A Method for Static Hand Gesture Recognition Based on Non-Negative Matrix Factorization and Compressive Sensing

Huiwei Zhuang, Mingqiang Yang, Zhenxing Cui, Qinghe Zheng

***Abstract*—Hand gesture recognition is becoming a more and more popular research field in human computer interaction. However, the recognition rate still remains to improve. In this paper, we present a novel static gesture recognition method based on non-negative matrix factorization (NMF) and compressive sensing (CS). Firstly, original images are projected to low-dimensional subspace by using NMF, and then gesture is recognized by the classifier which is designed by CS theory. Experimental results which are done on two gesture databases show that the CS classifier performs better than some other classifiers no matter on the recognition rate or resisting occlusion. The NMF also has a better occlusion resistance than the principal components analysis (PCA). This method can increase the gesture recognition rate in comparison to some previous methods.**

***Index Terms*—Compressive Sensing (CS), Hand Gesture Recognition, Non-Negative Matrix Factorization (NMF), Occlusion Resistance**

I. Introduction

ALONG with the development of the society, computers are playing a more and more important role in our daily life. Hence, human computer interaction (HCI) is becoming a hot research field. It uses biological features of humans to communicate with computers so as to control them. Some common used biological features include faces, hands, fingerprint, iris and so on. As we all know, hand gestures are considered as the second language of humans, deaf people mainly use gestures to communicate. So hand gesture recognition as a kind of HCI methods attracts more and more researchers' attention by its nature, convenience, intuition. Many fields, such as smart home, robot control etc take gesture recognition as a key technology [1].

There are two kinds of hand gesture recognition including non-vision based and vision based. Gesture recognition based on data glove is a kind of non-vision based method. In [2], the authors use data glove to extract the position of the hand and the angles of the joints, then these features are used to classify gestures by K-NN classifier. Although the system can achieve a good performance, the additional devices are inconvenient and make people feel uncomfortable. Comparatively speaking, vision based gesture recognition is more natural and convenient, but its performance is not as good as the non-vision based. So many researchers devote themselves to improve the performance of vision based gesture recognition in the aspects of recognition rate and recognition time. In this paper, we only study on the vision based static hand gesture recognition rate.

Totally speaking, the methods of vision based static gesture recognition can be divided into two groups. The first kind is based on feature extraction. It firstly uses some arithmetical operations to extract important features of gestures, such as local binary pattern (LBP), histogram of oriented gradients (HOG), scale-invariant feature transform (SIFT) and shape representations etc. Then these features are used in classifiers to classify gestures [3]. Many gesture recognition algorithms based on this method have been proposed. In [4], the author decomposed the hand silhouette into finger part and palm part, then computed the Zernike moments and pseudo-Zernike moments of the two parts with different importance respectively. But it can not recognize gestures correctly when two adjacent fingers are close or two gestures are similar. The authors in [5] proposed a novel hand gesture recognition method based on HOG descriptor and sequential minimal optimization (SMO). It has a good recognition performance of hand gestures under complex backgrounds, but its computation time still need to be optimized.

Another static gesture recognition method is based on subspace analysis. It represents the original image by a set of basis images, thus the high-dimensional original image can be projected to the low-dimensional subspace. Some common used subspace-based methods including principal components analysis (PCA), linear discriminant analysis (LDA) and so on. The non-negative matrix factorization (NMF) is a popular subspace-based method in recent years. It has been used in many fields such as face recognition, text analysis and so on. But there are not many people apply it to gesture recognition. In this paper, we focus on the gesture recognition based on subspace analysis and we apply the NMF to get the subspace representation of gesture images.

No matter the feature extraction method or subspace analysis method, we both need to apply a classifier to classify gestures. Now compressive sensing (CS) is becoming more

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and more popular, a lot of researchers apply it to reconstruct images, but not many people use it to classify gestures. Here, we use it to design the classifier. The architecture of the system is shown in Fig. 1.

The rest of the paper is organized as following: Section II introduces the NMF theory and its algorithm procedure in detail. Section III presents the CS theory and how to use it to classify gestures. In Section IV we do some experiments and discuss the experimental results. Lastly, we make a conclusion in Section V.

