JOURNAL OF INFORMATION SCIENCE AND ENGINEERING 35, 1249-1261 (2019)
DOI: 10.6688/JISE.201911_35(6).0005

# Research of Additive Iteration Step Sizes for SINMF*

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NMF has been extensively applied on various pattern recognition problems, including face recognition. To enhance the performance of NMF for face recognition, new additive iterative step sizes are proposed for the basic NMF method, which can raise the searching accuracy during the iteration, and then the recognition rate can be improved. The improved NMF method is named INMF. Meanwhile, the experiments results show that the proposed improved additive iteration can also raise the recognition rate of the SNMF and WNMF. Besides, we find that no sparse constraint is applied to INMF and lots of redundant information still exists, thus a threshold-sparse constraint is introduced to make the base matrix *W* to a 0-1 matrix, and then the feature data of the base matrix become sparse, therefore the recognition rate can be further improved. The INMF model with the threshold-sparse constraint is named SINMF. Finally, our extensive experimental results showed that the highest recognition rate of the SINMF method can achieve 99%, with improvement over the INMF, IWNMF, ISNMF and deep NMF methods by 11%, 5.5%, 11% and 8%, respectively. Meanwhile, compared with the deep convolutional neural network, the recognition rate of SINMF method is proved more efficient.

***Keywords:*** base matrix, new iteration step sizes, threshold sparse, weights coefficient matrix, nonnegative matrix factorization

## 1. INTRODUCTION

Face recognition is the process of feature extraction and classification of standard face images [1]. The quality of the extracted face image features directly affects the final recognition accuracy [2]. The more accurate the extracted facial features are, the higher the recognition accuracy will be. Face recognition methods mainly include geometric feature-based methods, model-based methods, deep learning methods and subspace analysis [3]. Face recognition based on geometric features is a simple and effective recognition method. Based on the geometric feature, a simple and novel feature descriptor for face recognition called local diagonal extreme number pattern is proposed in literature [4], with the new geometric feature descriptor, the recognition rate can be improved. Although the geometric feature extraction method has some effect on feature extraction, it overly depends on the accuracy of feature extraction, while facial expression changes and facial ornaments will directly reduce the face recognition rate. The model-based method mainly adopts the HMM (Hidden Markov Model) method. Different HMM parameters are used to represent different human faces, while multiple observation sequences generated by the same person due to changes in expressions and postures can be expressed by the same HMM [5]. However, the HMM model can only observe a certain

Received July 27, 2018; revised February 13, 2019; accepted March 25, 2019.
Communicated by Tzung-Pei Hong.
* This paper is sponsored by the research project of provincial teaching reform in Hubei Province (No. 2017301).

state and its corresponding observing object, which can't extract global features accurately and is sensitive to scale. In recent years, deep learning has shown tremendous advantages in feature extraction [6]. Convolutional neural network (CNN) is one of the most state-of-the-art deep learning methods, in which the convolution layer and pooling layer are introduced. However, the construction of CNN requires massive training data, to alleviate the dependence on data size [7].

Considering that the dimension of face image is usually very high, and the high redundancy exists between image pixels, thus the redundant information of the image can be reduced to improve the effectiveness of the facial extraction. The method of subspace analysis can map the high dimensional face image information into a low dimensional subspace by the linear or nonlinear transformations, which can effectively reduce the redundancy and extract the features of the face image [8]. Traditional popular subspace analysis is based on the principal component analysis (PCA), which can reduce the number of features of each image by reducing the columns of matrix images [9]. But it has common disadvantage that the decomposition matrices have negative elements. Negative appearance weakens the feature and reduces the recognition rate.

