u_i^v\right\|_2 < \varphi$$

The following two set sequences:

$$S^x = \left[S_1, S_2, \cdots, S_t\right],\ u_i^v = \left[u_{i,1}^v, u_{i,2}^v, \cdots, u_{i,n-n_x}^v\right]^T \in K^{n-n_x}$$

As an outreach sparse density. Outreach evacuation scale expressed as:

$$\sum_{i=1}^{n}\left\|U^T s_i - \sum_{j=1}^{n} P_{ij}^v U^T s_j\right\|^2 = U^T\left[\sum_{i=1}^{n}(s_i - SP_i^v)(s_i - SP_i^v)^T\right]U$$

Where the P_i^v is the i column vector of the P^v and the $P^v = (P_{ij}^v)$ is the outreach weighting matrix.

4 Sparse Representation of Principal Components in Uncontrolled Scenarios and Low Rank Decomposition Algorithm

For uncontrolled scenes, due to the influence of light change, frequent shelter blocking and changeable posture expression, the causes of interference are complex, the types and volume of data noise are huge, and the key data loss is serious. It is precisely because of the influence of various uncontrollable factors on the uncontrolled scene that the internal variation in this case far exceeds the outreach, which will also make the recognition effect drop sharply. In order to improve the accuracy of face recognition in uncontrolled scenes, a method of combining sparse representation of principal components with low rank decomposition algorithm in uncontrolled scenes is proposed. First, the principal component is extracted from the sample, then the principal component coefficient is sparse, zero is transformed, the low rank matrix and sparse error matrix of the principal component of the sample object are obtained, and then the final result is formed by iterative calculus through binocular weight setting.

In uncontrolled scenes, the effect of illumination on imaging quality is particularly obvious. In the case of non-uniform illumination, the key feature information in the face is difficult to capture and extract, and a large amount of light and shadow noise will seriously interfere with the principal component resolution process. Using low rank decomposition to separate the key features and sparse deviations of the objects to be tested, the low rank matrix is discretized and encoded to enhance the image recognition and processing ability under illumination. When the imaging process of the equipment is more complex and the illumination changes greatly, the pixel value of the key information points on the object to be tested, especially the face object, will have a very large jump. Lambert illumination model is an ideal diffuse reflection illumination model, which is reflected to all sides after the light source is irradiated to the surface of the object. According to the definition of the model, the pixel value of the feature point of the object to be tested can be expressed as $P(u,v)=R(u,v)\times S(u,v)$, where the $R(u,v)$ is the illumination vector of the point and the $S(u,v)$ is the reflection vector of the point. In general, the illumination vector is used to represent the global pixel information of the object point under the influence of illumination, while the reflection vector is used to represent the texture information reflecting the key essence of the object point to be tested. Because the illumination vector of the face object to be detected slows down and the key features are stored in the same rank low rank space, the principal component sparse representation and the low rank decomposition can be used to separate the image principal component features and illumination affected noise. Because of the low rank component decomposition between multiple facial imaging in continuous illumination background, the illumination effect will be weakened, so the illumination edge error will also be reduced, and then the facial key information in the reflection vector will increase. The detection object is decomposed into low rank matrix image. Taking P_s as the face object P the corresponding pixel value on the (u,v) pixel point can be obtained:

$$P_s(u,v)=\frac{\left|\nabla P(u,v)\right|}{P(u,v)}$$

A low rank step increment with $P(u, v)$ lower formula:

$$\left|\nabla P(u,v)\right|=\sqrt{\left(\frac{\partial P(u,v)}{\partial u}\right)^2+\left(\frac{\partial P(u,v)}{\partial v}\right)^2}$$

And the lower is the (u, v) of the point:

$$\theta(u,v)=\arctan\left(\frac{\partial P(u,v)/\partial v}{\partial P(u,v)/\partial u}\right)$$