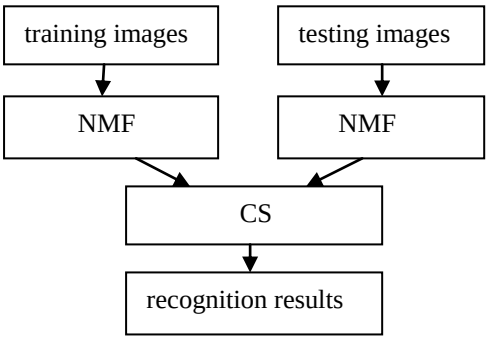


Fig. 1. The architecture of the system

II. NMF Theory And Algorithm Procedure

NMF is a kind of subspace analysis method, image processing based on it is more and more popular. In this section, we will introduce the basic theory of it and how to use it in our system.

A. NMF Theory

NMF was proposed by Lee and Seung in [6]. In the later paper [7], they gave the detailed derivation and proof of the formulas.

In [6] and [7] the NMF theory can be simply described as: Given the original high-dimensional non-negative matrix $V \in R_+^{m\times n}$, finding another two non-negative matrixes $W \in R_+^{m\times r}$ and $H \in R_+^{r\times n}$ to approximate V by the inner product of W and H, i.e. $V \approx WH$. The rank r generally satisfies $(n+m)\times r < n\times m$, so W and H are both smaller than V. They are the low-dimensional representation of V. Then we can get $v_i \approx Wh_i$. Where, v_i is the ith column of V, h_i is the ith column of H, this means that every column of V can be approximately indicated as the linear combination of all columns of W, the coefficients are the corresponding column of H [8].

In order to find the non-negative matrixes W and H, Lee and Seung defined two kinds of objective functions. One is based on the Euclidean distance between V and WH. The objective function is:

$$\min \|V - WH\|^2 = \min \sum_{i=1}^{m}\sum_{j=1}^{n}(V_{ij} - (WH)_{ij})^2 \quad s.t. W, H \ge 0, \sum_{i=1}^{m} W_{ij} = 1, \forall j \tag{1}$$

The authors found the following multiplicative update rules for solving (1).

$$W_{ik} \leftarrow W_{ik}\frac{(VH^T)_{ik}}{(WHH^T)_{ik}} \tag{2}$$

$$H_{kj} \leftarrow H_{kj}\frac{(W^TV)_{kj}}{(W^TWH)_{kj}} \tag{3}$$

The other objective function is based on generalized Kullback-Leibler divergence, it is

$$\min D(V \| WH) = \min \sum_{i=1}^{m}\sum_{j=1}^{n}\left(v_{ij}\log\frac{V_{ij}}{(WH)_{ij}} - V_{ij} + (WH)_{ij}\right) \quad s.t. W, H \ge 0, \sum_{i=1}^{m} W_{ij} = 1, \forall j \tag{4}$$

The multiplicative update rules for solving (4) is

$$W_{ik} \leftarrow W_{ik}\frac{\sum_{j=1}^{n} H_{kj}V_{ij}/(WH)_{ij}}{\sum_{j=1}^{r} H_{kj}} \tag{5}$$

$$H_{kj} \leftarrow H_{kj}\frac{\sum_{i=1}^{m} W_{ik}V_{ij}/(WH)_{ij}}{\sum_{i=1}^{m} W_{ik}} \tag{6}$$

In this paper, we employ the first objective function to obtain W and H. W is the basis image of V. Using $Y=W^+V$, we can get the projection Y of V in W subspace. Where $\cdot^+$ is the Moore-Penrose inverse operation. After the classical NMF algorithm being proposed, many improved methods have been presented, such as the local NMF (LNMF), sparse NMF (SNMF) etc [8].

B. NMF Algorithm Procedure

In this paper, we use the NMF subspace to analyze gesture images. We employ the objective function based on Euclidean distance, and we get W and H by update rules (2), (3). In the gesture recognition system the detailed procedure is as following:

Step 1: Normalize all gesture images to 80×80, then divide all images into two groups, training set and testing set, and supposing there are m training images. Because gray images are between 0 and 255, in order to avoid the numbers being too big during computing, in this step we map all gray images from [0,255] to [0,1].

Step 2: Vectorize every gesture image into a column vector, so every image is a vector of 6400×1. Then arrange all vectors vectorized by every training image to a training matrix $V=[v_1,v_2,\ldots\ldots,v_m]$. Where, v_i is the ith image vector. So V is a matrix of $6400\times m$.

Step 3: Assign the reduced dimension r and the maximum number of updating time *max_iter*. Then random initialize the $6400\times r$ matrix W and the $r\times m$ matrix H.

