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# SPARSE REPRESENTATION THEORY AND ITS APPLICATION FOR FACE RECOGNITION

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***Abstract- Face recognition aims at endowing computers with the ability to identify different human beings according to their face images. However, recognition rate will decrease sharply when it refers to the non-ideal imaging environments or the incorporation of users, such as illumination, pose, expression variations and so on. Besides, it will be also influence the recognition results when the database is too large or small. Sparse representation based classification for face images has been one of efficient approaches for face recognition in recent years. Discrimination performance by using the sparse representation can also be applied to the face recognition, and any test sample can be expressed as a linear span of the all training samples. Experimental results show that face recognition method based on sparse representation is comparable to others.***

**Index terms*:* Face recognition; recognition rate; non-ideal imaging environments; sparse representation**

# I. INTRODUCTION

Face is a complex, varied, high-dimensional pattern. Although people recognize familiar faces is easy, the machine is how to accurately identify the face is still a difficult task. However, due recognition in the authentication, security systems, and it has been obtained widely range of applications. This problem attracted many researchers, which is an important area of research in computer vision and pattern recognition [1-4].

Automatic face recognition aims at endowing computers with the ability to identify different human beings according to his face image. Such a research has both significant theoretic values and wide potential applications. As a scientific issue, face recognition is a typical pattern analysis, understanding and classification problem, closely related to many disciplines such as pattern recognition, computer vision, intelligent human-computer interaction, computer graphics, and cognitive psychology etc. Its research achievements would greatly contribute to the development of these disciplines, while as one of the key technologies in biometrics. This techniques arc believed having a great deal of potential applications in public security, law enforcement, information security, and financial security [5-7].

Facial feature extraction and description can be divided into two main categories based on the geometric characteristic and based on statistical characteristic. Early face recognition research is mainly focused on based on the geometric characteristic [8-9]. The main idea is to use a number of feature points of the person's face (such as nose, mouth, eyebrow, etc.), extracting the relative position and the relative distance, and then to supplement with the shape characteristic and related information of the face's contour. But its drawback is that its recognition accuracy is totally dependent on the extraction of geometric features, but geometric features extraction is very sensitive to changes in illumination, facial expression and gesture. Therefore, this stability of this method is very low. In recent years, many new methods are proposed that are based on statistical characteristics. These methods include template matching method [10] that trains face images from databases as a template, the experimental results show that the performance is significantly superior to the method based on the geometric characteristics.

To face recognition, the dimension of the original face image is usually very high, but also, the distribution of the original face image in such a high dimensional space is nosebleed. Therefore, the high dimension is not helpful to recognition, and what's more, the complexity in the calculation is also very large. To overcome these flaws and we can obtain more compact distribution for face images, Kirby and Turk firstly used analysis subspace method based on principal component to extract facial feature for face recognition [11], this method based on subspace analysis was obtained greater success and these related methods are widely used in recent years in image processing. Subspace analysis method then has aroused widely mentioned, and thus it has become one of the mainstream methods for face recognition. The core idea of subspace analysis is to find a linear or non-linear transform space, and then the original signal data will be projected to a low-dimensional subspace and to obtain the more compact distribution of the data in the subspace. So, subspace analysis that can provide a means of describing data subspace and effectively reduce computational complexity. Recently, many subspace analysis methods and improved methods are used for face recognition as following: principal component analysis (PCA) [11], independent component analysis (ICA) [12-13], linear discriminant analysis (LDA) [14-16], non-negative matrix factorization (NMF) [17] and so on. There are some additional subspace methods such as: kernel PCA (KPCA) [18], kernel fisher discriminant analysis (KFDA) [19] and so on.

In the statistical signal processing filed, the algorithmic problem of computing sparse linear representations with respect to an over-complete dictionary of base elements and signal atoms have seen a recent surge of interest [20]. The optimal representation is required sufficiently sparse, which can be efficiently computed by convex optimization [21-22]. The original purpose of sparse representation is to use a lower sampling rate than the Shannon theorem to represent and compress signals, not to inference and classification. Sparse express undoubtedly has the identification function, because of the sparse representation of the selected base is the most can represent the current sample. What's more, sparse representation is not sensitive to complex conditions with occlusion, noise, illumination, expression, pose and so on, which is due to its special nature. Therefore, sparse representation has been successfully applied to face recognition and related fields [21].