The $K=\left[l_{s1},l_{s2},\cdots,l_{sx}\right]$ is a set of x objects to be tested, $l_p\in S^m(i=1,2,\cdots x)$ is a m dimension vector composed of low rank step increment. The ultimate goal of low rank decomposition is to find the optimal solution to the lower rank:

$$MinRank(R)+\eta\left\|Q\right\|_0, s.t.K=R+Q$$

Where R is a K low-rank light vector and Q is a K sparse reflection vector. In order to simplify the problem linearly, the above problem can be optimized by convex optimization, and the calculation process is transformed into:

$$Min\left\|R\right\|_*+\eta\left\|Q\right\|_1, s.t.K=R+Q$$

According to the augmented Lagrangian multiplier method (Augmented Lagrange multiplier, ALM), the objective paradigm of the convex optimization processing paradigm can be obtained:

$$MinRank(B), s.t.R = B \times K$$

The above calculation process and paradigm are consistent with the initial low rank decomposition optimal solution paradigm, where the R is a K low rank illumination vector and Q is a K sparse reflection vector. After the low rank step increment decomposition and the combination of illumination vector and illumination reflection edge sparse error, the principal component sparse representation and the low rank decomposition algorithm show good robustness.

On top of that, the influence of shelter blocking and expression changes on imaging quality plays a comprehensively significant role in uncontrolled scenes. A great quantity of classical algorithms performs well in the field of face recognition, especially in the face key feature capture, however once in the uncontrolled open environment, there are shelter blocking and expression changes in the scene, meanwhile due to the impact of noise pollution, the recognition effect is less robust. In uncontrolled scenarios, the principal component sparse representation and low rank decomposition algorithm aims to decompose the object to be detected by the algorithm to separate the low rank global data containing facial key feature information. And sparse error data including noise such as shelter blocking and expression change. For scenes with shelter blocking and expression changes under uncontrolled conditions, the most difficult and important problem for image processing is the dimensionality reduction of altimeter images. How to project high-dimensional image data containing multivariate composite information into low-dimensional identification space. principal component analysis method is recognized as the best way to solve this problem. However, this method is particularly affected by noise. In this uncontrolled scenario, the algorithm will face a NP problem after performing decomposition. It needs to be transformed into nuclear norm again. The data in the data set are divided into key data sets and associated data sets according to their functions. They can be trained separately, and the decomposition results are directly used to initialize the low rank subspace. Key dictionaries and associated dictionaries are established to classify and extract principal components and interference information efficiently and accurately.

The classification of different face objects and the same person under different expressions and shelter blocking degrees is essentially similar. The calculation and comparison of Euclidean distance between the key points of face, such as eyes, eyebrows, nose, mouth and ear, and the addition of inline correlation as an additional term of regular expression will have a positive effect on the recognition effect. The images in the training set need to be vectorized into N categories, and the single category vector u can be represented by a set of members of the class:

$$u = \sum_{i=1}^{N} p_i$$

Where the p_i is the i column vector, the $p_i \in S^{z\times 1}$ and S are the global vector set, and the row rank is z. This assumes that each single-class p_i is mapped to the same rank space, and the projection relation is expressed as $U_i \in S^{z\times k_i}$, single-class vector u the rank space projection relation to the k_i dimension is expressed as $V_i \in S^{k_i\times z}$, which can be obtained:

$$p_i = U_i V_i u$$

Setting the noise item of a non-control scene $n \in S^{z\times 1}$, the upper formula evolves:

$$u = \sum_{i=1}^{N} U_i V_i u + n$$

Among them, the following formula is a group vector with sparse error relation, and its value represents the specific classification of u.