Step 4: Use the rules (2), (3) to update W and H *max_iter* times. During every updating, normalize every column of W to be 1.

Step 5: Compute the Moore-Penrose inverse W^+ of W.

Step 6: Use $y_i=W^+v_i$ to get the projection vectors $y_1, y_2,\ldots\ldots, y_m$ of every training vector $v_1, v_2,\ldots\ldots v_m$ in W subspace. In the same way, use $y_0=W^+v_0$ to get the projection vector y_0 of v_0 in W subspace, where v_0 is the vectorized vector of a testing image.

Step 7: Take y_0 and $y_1, y_2, \ldots\ldots, y_m$ to be the parameters of CS classifier, then we can get the recognition result. The CS classifier will be introduced in Section III.

In order to make these steps clearly to see, we draw the flow diagram in Fig. 2.

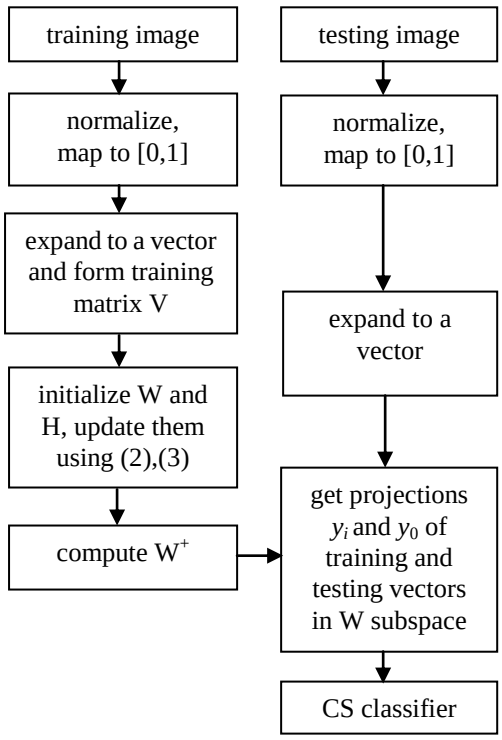


Fig. 2. The flow diagram of NMF

III. CS Theory And Classification

After getting the projection vectors of images in W subspace, we employ the CS classifier to classify them. CS is a hot research field in recent years. In this section, we will introduce the CS theory and how to use it to classify gestures.

A. CS Theory

CS theory was proposed in [9], [10] etc. This theory was proposed to solve some shortcomings of the Shannon/Nyquist sampling theorem. It reconstructs a signal based on the sparse representation of the original signal [11].

As the author in [11] said many signals can be represented sparsely in a certain transform domain. Supposing the original signal is $x \in R^{N\times 1}$. Then it can be represented as $x=\Psi\theta$ in a transform domain Ψ, $\Psi=[\Psi_1,\Psi_2,\ldots\ldots,\Psi_N] \in R^{N\times N}$ is the sparse basis, $\theta \in R^{N\times 1}$ is the sparse representation of x in Ψ. Generally, there are K (K<<N) nonzero or large coefficients in θ, then we call θ is K-sparse.

The measurement vector $y \in R^{M\times 1}$ of x can be expressed as $y=\Phi x$, where $\Phi \in R^{M\times N}$ is the measurement matrix. And considering $x=\Psi\theta$, so y can be written as

$$y=\Phi x+e=\Phi\Psi\theta+e=A\theta+e \tag{7}$$

where $A = \Phi\Psi$, $A \in R^{M\times N}$ is the metric matrix. Considering error, here we introduce a error factor e, $\| e \|_2 < \varepsilon$, ε is a small constant. If we can find a suitable Φ to make A satisfy the restricted isometry property (RIP), then we can reconstruct x by y. Fortunately, if Φ is a random matrix constituted by the independent identically distributed Gaussian variables, it can solve this problem well [11], [12].

Generally, we can get θ from (7) by the $l1$ norm optimization:

$$\theta = \arg\min \|\theta\|_1 , s.t. \|y - A\theta\|_2 \le \varepsilon \tag{8}$$

After getting θ, we can reconstruct x via $x=\Psi\theta$.

B. Classification

At Section II we have got the projection vector y_0 of testing image and projection vectors $y_1, y_2, \ldots\ldots, y_m$ of training images in W subspace. Here we will introduce how to use them and CS to classify gestures.