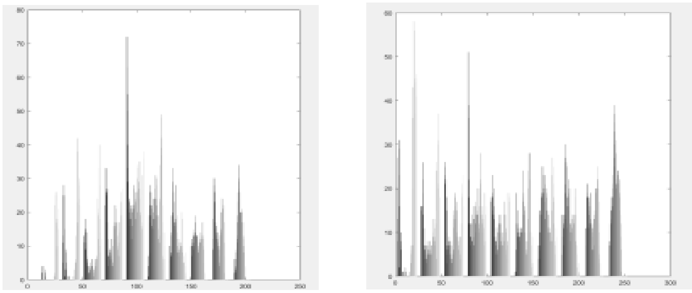
For these reasons, the nonnegative matrix factorization method for feature dimension reduction and extraction has developed greatly. Nonnegative matrix factorization is a powerful dimension reduction and pattern recognition technique, which is realized under the condition that all elements of the matrix are nonnegative [10]. Thus, the decomposition results of NMF have clear physical meaning, which can be widely used in image, video, and audio signal separation and recognition and facial feature extraction [11-13]. Recently, the improved NMF algorithms have been proposed, such as SNMF (sparse nonnegative matrix factorization) method [14] and the WNMF (weighted nonnegative matrix factorization) method [15]. But these models are all iterated by the multiplicative iteration rules, and the improvements for the iteration step sizes are not considered. Actually, it is difficult to improve the recognition rate when the iterative step sizes are not appropriate. To enhance the performance of NMF, new iteration step sizes are proposed in this paper, which can raise the searching accuracy for NMF during the iteration. And the proposed iteration is proved important since it can be further improved and applied to the SNMF and WNMF models, whose accuracy also can be raised. To further improve the accuracy of the improved NMF model based on the new iteration, the sparse constraint of threshold judgment to sparse the base matrix is added, which is different from the traditional sparse constraints based on the L-norm. Thus, the new additive and sparse NMF method, named SINMF, is realized. To verify the effectiveness, the face recognition rate of SINMF model is compared with the INMF, ISNMF, IWNMF and the deep NMF [16] methods. Meanwhile, the SINMF is also compared with the CNN on the recognition rate and reconstruction error.

## 2. PREPROCESSING FOR FACE SAMPLE

To ensure that the extracted features are robust to facial changes, face images need to be pretreated.

### 2.1 Histogram Equalization

Histogram equalization is used to make pixel values of image uniformly distributed at each gray scale, thereby improving the detailed contrast of the image. After histogram equalization, the probability density distribution of the gray scale for image conforms to a uniform distribution at [0, 1], and all gray levels have the same probability. A face image from the ORL face database was applied, and the result is shown in Fig. 1 (b).



(a) Face histogram. (b) Equilibrium histogram.
Fig. 1. Face histogram equalization.

As shown in Fig. 1, the gray ratio at all levels tend to be balanced after the histogram is equalized, and the detailed contrast for image can therefore be improved.

### 2.2 Extracting Low Frequency Information by Wavelet

Wavelet transform is a local transformation in the time and frequency domains. The local characteristics can be extracted from an image and represented effectively using the wavelet transform.

$$DWT(j,k,k) = 2^j \sum_{l_2} \sum_{l_1} f(l_1,l_2)\varphi(2^j l_1 - k_1, 2^j l_2 - k_2) \tag{1}$$

The corresponding two-dimensional discrete wavelet transform is defined by Eq. (1), which is used for the original input image, and four sub-images (*LL*, *LH*, *HL*, and *HH*) can be produced. In addition, *LL* is a low-frequency component for the image, which contains most of the information of the original image. When the wavelet transform is performed on *LL*, a second order wavelet transform is obtained. A face image in the ORL face database is used for a wavelet transform, the results of which are shown in Fig. 2. It can be seen that the low-frequency information can be used as an approxima-

(a) One-layer wavelet transform. (b) Two-layer wavelet transform.
Fig. 2. One and two-layer wavelet transform.

tion of the original image, and then the random noise and redundant information can be greatly suppressed. Meanwhile, a face image constructed through low-frequency information after second order wavelet transform is relatively obscured. Therefore, the low-frequency information obtained from first order wavelet transform is adopted in this paper.