$$\left[(V_1 u)^I, (V_2 u)^I, \cdots, (V_N u)^I \right]^I$$

In addition, the following coefficients are added to exclude the key points of facial commonality between vectors:

$$\sum_{i\neq j}\left\|V_i V_j^I\right\|_G^2$$

The ultimate goal paradigm can be defined as:

$$ArgMin\sigma^{(i)}\sum_{i=1}^{N}\left\|V_i\right\|_* + \varphi\sum_{i\neq j}\left\|V_i V_j\right\|_G^2 + \sigma_1\left\|E\right\|_1,\ s.t\begin{cases} T=\sum_{i}^{N}U_i V_i T_i + E \\ U_i^I U_i = Z \end{cases}$$

The T_i is a single sample in each category, E represents the member matrix in the case of incorrect information, and the Z is a unit vector in the form of matrix. The $\sigma^{(i)}$, σ_1 and φ are non-zero parameters. It is used to adjust the weight ratio of the three components in the target paradigm. A low rank matrix $\{X_i = U_i V_i T_i\}_{i=1}^{N}$ of training samples with only inline features and removed outreach features is extracted by nuclear norm transformation. An object that is not in use in the sample library is set as an association data set, which can be classified as a training sample set X_l and an association check set:

$$C_l = \left[C_l^{(1)}, C_l^{(2)}, \cdots, C_l^{(p)}\right]$$

On the basis of training construction, the optimization goal paradigm is further integrated:

$$Min\sum_{i=1}^{K}\lambda(C_l^{(i)} - [X_l, I][\begin{matrix}\beta_z^i \\ \beta_e^i\end{matrix}]) + \sigma\left\|\beta^i\right\|_1 + \varphi\lambda(C_l^{(i)} - X_l\theta_i(\beta_z^{(i)}) - I\beta_e^{(i)})$$

Among them, the following formula is the sparse error value of the object to be tested, $\theta_i(\beta_z^{(i)})$ is the generating vector.

$$\beta^{(i)} = [\beta_z^{(i)}, \beta_e^{(i)}]$$

Based on the sparse representation of the principal component and the low rank decomposition algorithm, the presence of facial expression changes and partial shelter blocking in the controlled scene can be better handled.

5 Experimental Results and Analysis

The accuracy of sparse representation of principal components and low rank decomposition algorithm for face recognition in uncontrolled scenes is verified by experiments. This experiment uses NNU Grace Dataset as the experimental data source. The experiment is supported by the data collected by the basic information system platform library of the information center. The experimental environment is configured as: 8-core 4.8 Ghz×8 CPU,256GB memory 32 TB hard disk, double 200 GB/s network card rack server. The virtual machine operating system selects 64 bits Linux, the maximum concurrent number of virtual machines is 1024, and the development tool is PhCharm2018.2.5. NNUFD face database is selected according to the test subjects. In this experiment, the library capacity is 404 photos per person, all of which are samples of good positive illumination standard, and the source acquisition environment is identically. Camera equipment, lighting, visual angle and shooting distance are consistent. At the same time, the images of the base sample face database are uniformly cut, keeping the same pixels as 180×240.

This experiment combines classroom teaching environment to evaluate the effect of face recognition, because the classroom environment belongs to the scene with better exclusive interference factors under uncontrolled conditions. The environment is characterized by continuous (approximate location of the object to be tested), single source of light shadow change (normal position fixed, light effect less abrupt), simple shelter blocking and facial expression change (mainly is small range movements such as bow, side face, chin, etc.), and less mixed interference (except for position illumination change and bow head, there are few other factors of shelter blocking and light shadow change). Fig. 2 is a part of examples from the NNUFD basic face library. The classroom sampling photos are segmented by principal component sparse representation and low rank decomposition algorithm, and the basic face library is used as a sample for matching recognition. The effects of low rank decomposition combined with principal component sparse representation in uncontrolled scenarios are compared. Table 1 shows the comparison of recognition rate data in five groups of experiments before and after low rank decomposition.