Step 1: Construct the sparse basis matrix Ψ by $y_1, y_2, \ldots\ldots, y_m$. Supposing there are J kinds of gestures and n images of each kind in the training set. Then Ψ can be written as $\Psi=[\Psi_1,\Psi_2, \ldots\ldots,\Psi_J]$, where $\Psi_i = [y_{i1}, y_{i2}, \ldots\ldots, y_{in}]$, y_{ij} is the jth training projection vector of the ith kind of gesture.

Step 2: Construct a random matrix constituted by independent identically distributed Gaussian variables. We take this matrix to be the measurement matrix Φ.

Step 3: Use the measurement matrix Φ to measure the sparse basis Ψ and the testing projection vector y_0 respectively. From $A = \Phi\Psi$, we can get the metric matrix A. Similarly, from $Y_0 = \Phi y_0$, we can get the observation set Y_0.

Step 4: Use (7) to represent the testing observation set Y_0 as a linear combination of the metric matrix A, i.e. $Y_0 = A\theta+e$. Then we can use $l1$ norm optimization to get the coefficient θ.

Step 5: Use the matrix Ψ_i formed by training projection vectors of the ith kind of gesture to get the ith testing observation set Y_i by the relevant optimal coefficient θ_i, i.e. $Y_i = \Psi_i\theta_i$, i=1,2, ……,J.

Step 6: Compute the reconstruction error between Y_0 and Y_i. Then we can determine the testing image belonging to the class with the smallest error. This can be expressed as

$$i^* = \arg\min \|Y_0 - Y_i\|_2^2 \tag{9}$$

Fig. 3 is the classification flow diagram, it follows up the procedure in Fig. 2.

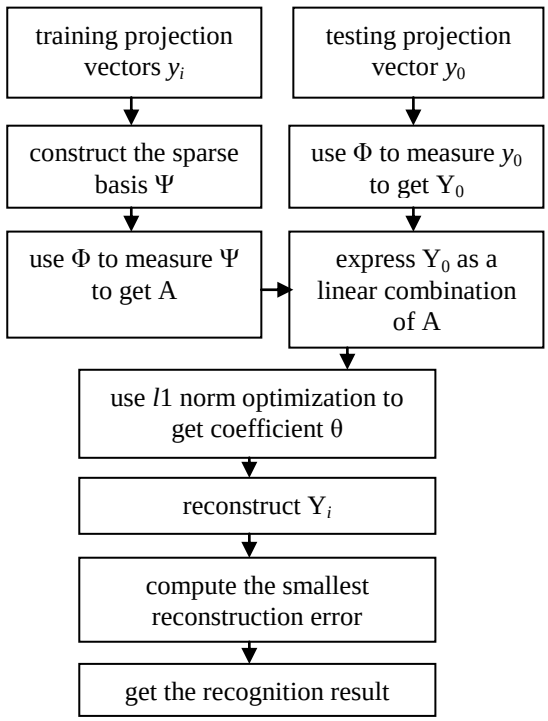


Fig. 3. The flow diagram of classification

IV. Experimental Results

In order to evaluate the performance of our method we will do some experiments. Cosine similarity measure (CSM) classifier [13], maximum correlation classifier (MCC) [13], minimum distance classifier (MDC) [14] and Bayesian classifier [15] are common used classifiers. So we do some experiments to compare the CS classifier with these classifiers. The PCA is a classic subspace method, here we also compare the performance of NMF with PCA. At last we do a experiment to compare the recognition rate of our system with some other methods. Because when we do NMF, W and H are initialized randomly, the results may fluctuate a little.

Our experiments are done on two gesture database. Database I is the Jochen Triesch Database [16]. It is a benchmark database in the field of gesture recognition. This database contains 10 hand gestures performed by 24 different individuals in 3 different backgrounds: uniform light, uniform dark and complex. In this paper, we only use the 480 images under the two uniform backgrounds independent of the complex ones. Before doing experiment, we crop all these images to 80×80 size. Fig. 4 shows some images of the 10 gestures against the uniform backgrounds of the Database I.