## 3. CONSTRUCTION OF SINMF MODEL FOR FACE RECOGNITION

The NMF method decomposes a nonnegative matrix $V$ of high dimensionality into the product of two low-rank nonnegative matrices $W$ and $H$ [17]. The face image sample set constructs a nonnegative matrix $V$, and then the NMF method is adopted to obtain $W$ and $H$, where $W$ is the base matrix, which represents the features of the image, the dimensions of which are $m$ by $r$. In addition, $H$ is the coefficient matrix, which represents the weight coefficient of the image feature, the dimensions of which are $r$ by $n$.

### 3.1 INMF with the New Additive Iteration Step Sizes

The objective function of nonnegative matrix factorization is defined by Eq. (2).

$$J(W,H)=\tfrac{1}{2}\sum_{ij}[V_{ij}-(WH)_{ij}]^2 \tag{2}$$

The iteration step sizes are set as $\alpha$, $\beta > 0$, and the iterative rules in Eq. (3) can then be obtained using the gradient descent method. When $\alpha$ and $\beta$ take positive values, Eq. (3) represents that the iteration direction is along the fastest decreasing direction of the target function $J$, which is defined in Eq. (2).

$$W'_{ir}=W_{ir}-\alpha\frac{\partial J}{\partial W_{ir}},\ \ H'_{rj}=H_{rj}-\beta\frac{\partial J}{\partial H_{rj}} \tag{3}$$

Solving the partial derivatives of Eq. (2), the partial derivatives $\partial J/\partial W_{ir}$ and $\partial J/\partial W_{rj}$ can be obtained. Substituting them into the Eq. (3), the iteration rules described as Eq. (4) are obtained, and $\alpha$, $\beta > 0$.

$$W'_{ir}=W_{ir}+\alpha[(VH^T)_{ir}-(WHH^T)_{ir}],H'_{rj}=H'_{rj}+\beta[(W^TV)_{rj}-(W^TWH)_{rj}] \tag{4}$$

The new iteration step sizes $\alpha$ and $\beta$ are set as Eq. (5), and they are obviously smaller than the original iteration step sizes, thus, the search accuracy of gradient descent method can be improved.

$$\alpha=\frac{W_{ir}}{(WHH^T)_{ir}}-\frac{W_{ir}}{(WHH^T+VH^T)_{ir}},\beta=\frac{H_{rj}}{(W^TWH)_{rj}}-\frac{H_{rj}}{(W^TWH+W^TV)_{rj}} \tag{5}$$

Meanwhile, the new iteration step sizes of $\alpha$ and $\beta$ are positive, thus, the gradient iteration descending criterion are also satisfied, which can definitely decrease the target function as Eq. (2). Substituting the new iteration step sizes as Eq. (5) into Eq. (4), the new additive iteration rules of the base matrix $W$ and coefficient matrix $H$ are then obtained as shown in Eq. (6).

$$W'_{ir} = W_{ir} + W_{ir}\frac{(VH^T)_{ir}((VH^T)_{ir} - (WHH^T)_{ir})}{(WHH^T)_{ir}(WHH^T)_{ir} + (VH^T)_{ir}}, H'_{rj} = H_{rj} + H_{rj}\frac{(W^TV)_{rj}((W^TV)_{rj} - (W^TWH)_{rj})}{(W^TWH)_{rj}((W^TWH)_{rj} + (W^TV)_{rj})}. \tag{6}$$

The computational complexity for new iteration rule of $W$ is O($N$×($mnr$+($mrn$+$mnr$) +$mr$)), that is O($N$×($mnr$+$mr$)), where $N$ is the number of iterations to convergence, $m$ is the rows of data $V$, $n$ is the columns of data $V$ and $r$ is the rank of decomposition. And the computational complexity for new iteration rule of $H$ is O($N$×($rmn$+$mr^2$+$nr^2$+$rn$)). The original iteration rules of basic NMF are described as Eq. (7), and the computational complexities of $W$ and $H$ are O($N$×($mnr$+$mr$)) and O($N$×($rmn$+$mr^2$+$nr^2$+$rn$)), respectively.

