

PAPER • OPEN ACCESS

Face recognition method with feature fusion and error feedback

To cite this article: Fan Yeping *et al* 2019 *IOP Conf. Ser.: Mater. Sci. Eng.* **569** 052100

View the [article online](#) for updates and enhancements.

Face recognition method with feature fusion and error feedback

Fan Yeping¹, Li Yu¹, Yang Desheng¹, Wan Tao¹, Ma Dong¹, Jiao Dian^{2,*}, Cai Yiting³, and Chen Mengxian³

¹ Anhui Jiyuan Software CO., LTD, Hefei, Anhui, 230088, China

² School of Electric Engineering and Automation, Hefei University of Technology, Hefei, Anhui, 230009, China

³ State Grid Wenzhou Power Supply Company, Wenzhou, Zhejiang, 325000, China

*Corresponding author's 1149696122@qq.com

Abstract. A face recognition method with feature fusion and error feedback is proposed to imitate human cognition process. The intelligent recognition mode with multi-level feedback from global to local and from coarse to fine is implemented. Firstly, based on the idea of feedback control, a multi-level feedback model of face recognition with performance index constraints and supervised learning under finite domain is established. Secondly, based on entropy theory and Stochastic Configuration Networks (SCN), a facial feature space and face image classification network model with multi-feature fusion and sufficient separability under certain feature performance conditions are established from the perspective of information theory. Thirdly, based on entropy theory and error theory, the face recognition error representation and calculation model under certain feature performance conditions is established. Finally, the adjustment index of facial feature performance based on recognition error is constructed, and the face recognition algorithm with feature fusion and error feedback is given out. Test and comparison experiments show that our method is effective and feasible.

1. Introduction

Face recognition is one of the most challenging topics in the field of computer vision, which has broad application prospects in the fields of monitoring security and identity verification [1-3]. In recent years, the level of face recognition has made great progress. With the rapid development of computer-related technologies, various theoretical methods and techniques related to face feature expression, face detection and face image classification have emerged. Under ideal conditions, face recognition technology and its effects are relatively mature, however the face images actually collected in various current production and life are mostly affected by external disturbances, such as illumination and expression, which affect image quality and recognition effect. Therefore, the development of a stable and reliable face recognition method is an urgent need to further enhance the smart life experience.

Human beings are the most advanced agents, whose cognition thinking is based on the collected information by vision, tactility, audition, etc., and the relevant prior knowledge of the human brain at different levels to repeatedly deliberate and compare, so as to obtain the optimal cognitive results under limited information. Here, the information collection and the repeated deliberation and comparison with the prior knowledge correspond to the information processing processes, such as object feature extraction, classification recognition, and feedback adjustment based on the cognition result,



Content from this work may be used under the terms of the [Creative Commons Attribution 3.0 licence](https://creativecommons.org/licenses/by/3.0/). Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.

respectively. The traditional face recognition system mostly adopts the one-way and open-loop mode, namely, for the face image inputs, after the face image pre-processing, feature extraction, and classification recognition, etc., the recognition result output is obtained. Obviously, this recognition mode lacks the evaluation of the performance of the recognition result, then the feedback adjustment based on the recognition result is impossible to talk about, which is obviously inconsistent with human cognitive thinking. Simulating human cognitive thinking, using a pattern recognition model with feedback mechanism is an effective means. Refs [4-6] introduced the effective application of the feedback mechanism in the fields of rotary kiln burning state recognition, green plum grade classification, human health evaluation and fog grade recognition. In the field of face recognition, Ref [7] introduced the face image retrieval method based on correlation feedback, however the face classification recognition algorithm with feedback mechanism is rare.

Accurate representation and efficient use of facial information is one of the key factors to improve the accuracy of face recognition. From the early recognition based on geometric features to the later recognition based on statistical features, the development of face recognition technology has achieved better and better results. In recent years, with the development of computing technology and data mining technology, multi-information fusion has received more and more attention. Compared with statistical features, the geometric features of face images are more robust to illumination changes and have faster information processing speed, while the statistical features have strong data mining ability for complex information. Therefore, the feature extraction method based on the fusion of statistical features and geometric features helps to improve the expression ability of face images. Furthermore, multi-feature fusion will inevitably lead to a relative "curse of dimensionality". Thus, on the basis of multi-information fusion, how to construct a simple feature space of face images with powerful classification ability is a meaningful research direction.

Aiming at the problem that the traditional open-loop face recognition method lacks the evaluation of classification performance under the finite universe condition, this paper proposes a face recognition method based on feature fusion and error feedback, which simulates the human cognitive thinking with repeated deliberation and comparison. Represents and classifies the facial images in different feature levels, evaluates the face classification performance, and feedback adjusts the feature space and classification criterion based on the evaluated results to realize the multi-level feedback recognition mode from whole to local and from coarse to fine. Firstly, based on the idea of feedback control, a face recognition multi-level feedback cognition model is established with the performance constraints and supervised learning under the finite universe. Secondly, based on the entropy theory and stochastic configuration networks (SCN), from the perspective of information theory, facial feature space and face image classification network model are established with multiple feature fusion and sufficient separability characteristic under the condition of specific feature effectiveness. Thirdly, based on the entropy theory and error theory, the calculation model of the face recognition error representation is established under the condition of specific feature effectiveness. Finally, to simulate human cognitive thinking, the adjustment index of facial feature effectiveness based on recognition error is constructed, and the face recognition algorithm is given based on feature fusion and error feedback. Experimental results show that the proposed method is effective and feasible.