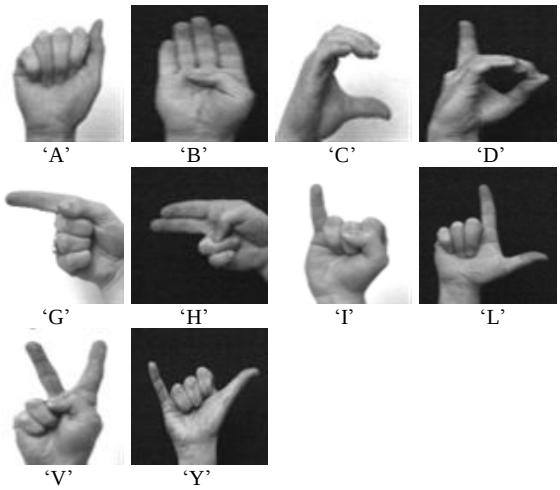


Fig. 4. The 10 gestures of the Database I

Database II is the MU_HandImages_ASL [17]. It is based on the American Sign Language (ASL) hand gestures. Every gesture is peformed by 5 individuals with variations in lighting conditions and hand postures. In this paper, we only use the 700 images of 10 number gestures and we crop all these images to 75×120 size. Fig. 5 shows some images of the 10 gestures of the Database II. Because the Database II is a color database, before we use it, we change its images to gray images.

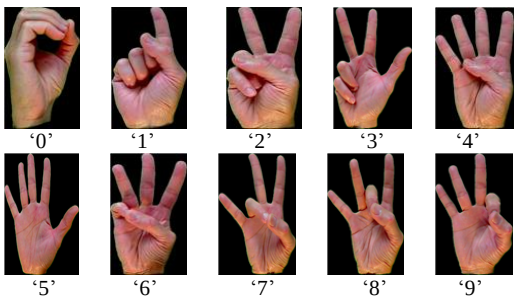


Fig. 5. The 10 number gestures of the Database II

In the first three experiments, we respectively divide the two databases into two subsets: training set and testing set. In the Database I, images of the first 12 persons form the training set, and the remaining images of the other 12 persons are used for testing. In the Database II, the first 20 images of every gesture form the training set, and the remaining 50 images of each gesture are used for testing.

A. Experiment 1

NMF projects the original high-dimensional image to the low-dimensional NMF projection subspace. Based on Section II, r is the dimension of the projection subspace. Different r may influence the recognition rate largely. In this experiment we compare the recognition rates of different classifiers when r = 1,2,3,……,60 respectively. Here we update W and H 50 times, i.e. *max_iter* = 50. Fig. 6 and Fig. 7 respectively shows the experimental results of Database I and Database II.

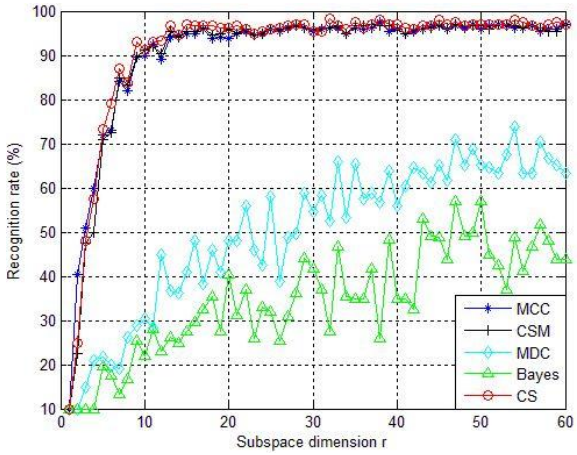


Fig. 6. The figure of recognition rates of different classifiers under different subspace dimensions on the Database I

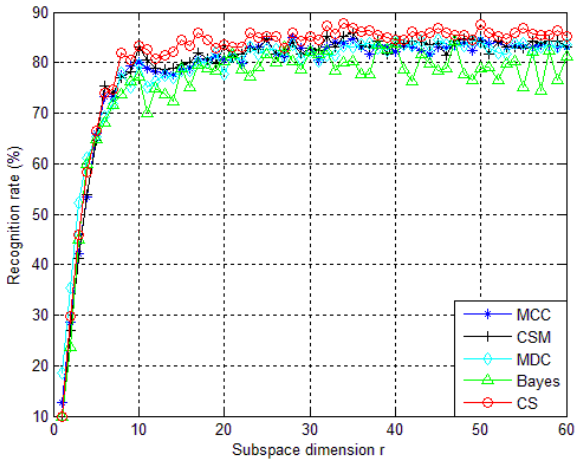


Fig. 7. The figure of recognition rates of different classifiers under different subspace dimensions on the Database II

Fig. 6 and Fig. 7 indicate that at the beginning of all these 5 classifiers, with r being larger from 1, the recognition rates also increase gradually. When $r > 20$, the recognition rates of MCC, CSM and CS classifiers are almost invariant. In order to see the figures clearly, we respectively compute the mean values and the maximum values of each curve in Fig. 6 and Fig. 7 when $r > 20$. We list them in Table I and Table II. Combine the figures and the tables, we can see that among these 5 classifiers, CS can gets the best recognition rate, it is better than other four classifiers.