In this paper, we mainly study the face recognition method based on sparse representation. This is a new theory is used for recognition, and sparse representation of the selected base is the most can represent the current sample. The concept of sparse representation is detailed in this paper. Discrimination performance by using the sparse representation can also be applied to the face recognition, and any test sample can be expressed as a linear span of the all training samples.

To verify the effectiveness of the algorithm, we compare face recognition based sparse representation (SR) with the common methods such as nearest neighbor (NN), linear support vector machine (SVM), nearest subspace (NS). Experimental results show that RS method obtains better performance than the other methods.

This rest paper is organized as follows. Section 2 concisely introduces the basic theory of face recognition. Then we introduce the basic theory of sparse representation and its applications in image processing fields. The basic face recognition flow and steps based on sparse representation are detailed in Section 4. Experimental results are drawn in Section 5 and conclusions are described in Section 6.

## II. FACE RECOGNITION

Face recognition is to use the facial characteristic for recognition and judgment. Identification devices whose uses the existing face database, from a given image or video scene, identify one or a few people's identity. Features are divided into the external geometry of the face including the eyes, nose, mouth, or relations geometry, and the inner face of the structural relationship, such as through the converted linear and nonlinear relations.

The advantage lies in its natural recognition and non-contact characteristic. The so-called natural characteristic, which refers to the identification when the individual identification method using the same biological characteristics. In other words, human beings are by observing and comparing differentiate and confirm the identity of the face, but fingerprint recognition and iris recognition, etc. do not have natural resistance, because humans or other organisms do not distinguish individuals through such biological characteristics. To the characteristics of non-contact recognition method can get face image using visible information, which is different from fingerprint or iris recognition, fingerprint requires the use of electronic instruments, or using infrared iris image acquisition, this acquisition mode allows subjects They are easy to accept, and is easy to search in a public place, to identify a specific object.

Face recognition has many other means of identification incomparable advantages, but in practice there are many difficulties. These difficulties are mainly brought by the face being as the biological features. These confounding factors include changes in between classes and classes. Among them, the main difference between classes of a person face structural differences, because most people are similar to the structure of the face, the face organ or structure very similar shape, which search for the face and the detection is beneficial, but for the use of the face distinguish individual is detrimental; within-class differences mainly represent imaging differences caused by external factors, such as lighting conditions (such as day and night, indoors and outdoors, etc.), facial expressions, shelter materials (such as masks, sunglasses, beard, etc.), age, etc. , the degree of difference of face great influence.

Face recognition consists of three main steps: face detection, facial feature extraction and classification, as shown in Fig.1. Through the most efficient development of recent decades, face recognition technology has been known as a very mature research topic, and is widely used in all aspects of social life. In recognition of the history produced a large number of different algorithms, as well as for the various phases of the detection, extraction and recognition of classification algorithms. Also, because the study focuses on the differences and academic background, as well as the constraints of their environment and for the different applications, large numbers of face recognition with a larger difference between the methods. Here we briefly introduce three key steps in face recognition and the corresponding number of related algorithms.

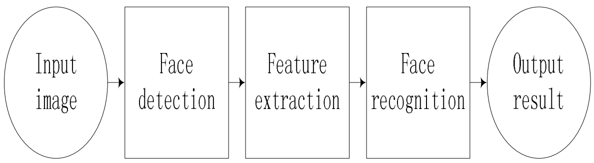


Figure 1.Face recognition system

The aim of face detection is to judge whether one face exists or not in these input facial images, and it is determined the face’s position when one face existed and which can give further the specific location of the various organs, size information and so on. Common detection algorithm is susceptible to light, noise, and various block and the face angle and other factors. The typical face detection algorithm consists of detection algorithm based on heuristic, detection algorithm based on the detection of skin color region and detection algorithm based on statistical template.