$$W'_{ir} = W_{ir}\frac{(VH^T)_{ir}}{(WHH^T)_{ir}}, H'_{rj} = H_{rj} + H_{rj}\frac{(W^TV)_{rj}}{(W^TWH)_{rj}}. \tag{7}$$

Therefore, the computational complexities are unchanged when the proposed improvement iteration works on the NMF model. And the new iteration step sizes as Eq. (5) are obviously smaller than the original iteration step sizes, thus the accuracy of search and iteration based on Eq. (6) is higher than that of the original NMF method.

### 3.2 Further Application of the New Iteration Step Sizes for SNMF and WNMF

Actually, the iteration rules of WNMF and SNMF can also be solved by gradient descent method. Based on the Eq. (3) and the partial derivatives of the objective function of SNMF model, the above new iteration step sizes can be directly applied to the SNMF model. Meanwhile, compared with the objective function of basic NMF, the weights of sample are considered, and then the objective function of WNMF is get. Thus, the above new iteration step sizes are weighted and then can be applied to the WNMF model.

Consider the SNMF method [14], which is the nonnegative matrix factorization model with sparse constraints based on the sparse metric function of Ll-norm and L2-norm. The objective function of SNMF is described as Eq. (8).

$$J(W,H) = \frac{1}{2}\sum_{ij}\|V - WH\|^2 + \frac{\mu}{2}\|W\|^2 + \frac{\lambda}{2}\|H\|^2 \tag{8}$$

From Eq. (8), it adds the sparse items based on the objective function of basic NMF. Thus, the improved iteration step sizes described as Eq. (5) can be directly applied on SNMF. By the gradient descent method described as Eq. (3) and the new iteration step sizes as Eq. (5), the new iteration rules are obtained as Eq. (9).

$$W'_{ir} = W_{ir} + W_{ir}\frac{(VH^T)_{ir}((VH^T)_{ir} - (WHH^T)_{ir} - \mu W_{ir})}{(WHH^T)_{ir}(WHH^T)_{ir} + (VH^T)_{ir}}, H'_{rj} = H_{rj} + H_{rj}\frac{(W^TV)_{rj}((W^TV)_{rj} - (W^TWH)_{rj} - \lambda H_{rj})}{(W^TWH)_{rj}(W^TWH)_{rj} - (W^TV)_{rj}}. \tag{9}$$

Computational complexities of the two new iteration rules are O($N$×($mnr$+$mr$)) and O($N$×($rmn$+$mr^2$+$nr^2$+$rn$)), respectively, which is the same as original SNMF. And the new iteration step sizes of new iteration rules are obviously smaller than the original iteration step sizes, thus the accuracy of SNMF based on new iteration can be improved.

The WNMF is the weighted non-negative matrix factorization model [15]. The objective function of WNMF method is described as Eq. (10).

$$J(W,H)=\frac{1}{2}\sum_{ij}T_{ij}[V_{ij}-(WH)_{ij}]^2 \tag{10}$$

In Eq. (10), the $T_{ij}$ is the element value of weighted matrix for the sample, and compared with the objective function of basic NMF, only the weight of sample is added. Thus, the new iteration step sizes of WNMF can be set as Eq. (11).

$$\alpha=\frac{W_{ir}}{T_{ir}(WHH^T)_{ir}}-\frac{W_{ir}}{T_{ir}(WHH^T+VH^T)_{ir}},\beta=\frac{H_{rj}}{T_{rj}(W^TWH)_{rj}}-\frac{H_{rj}}{T_{rj}(W^TWH+W^TV)_{rj}}. \tag{11}$$