TABLE I
STATISTICS OF ACCURACY IN FIG. 6

Classifier	Best	Mean
MCC	97.50%	96.03%
CSM	97.08%	96.19%
MDC	73.75%	59.88%
Bayes	57.08%	40.72%
CS	98.33%	96.76%

TABLE II
STATISTICS OF ACCURACY IN FIG. 7

Classifier	Best	Mean
MCC	85.0%	83.0%
CSM	86.0%	83.4%
MDC	84.6%	82.8%
Bayes	84.2%	79.8%
CS	87.8%	85.5%

B. *Experiment 2*

In the above experiment, we update W and H 50 times and change the subspace dimension *r*. In this experiment, we fix *r* = 50 and compare the recognition rates of different classifiers under different iterations of NMF. The experimental results of Database I and Database II are shown in Fig. 8 and Fig. 9 respectively. And the same as above, we compute the mean values and the maximum values of each curve in the two figures. We list them in Table III and Table IV.

Fig. 8, Fig. 9, Table III and Table IV demonstrate that the iterations can influence the accuracy of these classifiers. But no matter how many is the number of iterations , CS classifier can reach a higher recognition rate than other four classifiers.

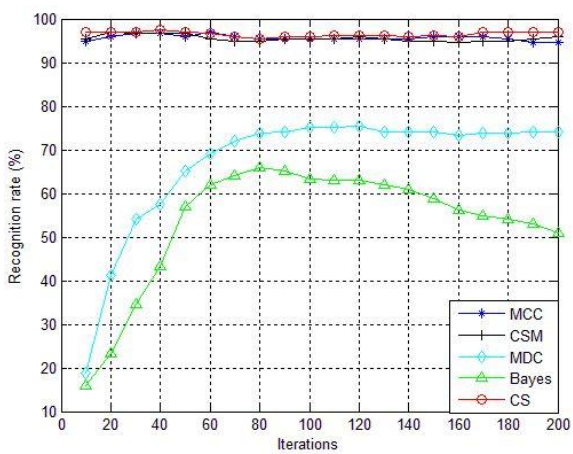


Fig. 8. The figure of recognition rates of different classifiers under different iterations on the Database I

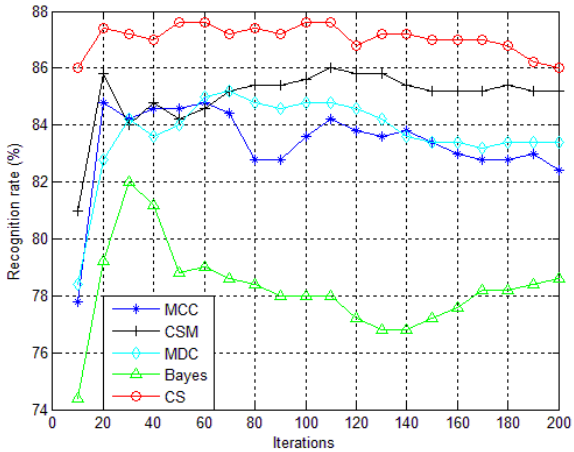


Fig. 9. The figure of recognition rates of different classifiers under different iterations on the Database II

TABLE III
STATISTICS OF ACCURACY IN FIG. 8

Classifier	Best	Mean
MCC	97.08%	95.65%
CSM	97.08%	95.56%
MDC	75.42%	67.15%
Bayes	65.83%	53.56%
CS	97.50%	96.52%

TABLE IV
STATISTICS OF ACCURACY IN FIG. 9

Classifier	Best	Mean
MCC	84.8%	83.4%
CSM	86.0%	85.0%
MDC	85.2%	83.7%
Bayes	82.0%	78.2%
CS	87.6%	87.1%

From the experiment 1 and experiment 2 we can see when we project hand gestuer images to NMF subspace, no matter we change the subspace dimension or iterations, the CS classifier always has a better recognition performance than the other 4 classifiers.