The purpose of feature extraction is detected by the human face images to extract individual differences can distinguish different identification characteristics. These characteristics for the same individual must be stable, and for different individuals to have individual differences, which is characterized to satisfy the difference between different individuals and can be distinguished. On the other hand, the purpose is to extract facial features from the high-dimensional image data to obtain useful information to describe and characterize the key human face information that can be extracted through the data dimensionality reduction and the relative importance of the main facial features so that subsequent classification. Feature extraction is the face recognition technology is the most critical step, which will have a direct impact on subsequent recognition performance and accuracy.

Through face detection and facial feature extraction, the next step is to choose the appropriate classification for face identity identification. Classification is based on the characteristics of the extracted facial identity comparison, judgment and classification, and its essence is to determine the new test also face image and the training set of face images which have a high affinity. This stage of the process is dependent on the results of feature extraction, and feature extraction will directly affect the quality of identification of the results. What's more, classification and identification methods are selected according to the type of feature extraction. More typical classification method has recently distance classifier based on SVM classifier, Bayesian classifier and so on.

In summary, the recognition process is the first on the face of the image containing human face localization and detection, followed by extraction can effectively describe and characterize Facial feature vector information, the final selection based on feature information extracted appropriate classifier for classification. The above three steps are closely linked, usually combined with a variety of algorithms can be used for face detection, feature extraction, and ultimately can effectively combine multiple classifiers to get more satisfactory results and recognition face recognition rate.

## III. SPARSE REPRESENTATION

### A. The concepts of sparse representation

People's cognitive process to things is often experienced from simple to complex, again by complex regression in this simple way. In practice, many complicated things are composed of many simple elements. In today's society is a complicated information age, but people pursue expressed in most effective and convenient way to said. Whether auditory signal or visual signals, are made up of simple signal after a series of transformation and the combination of what we get information. People want to in the process of signal representation and processing in the most straightforward way to represent data. But if you want to analyze the information have to revert to the initial simple signal.

In image and video processing, the commonly decomposition method is implemented by non-redundant orthogonal transformation, for example, discrete cosine transform, wavelet transform. Usually the digital signal after sampling is expressed as a function of time and space of Delta and that such analysis of the signal representation of a great deal of inconvenience. Such as discrete cosine transform can't effectively advance with local characteristics of the video signal characteristics, and changes can't be sparse wavelet representation of the outline of the image structure feature, so you want to improve the signal processing capabilities, you must choose a better representation. The researchers found that the dilution means to approximate replace the original data signal processing to reduce costs and improve compression efficiency.

In recent years, researchers have changed traditional signal representation method, and a new method is proposed in this filed. They used so called atomic over-complete system redundancy function to replace the original basis function, with the atomic elements from the library called atoms. Atomic bank selection signal system can make a good approximation of the structure, and its structure without any restrictions. To find the best linear combination with $n$ items atoms to represent a signal from atomic library is called sparse representation or highly nonlinear approximation for signal.

To assume the selected groups are orthogonal, so we can obtain: $y = Xs$, and these atomic coherence coefficients are used to measure the relationship between the various atoms. When coherence is small, we believe that non-coherent dictionary, a close approximation of the orthogonal group. The purpose of sparse representation is to obtain sparse solution to$s$.

Sparse representation mainly uses sparse approximation theory and also highly nonlinear approximation theory to solve the following questions:

Assume a set $D = \{g_k; k = 1,2, \cdots K\}$, whose elements are the unit vectors of the Hilert space $(H = R^N)$.When $K > N$, $D$ is atomic repository and whose elements are atoms. To any given signal $f \in H$, to adaptively select $m$ atoms from $D$ to approximate the signal $f$:

$$f_m = \sum \alpha_i g_i \quad (1)$$

To define the approximation error as following:

$$e_m(f, D) = \underset{f_m}{int} \|f - f_m\| \quad (2)$$

Because $m$ is so far smaller than the dimension $N$ of the space, so this approximation is also known as sparse approximation. Inventory due to atoms in redundancy it will have a variety of solutions to the above formula. The purpose of sparse representation is to find the best sparse coefficients from a variety of combinations of solutions, or to obtain the minimum value for $m$. Also to find the best sparse signal representation, it is equivalent to solve the following problems:

$$\min imize\|\alpha\|_0 \quad subject\ to \quad f = \sum_{K=0}^{K-1} \alpha_k g_k \quad (3)$$

The purpose of equation (3) is to find the number of non-zero entries in this equation. When the signal subjects to noise, however, to use L0 norm is not very effective and easy to solve the equation. L0 norm is non-convex, in the case of redundancy, to acquire images sparse decomposition is a need to combine search NP with Hard question. There are not existing polynomial decomposition methods, so we need to use a sub-optimal approximation algorithm to solve the question. Many related approximation algorithms have been proposed in recent years, such as $L_p$ norm transformation, greedy algorithm and global optimization methods.