From Eq. (11), we can find that it adds the weight coefficient of $T_{ij}$ based on the Eq. (5). Thus, by the new iteration step sizes and the gradient descent method described as Eq. (3), the new iteration rules are obtained as Eq. (12).

$$\begin{aligned} W'_{ir}&=W_{ir}+W_{ir}\frac{(T\cdot VH^T)_{ir}((T\cdot VH^T)_{ir}-(T\cdot WH)H^T)_{ir}}{(T\cdot(WH)H^T)_{ir}+(T\cdot VH^T)_{ir}(T\cdot(WH)H^T)_{ir}},\\ H'_{rj}&=H_{rj}+H_{rj}\frac{(W^T(T\cdot V))_{rj}((W^T(T\cdot V))_{rj}-(W^T(T\cdot WH))_{rj})}{(W^T(T\cdot(WH)))_{rj}+(W^T(T\cdot V)_{rj}(W^T(T\cdot(WH)))_{rj}}. \end{aligned} \tag{12}$$

The computational complexities of the two new iteration rules are all of order O($N\times(mnr+mr+mn)$), which is the same as original WNMF. Meanwhile, the new iteration step sizes of new iteration rules are obviously smaller than the original iteration step sizes, thus the accuracy of WNMF model can be improved based on the new iteration.

When the rank $r$ of matrix factorization takes different values, the recognition rates for 200 face samples with NMF, SNMF, WNMF models, the improved NMF (INMF), improved SNMF (ISNMF) and improved WNMF (IWNMF) models based on new iteration step sizes are respectively shown in Fig. 3.

From Fig. 3, the recognition rates with the different $r$ of the INMF, IWNMF and ISNMF models based on the new additive iteration are respectively higher than that of the original models, which illustrate that the recognition rate can be effectively improved by the new additive iteration and the proposed improvement iteration can work well on the NMF, SNMF and WNMF models. The experiment results also proved that the recognition accuracy is improved when the iteration step sizes are reduced. Meanwhile, as can

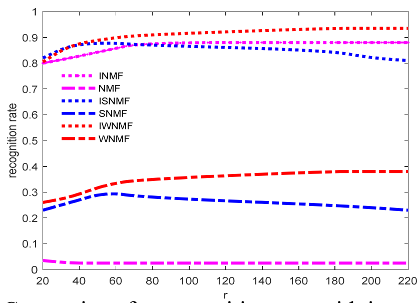


Fig. 3. Comparison for recognition rate with increasing $r$.

be seen from the complexity of the above methods, we find that the proposed improvement iteration doesn't change the computational complexity.

### 3.3 Sparsification for the INMF Model

Although the iteration are improved, no sparse constraints are considered in the improved NMF model and lots of redundant information still exists. Therefore, a simple sparse strategy of threshold judgment for base matrix is adopted to enhance sparseness of the INMF model, and then we can get the sparse INMF, named SINMF model. Threshold judgment can make the base matrix $W$ to a 0-1 matrix during the iteration process. The enhancement of sparseness can further improve the recognition rate.

During the iteration process described as Eq. (6), a threshold is given to sparse the base matrix $W$. That is, when $W$ is produced each iteration, all data in the columns of base matrix $W$ is reset according to the threshold. If the data are greater than the threshold, the values are set to 1, otherwise, the data are set to 0. Thus, the base matrix is transformed to 0 and 1 matrix, and then the weights of the important features are enhanced, whereas the weights of the less important features are suppressed, and then the facial features become more concentrated. Thus, the region representing facial features can be intensely extracted, and the interferences of other unrelated areas are reduced.

The features for face samples are extracted by SINMF method, and the "feature face" can be obtained by visualizing the base matrix. Meanwhile, the "feature face" extracted by SINMF are compared with those extracted by other NMF methods. Fig. 4 (a)-(d) show the visual "feature face" of the optimal base matrix respectively extracted by the INMF, ISNMF, IWNMF and SINMF methods, respectively. Here, the initial values of $W$ and $H$ are random numbers between 0 and 1, therefore, the threshold is set as a value between 0 and 1. Usually, the threshold is smaller, the less redundant information exists, and the data are more centralized. Thus, the threshold is set to 0.02.