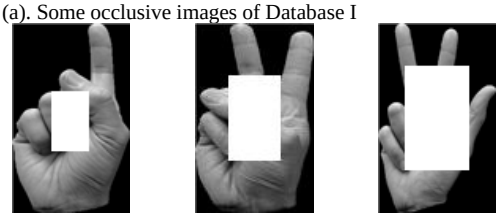
C. *Experiment 3*

In the field of image processing, PCA is a classic subspace analysis method [18], but PCA does not have the non-negative constraints, the negative components of the results are meaningless to image processing. Comparatively speaking, NMF has the non-negative constraints. In a sense, the result of NMF is sparse. Sparsity is good in resisting occlusion. On the one hand, in this experiment we compare the occlusion resistance between NMF with PCA in gesture recognition. On the other hand, from Section III we know CS is based on sparse theory. So in the theory, CS classifier

should be robust to occlusion too. In this experiment we also compare the occlusion resistance between CS classifier with the other 4 classifiers in gesture recognition.

Here the occlusion is made by adding different size white squares to the middle of all testing images. To the Database I, the sizes of the occlusion squares are 5%, 10%, 15%,……,60% proportion of the testing images. In Fig. 10 (a) we show some occlusive testing images of Database I. To the Database II, the sizes of the occlusion squares are 5%, 10%, 15%,……,30% proportions of the testing images. In Fig. 10 (b) we show some occlusive testing images of Database II.

(a). Some occlusive images of Database I



(b). Some occlusive images of Database II

Fig. 10. Some occlusive images of the two database

Fig. 11 and Fig. 12 respectively are the figures of the recognition rates of different classifiers under different occlusions of Database I and Database II. Here the NMF iterations is 50 and *r* is 50. From the two figures we can see that along with the occlusion being larger, the recognition rates of all these classifiers decline gradually, but the CS classifier outperforms the other four classifiers obviously. This demonstrates that to hand gesture recognition, CS classifier has a preferable occlusion resistance.

In the experiment of Fig. 13 and Fig. 14, we employ the CS classifer and compare the performance of NMF with PCA under different occlusions on Database I and Database II. The NMF iterations is 50 and the subspace dimension of PCA and NMF both are 50. From the two figures we can see that along with the occlusion being larger, the recognition rate of NMF falls slower than PCA. This demonstrates that to hand gesture recognition, the occlusion resistance of NMF is better than PCA.

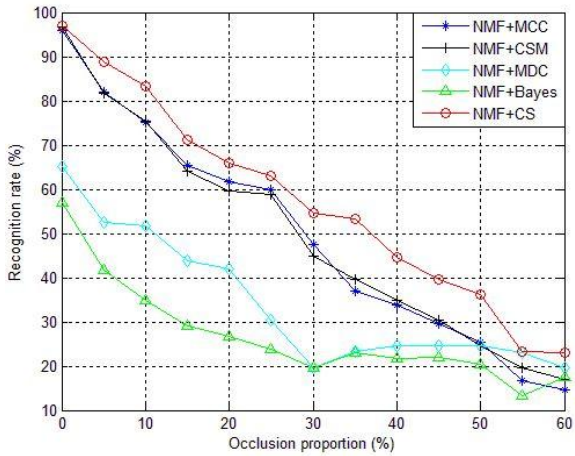


Fig. 11. The figure of recognition rates of different classifiers under different occlusions on Database I

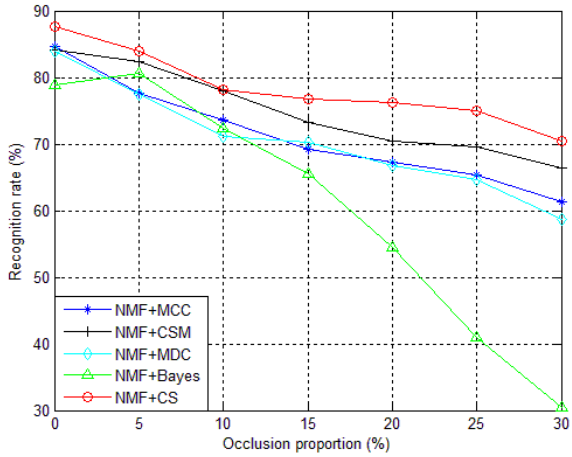


Fig. 12. The figure of recognition rates of different classifiers under different occlusions on Database II