$L_p$ norm can measure the number of non-zero coefficients, and its definition is as following:

$$\|x\|_p = [\sum|x_i|^p]^{1/p} \quad (4)$$

when $0 < p < 1$, $L_p$ can measure the sparsity of coefficients. There is a certain link between $L_0$ and $L_p$. $L_0$ will be limited with $L_p$ norm when $p \to 0$. So, we can obtain as following:

$$\|x\|_0 = \lim_{p\to 0} \sum_{k=1}^{m} |x_k|^p \quad (5)$$

Greedy algorithm was first used to solve statistical problems. Devore firstly studied the theoretical background of the greedy algorithm [23]. Jones firstly analyzed the convergence of greedy algorithm [24-26]. The greedy algorithm is to select the dictionary matching and signal, which iteratively construct and create the signal approximation terms. Matching pursuit is the pure greedy algorithm, and there are various variants from greedy algorithm, such as weak greedy algorithm and greedy algorithm of vector.

Global optimization refers to satisfy certain constraints, to minimize the particular objective function. Typical target function is convex, and any local minimum is also the global minimum. Commonly global optimization algorithm includes basis pursuit method. For sparse representation involves non-convex optimization problem is a problem, so the use of standard optimization algorithms can't determine a global optimal solution. Basis tracking algorithm uses $L_1$ norm to replace the $L_0$ norm, which can convert the solved problem to a convex problem. The converted solution is as follows:

$$\min imize\|\alpha\|_1 \quad subject\ to \quad f = \sum_{K=0}^{K-1} \alpha_k g_k \quad (6)$$

## B. Applications of sparse representation

The initial sparse representation is used for signal representation and compression, evaluation criteria and the sparsity of the original signal fidelity. Later sparse decomposition has been used for image processing, such as image compression, image denoising, image decomposition and other fields. The above problems have been found similarly to Lasso question in statistics, and then it is converted to L1 norm problem by a linear analysis eventually. Furthermore sparse representation has been used for face recognition. Fig.2 shows the applications of sparse representation.

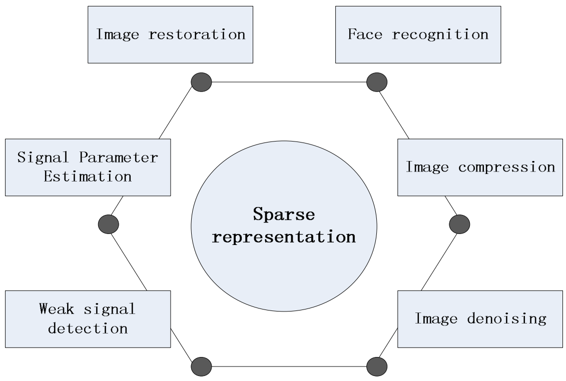


Figure 2. Applications of sparse representation

(1) Applications in signal processing

The signal representation and processing of people want to use the most straightforward way to represent data. Diluted to approximate representation instead of the raw data signal processing to reduce costs and improve compression efficiency.

In image and video processing, the commonly used signal decomposition is through non-redundant orthogonal transformation to achieve, for example, discrete cosine transform, wavelet transform. However, discrete cosine transform can effectively extract the local visual characteristics, and changes can't be sparse wavelet representation of the outline of the image structure feature, so you want to improve the signal processing capabilities, you must choose a better representation. Sparse representations or so-called signal sparse approximation or highly nonlinear approximation, through the use of over-complete redundancy atom libraries for signal sparse decomposition, and the use of matching tracking algorithm of signal processing, very suitable solution for low-yard rate video encoding and other issues.