(a) INMF (b) ISNMF (c) IWNMF (d) SINMF

Fig. 4. Visual images of the optimal base matrix respectively obtained by the NMF methods.

A "feature face" of the optimal base matrix obtained using the SINMF based on iterative method is shown in Fig. 4 (d), which can accurately reflect the features of the eyes and nose, and make the facial feature data more clear and concentrated. The images of the optimal matrices obtained by the other three methods are shown in Figs. 4 (a)-(c), and their feature information is diffuse and vague. Therefore, compared with the other methods, the SINMF method proposed in this paper can make the data of base matrix $W$ more sparse, which can result in the feature information being more accurate and concentrated, and thus the recognition based on the corresponding coefficient matrix $H$ for weight $W$ will be more accurate.

## 4. CLASSIFIER DESIGN

Support Vector Machine (SVM) is a non-linear mapping classifier that uses inner product kernel function instead of direct high-dimensional space operations. Based on the strict guarantee of statistical learning theory, SVM classification model has good generalization ability. Moreover, the SVM method can give a strict bound on the generalization ability of the model. At the same time, compared with other methods, the establishment of SVM classifier requires less prior intervention, and the classification results are more objective.

Forty faces were used in the experiments, and then the 780 classifiers can be constructed based on one-to-one strategy of SVM. The coefficient matrix $H$ of the face data set and the corresponding category label set were set as the input training set of the SVM classifier. The parameters of each correct binary classification of training set were stored, and a multiple classification parameter file was obtained. This file can be called to obtain the parameter information of the multi-classifier to classify the test set. Even if the sample is insufficient, SVM also can achieve accurate recognition.

In addition, many classifiers have emerged at present, such as the deep learning method, which is also widely applied on face classification and recognition. The deep network decomposes the visual feature into several sub-features, and by the layer-by-layer decomposition and combination, the visual system is constructed, so that it can recognize the object correctly even if it has displacement or slight deformation. That is, the deep network can extract features from multiple layers and classify features at the full connection layer of the last layer. However, in order to converge, the deep network needs sufficient learning and training based on a large number of learning samples, thus, its efficiency is not very high. In this paper, the ISNMF method with the SVM will be compared with the deep convolutional neural network for the same sample set.

## 5. EXPERIMENTAL RESULTS AND ANALYSIS BASED ON SINMF

The SINMF method was adopted to identify the human face in the ORL library provided by Cambridge University. There are 40 people in the ORL gallery, with ten faces for each person, and thus there are 400 faces in total. Each face has 256 levels of gray scale, and the size is 112×92. The facial expressions and facial details of each person differ, including smiling and not smiling, eyes opening and closing, wearing and not wearing glasses, and so on. The facial postures are also different, and variations in the rotation angles of the depth and plane can reach 20°, and the variation in the size of the facial image reaches 10%. The first five images were randomly selected for training, and the remaining five images were used for testing, and thus the training and test galleries have 200 images, respectively. Results of comparison experiments for face recognition rate changes with different values of $r$ based on the SINMF, INMF, ISNMF, IWNMF and Deep NMF, respectively, are shown in Fig. 5.

It can be seen from Fig. 5 that the recognition rate of the new additive iterative SINMF method proposed in this paper is obviously higher than the other methods with different values of $r$. Meanwhile, the recognition rate of SINMF method based on the new additive and sparse iterative rules continues increasing with the increasement of $r$. When $r = 75$, the highest recognition rate of 99% is obtained, and when r continues to increase, the recognition rate remains unchanged at 99%. For the INMF method, the highest recognition rate is only 88%, and when $r$ continues to increase, the recognition rate remains unchanged at 88%. Meanwhile, the recognition rates of ISNMF, IWNMF and Deep NMF are lower than the new additive and sparse iterative SINMF method. In addition, the highest recognition rate of the new SINMF method is 11% higher than the INMF method and ISNMF method, 5.5% higher than the IWNMF method, and 8% higher than the Deep NMF.