Fig. 2. Example of base face library NNUFD

Table 1. The Comparison of the Effect of the Principal Component Sparse Representation Combine the Low-rank Decomposition Superposition

(LRD: Low Rank Decomposition EG ID: Experimental Group ID)

LRD / EG ID	Low rank decomposition recognition rate	No low rank decomposition recognition rate
Experimental group 1	91.1%	79.3%
Experimental group 2	90.5%	79.5%
Experimental group 3	90.9%	83.1%
Experimental group 4	90.9%	76.9%
Experimental group 5	92.4%	81.3%

Fig. 3 is the recognition result of the sparse representation of principal component and the low rank decomposition algorithm in the uncontrolled scene of classroom teaching. The face recognized and matched NNUFD the basic face library is selected and the identification number (Student ID) is identified explicitly. Five groups of experiments were set up for superposition of low rank decomposition and various interference factors respectively. From the experimental results, the recognition effect of superposition low rank decomposition by principal component sparse representation in uncontrolled scenarios is robust to illumination changes. The effect on shelter blocking is relatively obvious. From the results of different experimental scenes, the recognition effect of illumination shadow factors is very small. Once there exist shelter blocking, especially serious shelter blocking, the recognition effect drops sharply when the image is partially incomplete. From the point of view of face position in the image, the algorithm also performs good stability and no obvious change in the recognition effect. Table 2 shows the effect of illumination, shelter blocking and position change on the experimental recognition rate in five groups of experiments with and without interference.

The results show that the comprehensive highest recognition accuracy is 92.4%, but the highest recognition accuracy is only 83.1% while not combined low rank decomposition method. It can be seen that the sparse representation of principal components combined with low rank decomposition of face recognition algorithm has achieved better results in uncontrolled scenarios.

In addition to the verification of the uncontrolled environment of classroom teaching, the open uncontrolled scene is also experimented. The pictures are compared and analyzed mainly through campus monitoring, information center monitoring, dormitory gate monitoring and so on. Compared with the classroom experimental environment, the recognition accuracy is reduced, which mainly depends on the depth of imaging of the monitoring object in the photo, but on the probability of being affected by various case of shelter blocking.

Fig. 3. Recognition results of principal component sparse representation and low rank decomposition algorithm in uncontrolled scenario

Table 2. Influence of interference factors on principal component sparse representation combine the low-rank decomposition superposition

(IF: Interference Factors IEG: Interference in the Experimental Group IRR: Interference Recognition Rate)

IEG \ IF	Light	Shelter blocking	Location
Experiment 1 IRR	92.1%	68.3%	87.4%
Experimental 1 No-IRR	90.3%	91.5%	91.1%
Experiment 2 IRR	91.5%	73.9%	89.4%
Experimental 2 No-IRR	91.2%	90.5%	92.0%
Experiment 3 IRR	90.0%	43.6%	91.3%
Experimental 3 No-IRR	90.7%	92.1%	90.8%
Experiment 4 IRR	90.6%	83.2%	90.9%
Experimental 4 No-IRR	92.4%	91.5%	88.7%
Experiment 5 IRR	91.5%	77.4%	89.0%
Experimental 5 No-IRR	91.8%	89.4%	90.2%

6 Conclusion

In this paper, we use the algorithm based on principal component sparse representation and low rank decomposition to recognize the images in uncontrolled scenes. This work is based on the comparison of scene image decomposition results with the basic face database to obtain the matching results. The experimental results show that the method can effectively detect faces in uncontrolled scenes, and the highest overall recognition accuracy can reach 92.4%. As an applied recognition algorithm, the recognition effect of mixed complex patterns in pervasive scenarios is the ultimate goal. This is also the next step of the algorithm research and improvement direction.

Acknowledgements

Supported by Research on Intelligent Campus of Modern Educational Technology in Jiangsu Province (NO: 2020-R-84351 and NO: 2020-R-84369). Natural Science Research Project of Colleges and Universities in Jiangsu Province (NO: 18KJB520027). CERNET Innovation Project (NO: NGII20170524).

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