Sparse representation has been obtained a wide range of applications in signal processing, such as signal compression, signal recognition, time-frequency distribution of research in the field, also in signal de-noising, weak signal detection and parameter estimation in array signal have a good effect.

(2) Applications in image processing

In general, the dimension of original image is very high, but for image processing to identify the classification is based on the characteristics of only a small part of the original image. The aim of sparse representation for image is to select some basis functions from original domain and transform domain, then the image is expressed as linear expansion on this basis functions. So, a fraction of feature data can represent the image. The selected group is called atomic functions, the set of all atoms signal called a dictionary. The basic principle is that the signal compressed sensing, the theoretical basis for the multi-scale analysis.

Sparse decomposition can be used for image denoising. Affected by the environment, in practice, the collected images often contain noise. The traditional image noise reduction methods can be divided into spatial domain and frequency domain denoising image denoising. Noise are distributed generally, the main information and the image focused on the low-frequency part, so either the common method in the spatial domain or in the frequency domain are carried out using the frequency division. However, details of the image and the edges contain high frequency components, the noise in the low frequency component is also part of, only not fully distinguish between the use of frequency noise and useful information. Sparse image denoising method is in accordance with whether the image in a sparse component of the image information and noise separated. For sparse representation of the atomic structure is a specific image in a certain structure. Composition useful information is expressed can be atomic. But present in the image noise is random with no structure, so you can't use atomic representation. This image can be distinguished from noise, to achieve the purpose of removing noise.

The cost of saving data and its applications is high with the high dimension. To change the image compression is reasonable, need to adapt themselves to the development of multimedia technology is a valuable research field in image processing. Image compression had been brought widely concerned since many years ago, and there are many matured compression algorithm. By letter on the over-complete decomposition of the original font, the basis can be used to represent the signal adaptively according to the characteristics of the signal itself flexible selection. Result of decomposition, will be able to get the signal of a very simple expression, namely sparse representation. Get the signal sparse representation process called signal sparse decomposition. Using the sparse representation of image compression is theoretically very promising, but there are practical applications for computationally intensive and too difficult to construct complete dictionary and other issues.

## IV. FACE RECOGNITION BASED ON SPARSE REPRESENTATION

### A. Algorithm Flow

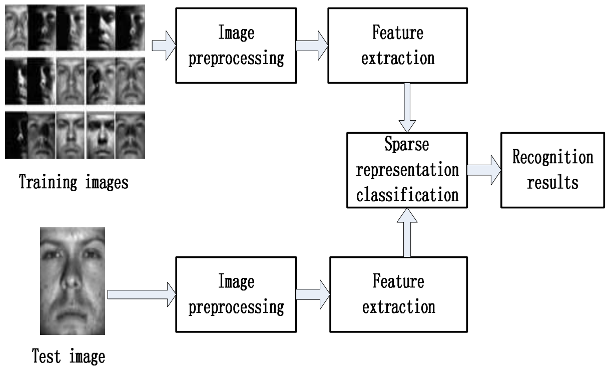


Figure 3 .the diagram of face recognition based on sparse representation

Assuming a given training set $A$ with $k$ classes labeled samples, and the *i-th* class contains $n_i$ samples. Then the *i-th* class samples can constitute a collection $A_i = [a_{i1}, a_{i2}, \cdots a_{in_i}] \in R^{m\times n_i}$, and each column vector represents a sampling facial image, $m$ is the dimension of the column vector. To improve efficiency, we assume that the matrix corresponding to each category on training as a dictionary for sparse representation. Then for any given test sample $y$, as long as the part of the categories included in the training set, it can be represented as a linear combination from the set $A$.