The recognition rate of the new additive and sparse iterative SINMF method is higher than the other methods because that the search accuracy is higher based on the new smaller iteration step sizes, and the higher search accuracy can result in the higher recognition. Moreover, the threshold judgment is adopted, which make the feature data obtained by the new additive iterative rules sparser and more concentrated than the feature data obtained by the multiplicative iterative rules. Therefore, the weight coefficient of the feature is more concentrated and easier to recognize, and thus a higher recognition rate based on the new additive and sparse iterative rules can be achieved.

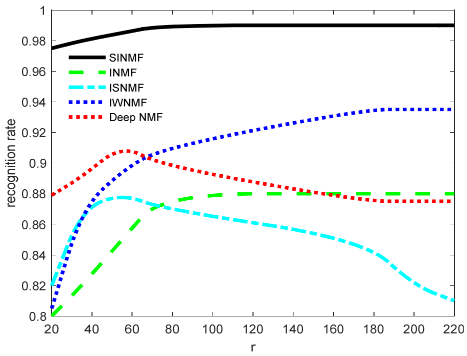



Fig. 5. Comparison for recognition rate with increasing $r$ for five NMF methods.

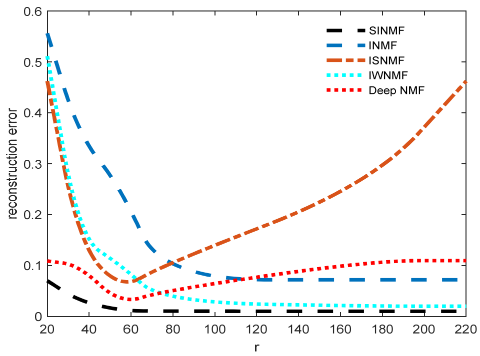



Fig. 6. Comparison of error of $V$-$WH$ for five NMF methods with different $r$.

Consider the error of reconstructing the original data matrix $V$ by the final matrix $W$ and $H$, which can also reflect the accuracy of the proposed SINMF method. And the comparison of the reconstruction errors respectively based on the five NMF methods is shown in Fig. 6. As shown in Fig. 6, the reconstruction error of the new additive and sparse iterative SINMF method proposed in this paper is obviously lower than the other four methods with different values of $r$. In addition, the lowest error of $V$-$WH$ of the new additive and sparse iterative SINMF method is 80% smaller than that of the INMF method and ISNMF method, 36% smaller than that of the IWNMF method and 57% than that of Deep NMF method. Thus, the original data matrix $V$ can be reconstructed most accurately by the base matrix based on the new additive and sparse iterative SINMF model proposed in this paper.

As shown in Figs. 5 and 6, when the recognition rate is higher, the error of *V*-*WH* is smaller. And the new additive and sparse iterative SINMF method proposed in this paper can guarantee both a higher recognition rate and high-quality reconstruction than other methods. Therefore, considering the comprehensive factors of the recognition rate and accuracy of reconstruction for original data, the method proposed in this paper is better than the other methods.

Fig. 7. Different facial expressions of the same person are correctly identified.

Fig. 8. Correct face recognition when eyes are open or closed, and when wearing glasses or not.

Based on the new additive and sparse iterative SINMF method, considering such factors as the recognition rate and image reconstruction, $r = 75$ is selected, and face recognition software based on MATLAB has been realized. The program results are shown in Figs. 7 and 8. Randomly picking out the faces of different people from 200 faces with a probability of 0.99, and for cases such as eyes open or closed, and whether or not glasses are worn, the software consistently results in a correct recognition. That is, a person can be identified, and their face can be correctly recognized with a probability of 0.99, as shown in Figs. 7 and 8. In addition, the recognition rate for the face category is also shown in the text box in Figs. 7 and 8. As shown from the results of the software simulation, a significantly high face recognition rate can be achieved using the new additive and sparse iterative SINMF face recognition method.