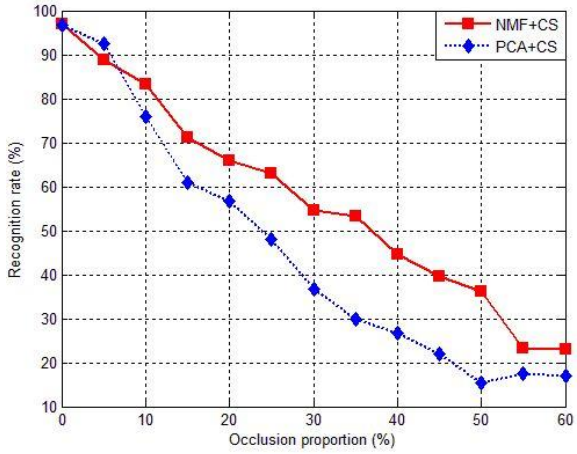


Fig. 13. The figure of recognition rates of NMF and PCA under different occlusions on the Database I

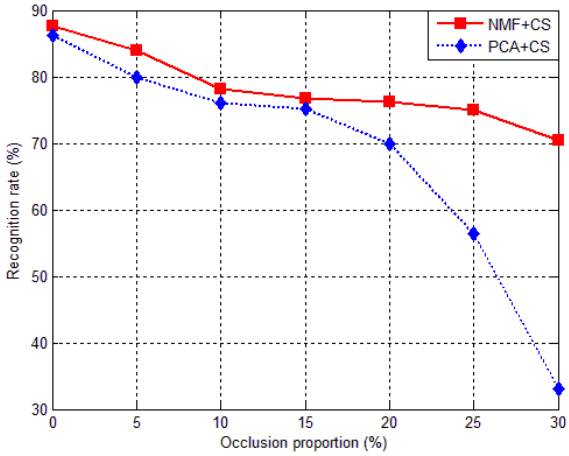


Fig. 14. The figure of recognition rates of NMF and PCA under different occlusions on the Database II

D. *Experiment 4*

In the above experiments, we all use the NMF to project the original gray images to subspace. In this experiment, we first segment the hand regions from the original images and then use NMF to project the segmented images to subspace, at last we use the CS classifier to recognize. And we compare the recognition rate of this method with some other recognition techniques. This experiment is only done on the Database I.

In order to segment the hand regions, at first, we get the binary images from original images by using threshold method [19]. In the binary images, the hand regions are black and others are white. Then we do some morphological

opening and closing operations on the binary images to get the smooth hand regions. To this step, the binary images we get are smooth and some noise points have been removed. Fig. 15 shows some binary images and their corresponding gray images of Database I.

In order to compare the performance of our method with some other researches, we employ two evaluation protocols P_1 and P_2 to divide the Jochen Triesch database. The P_1 protocol is based on [20]: images of 3 persons against uniform backgrounds form the training set and the remaining 21 persons against uniform backgrounds are taken as testing set. The P_2 protocol is based on [21], it is simlar with P_1, it takes 8 persons as training set and the rest 16 persons are used for testing.

(a).Original gray images

(b).Binary images

Fig 15. Some hand region images

In [22], the authors combined weight eigenspace Size Function and Hu moments features, then they used support vector machine (SVM) to classify hand postures. The authors in [23] also do some experiments on the Jochen Triesch database using protocols P_1 and P_2 based on kernel feature extraction methods including kernel principle component analysis (KPCA) and kernel discriminant analysis (KDA). And the SVM classifier is used.

For the comparison, we list the highest recognition rates achieved by our method and methods of [20], [21], [22], [23] in Table V. From this table we can see that our method in this experiment can reach a better recognition performance in comparison with some other previous methods.

TABLE V
RECOGNITION RATE OF SOME METHODS OF DATABASE I

Protocol	Method	Accuracy
P_1	[20]	95.2%
	[22]	85.1%
	[23] KPCA	89.5%
	[23] KDA	89.7%
	Ours	96.67%
P_2	[21]	89.9%
	[22]	91.8%
	[23] KPCA	95.3%
	[23] KDA	92.8%
	Ours	98.13%

V. CONCLUSION

In this work, we have discribed a new static hand gesture recognition system. The method mainly include two steps: firstly we project images to subspace using NMF, then we design a classifier based on the CS theory. In order to evalute our system, some experiments have been carried out on two common used gesture databases. The results indicate that the CS classifier can achieve a higher recognition rate and has a better occlusion resistance in comparison with other classifiers. The results also demonstrate that in resisting occlusion NMF performs better than PCA. And the recognition rate of the overall system is higher than some other traditional techniques. In the future, we will focus on speeding up the calculation of the method so as to use it in the real-time system.

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