To assume $y_1$ is the test sample and it belongs to the *i-th* class. So, they will have common class attribute from the training set $A_i$, and then $y_1$ can be expressed a linear combination by these samples from $A_i$:

$$y_1 = x_{i1}a_{i1} + x_{i2}a_{i2} + \cdots x_{in_i}a_{in_i}, x_{ij} \in R, j = 1,2, \cdots n_i \tag{7}$$

In general, these labeled categories of test samples are not known. Therefore, sample dictionary is constructed by using the all k classes sample set. This sample dictionary is expressed as follows:

$$A = [A_1, A_2, \cdots A_k] = [a_{11}, a_{12}, \cdots, a_{1n_1}, \cdots, a_{k1}, \cdots, a_{kn_k}] \tag{8}$$

Therefore, any test samples $y_0$ can be expressed as a linear combination of dictionary:

$$y_0 = Ax_0 \tag{9}$$

where $x_0 = [0,0,\cdots,x_{i1},x_{i2},\cdots,x_{in_i},\cdots,0,\cdots,0]^T \in R^m$ is a coefficient vector whose entries are zero except those associated with the *i-th* class.

Obviously, if $m > n$, the above equation is over-determined, and the $x_0$ can be solved as its unique solution. But for the face recognition problem, after the sample after the dimension reduction of equations constituting a typical underdetermined, therefore its solution is not unique. By the sparse representation and compressed sensing theory,

If the vector is sparse enough, L0 norm sparse solution problem can be converted to solve the L1 norm problem. Then we can obtain as following:

$$x_1 = arg\ min\ \|x\|_1,\ s.t.\ Ax = y \qquad (10)$$

with the *i-th* class, and other entries are as much as possible to zero. It can approximate the input text face image as $y_i = \delta_i(x_i)$. Then, we classify the input image by assigning it to the class that minimizes the residual between $y_i$ and $y$, the residual error is expressed as following:

$$\min_i e_i(y) = \|y - A\delta_i(x_i)\|_2 \qquad (11)$$

So, we can classify the class to minimize the above equation.

**B. Experimental results and analysis**

In this experiment, we use some face databases to verify the performance of different face recognition methods. Fig.4 and Fig.5 show partial images from ORL face database and Yale database respectively. Fig.6 and Fig.7 show partial images from Weizmann face database and IMM database respectively. We compare face recognition based sparse representation (SR) with the common methods such as nearest neighbor (NN), linear support vector machine (SVM), nearest subspace (NS). In our experiments, PCA is used to reduce the dimensionality of original image vector, and then these low dimension features are as facial feature. We randomly separate each database into two halves. One half was used as the dictionary, and the other half as testing samples.

Figure 4 .partial images from ORL face database

Figure 5 .partial images of Yale database

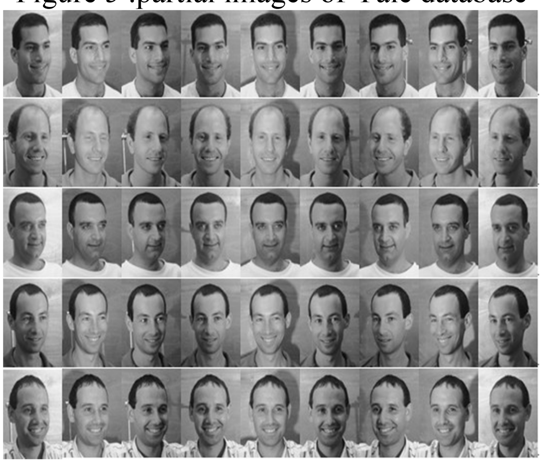

Figure 6 .partial images of Weizmann database

After conversion problem, the optimal solution can be solved by a standard linear programming method to obtain. Obviously, if we directly use the original high-dimensional image to construct the training dictionary, with the corresponding equations must be over-determined, but there is the corresponding high computational complexity. To reduce the computational complexity and maintain the sparsity of the solution vector, the original facial image vector is projected by PCA to obtain the low dimension face vector. Then the low dimensional vectors are as the facial features of the face, the next step is to implement face recognition by the flow for *i-th* class, let $\delta_i$ be the given function which can select the coefficients associated with the *i-th* class from the optimal coefficient as $x_1$. So $\delta_i(x_i)$ is a vector whose only non-zero entries that are associated.