In addition, deep learning is also widely used in face recognition, and CNN is the most widely adopted network structure in deep learning. The facial features can be extracted by the convolution and pooling layers, and are classified by the full connection layer. Therefore, the SINMF model proposed in this paper is also compared with CNN method by experiments. For comparing the performance of SINMF and CNN, the deep learning toolbox of CNN is also applied on the ORL data set. The CNN model has seven hidden layers, including three convolutional layers, three sampling layers and one full connection layer. The first convolutional layer has five filters, the second convolutional layer has ten filters, and the third convolutional layer is same as the first layer. The filter size is set as 3×3, and step size of subsampling is set as 2.

The experiments results of CNN are shown in Table 1. The epoch increases from 500 to 2000, and the recognition rate increases from 5.5% to 83%, while the recognition time increases rapidly. By the experiments of comparing the SINMF method, the Table 2 can be obtained. We can find that the highest recognition rate of CNN is 83% while the recognition time arrived at 420s, however, the recognition rate of SINMF ($r$ = 75) can reach 99% within 22.5 seconds. That is, when the recognition rate reaches the high value, CNN will take longer time than the SINMF. So the deep learning requires enough learning and training process to extract features accurately, which will consume too long time. However, the SINMF method can accurately extract features within shorter time.

**Table 1. Recognition rate and recognition time for CNN.**

| epoch | recognition rate | recognition time |
|---|---|---|
| 500 | 5.5% | 104s |
| 1000 | 67.5% | 215s |
| 2000 | 83% | 420s |

**Table 2. Comparison of recognition rate and recognition time of CNN and SINMF.**

| | highest recognition rate | recognition time |
|---|---|---|
| SINMF | 99% | 22.5s |
| CNN | 83% | 420s |

The experiments results proved that the SINMF method is more efficient than CNN, since the CNN needs a large number of samples and adequate training or learning, which usually takes long time. From the comparison experiments, we can derive that when the depth of network layer is further deepened, even if the recognition rate can be further improved, the learning and training time will be longer. Thus, the efficiency of the deep neural network is still lower than SINMF method.

## 6. CONCLUSIONS

New additive and sparse iterative rules are proposed for face recognition based on nonnegative matrix decomposition, and they also can be improved to apply on the SNMF and WNMF model to raise the recognition rate. First, the face images are preprocessed by histogram equalization and wavelet transform to reduce the influence of light and the high-frequency noise. Then the new additive iteration rules are adopted to update $W$ and $H$, and the base matrix $W$ is made sparse by the threshold sparse constraint, and then can the features of the face can be effectively extracted. Finally, the testing images set is decomposed in the optimized feature subspace represented by the base matrix $W$, and the feature weight coefficient matrix $H$ can then be classified accurately by the SVM.

Comparative experiments with different $r$ on the face recognition rate and the reconstruction error of $V$-$WH$ based on the INMF, ISNMF, IWNMF, Deep NMF method and the SINMF method were conducted. From the experimental results, the new additive and sparse iterative SINMF method has the highest recognition rate, which is 11%, 5.5%, 11%, and 8% higher than that of INMF, IWNMF, ISNMF and Deep NMF, respectively, and the least error of *V-WH*, which is 80%, 36%, 80% and 57% smaller than that of the INMF, IWNMF, ISNMF and Deep NMF, respectively. Meanwhile, the popular deep learning method of CNN is compared with the SINMF model on the recognition rate, and it can be found that the SINMF method is more efficient and can extract features accurately within shorter time based on the experiment results. Therefore, the SINMF method doesn't require the sufficient sample and learning, and it is more suitable for scenarios with insufficient sample information.

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