Figure 7 .partial images of IMM database

TABLE 1. COMPARISON OF RECOGNITION RATES ON ORL FACE DATABASE.

| Dimension | 20 | 30 | 50 | 100 |
|---|---|---|---|---|
| NN | 61.5% | 69.0% | 72.4% | 83.5% |
| SVM | 66.4% | 72.3% | 79.9% | 86.3% |
| NS | 63.3% | 70.7% | 78.9% | 84.2% |
| SR | 67.9% | 82.1% | 88.3% | 93.7% |

Tab.1 shows the comparison of recognition rates versus different feature dimension by NN, SVM, NS and SR method. We can see that RS obtains better performance than the other methods in all different dimension of facial feature. The best recognition rate of SR is 93.7% when the dimension is 100, compared to 83.5% for NN method, 86.3% for SVM and 84.2% for NN method. So the face recognition method based sparse representation is efficiently and it can obtain the best performance than other methods.

Tab.2 shows the comparison of recognition rates versus different feature dimension by NN, SVM, NS and SR method on Yale database. Again, we can also see that SR obtains much better performance than all of other three methods in different dimensions. From experimental results, the best recognition rate of SR is 94.6% when the dimension is 100, compared to 82.7% for NN method, 87.6% for SVM and 85.2% for NN method. These experimental results verify that face recognition based sparse representation is efficiently and robustly.

TABLE 2. COMPARISON OF RECOGNITION RATES ON YALE DATABASE.

| Dimension | 20 | 30 | 50 | 100 |
|---|---|---|---|---|
| NN | 71.5% | 74.7% | 80.4% | 82.7% |
| SVM | 80.4% | 83.0% | 84.9% | 87.6% |
| NS | 73.1% | 76.7% | 78.9% | 82.2% |
| SR | 82.3% | 87.1% | 90.3% | 94.6% |

Tab.3 shows the comparison of recognition rates versus different feature dimension by NN, SVM, NS and SR method in Weizmann face database. This database has 28 subjects under 5 different poses, 3 illuminations and 3 expressions. We select 24 subjects under 3 poses and 3 illuminations from the database as our training set. We can see that RS obtains better performance than the other methods in all different dimension of facial feature. The best recognition rate of SR is 95.1% when the dimension is 100, compared to 80.1% for NN method, 89.6% for SVM and 80.2% for NN method. So the face recognition method based sparse representation is efficiently and it can obtain the best performance than other methods.

TABLE 3. COMPARISON OF RECOGNITION RATES ON WEIZMANN DATABASE.

| Dimension | 20 | 30 | 50 | 100 |
|---|---|---|---|---|
| NN | 61.5% | 74.3% | 76.4% | 80.1% |
| SVM | 80.4% | 82.0% | 85.2% | 89.6% |
| NS | 70.1% | 74.2% | 77.3% | 80.2% |
| SR | 81.3% | 84.5% | 89.0% | 95.1% |

Tab.4 shows the comparison of recognition rates versus different feature dimension by NN, SVM, NS and SR method in IMM face database. We can see that RS obtains better performance than the other methods in all different dimension of facial feature. The best recognition rate of SR is 96.4% when the dimension is 100. So the face recognition method based sparse representation is efficiently and it can obtain the best performance than other methods.

TABLE 4. COMPARISON OF RECOGNITION RATES ON IMM DATABASE.

| Dimension | 20 | 30 | 50 | 100 |
|---|---|---|---|---|
| NN | 72.5% | 75.3% | 82.4% | 83.5% |
| SVM | 81.4% | 84.3% | 84.8% | 88.6% |
| NS | 72.7% | 79.0% | 80.9% | 82.2% |
| SR | 84.3% | 87.5% | 91.3% | 96.4% |

## V. CONCLUSIONS

With the rapid development of science technology, artificial intelligence, pattern recognition, computer vision, machine learning and other new technologies, face recognition has been widely used in public safety, information security, finance and other fields, which has become one of the hot topics of research in recent years. Face recognition is used to implement identification of identity, which mainly includes image obtained, image preprocessing, image matching, face detection, feature extraction, classification and recognition. The concept of sparse representation is detailed in this paper. Discrimination performance by using the sparse representation can also be applied to the face recognition, and any test sample can be expressed as a linear span of the all training samples. To verify the effectiveness of the algorithm, we compare face recognition based sparse representation (SR) with the common methods such as nearest neighbor (NN), linear support vector machine (SVM), nearest subspace (NS). Experimental results show that RS method obtains better performance than the other methods

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