2. Face intelligent recognition model based on feature fusion and error feedback

In this paper, an intelligent face recognition model based on feature fusion and error feedback is proposed. This model uses the three-layer coupling structure, including the training layer, the cognitive layer and the feedback layer, to achieve accurate mapping between images and biometric information, as shown in Figure 1.

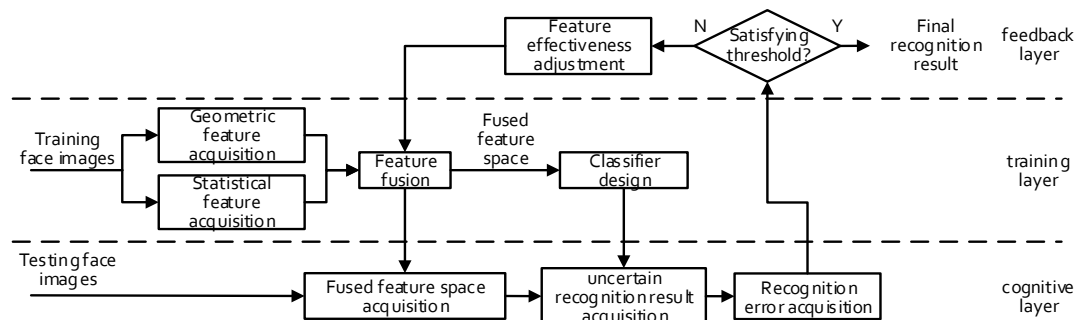


Fig.1 Face recognition model based on feature fusion and error feedback

1) Training layer

For the collected training face image dataset, the fusion extraction methods of the structural feature and statistical feature are adopted. Under the condition of the feature effectiveness index issued by the feedback layer, the intelligent cognition decision information system with sufficient representation of the training dataset is established. Using the fused and compacted face feature space as the inputs, a classifier is constructed to obtain the face image classification criterion. The training layer provides the templates for the fused feature space acquisition and the uncertain recognition result acquisition of testing images at the cognitive layer.

2) Cognitive layer

For the collected testing face image dataset, based on the feature space construction and face image classification criteria provided by the training layer, the uncertain recognition result of the testing face images under the condition of specific feature effectiveness is obtained, and then the calculation model of face recognition error is established under specific feature effectiveness based on generalized error theory, which provides the heuristic feedback information for the error evaluation and feature space adjustment at the feedback layer.

3) Feedback layer

For the face recognition error under the condition of specific feature effectiveness, the recognition error evaluation model of testing samples based on entropy theory is established, and the final recognition result is outputted for the samples with reliable result. Otherwise, the feature effectiveness index is adjusted by self-optimization, to guide the reconstruction of the fused feature space at the training layer.

3. Face recognition classification model based on feature fusion

3.1. Construction of fused feature space based on facial geometric features and statistical features

3.1.1. Extraction of facial geometric features. The geometric features describing the facial parts and structural relationship is an important characteristic of face recognition, which has the advantages of the stronger robustness to the illumination changing and the smaller feature dimension. However, the extraction methods of the facial geometry feature based on feature points are not satisfied in the accuracy of face recognition applications. Therefore, this paper adopts the extraction method of geometric Gabor texture feature [8] to obtain the facial features of geometric information and texture information for the face sample images, which is beneficial to the subsequent classified cognition step.

For the input training face image U_i , firstly the gray image point set is obtained based on the facial geometric feature, and then several two-dimensional Gabor wavelet kernels are used to perform the filtering processing, to obtain the $\tilde{m}$ -dimensional geometric Gabor texture feature vector $\tilde{\mathcal{C}}_i = [\tilde{c}_{i,1}, \dots, \tilde{c}_{i,\tilde{m}}]$ of the sample U_i . Here, $\tilde{m} = u + v$, where u and v are the directions and dimensions of the two-dimensional Gabor wavelet kernel function, respectively.

Thus, for the training face image sample dataset $U = \{U_1, \dots, U_n\}$, the facial geometric Gabor feature set $\tilde{C} = \{\tilde{C}_1, \dots, \tilde{C}_{\tilde{m}}\}$ can be obtained, where U_i is the i^{th} training sample, $i \in [1, n]$, $\tilde{C}_j$ is the j -dimension geometric Gabor eigenvector, and $j \in [1, \tilde{m}]$.

3.1.2. Extraction of facial statistical features. Deep learning has powerful expression ability for complex functions, which has great advantages for the discriminative feature mined from samples [9]. In this paper, the construction method of convolutional neural network (CNN) based on the maximal information entropy is used to extract the multi-layer facial statistical features of training face image samples.

The face statistics feature is obtained by using the CNN architecture with l ($l \geq 0$, and l is an integer) layers. Each layer of the convolutional neural network includes a convolutional layer and a pooling layer, and the convolutional layer and the pooling layer in the same layer have the same feature map number. For the input training face image sample U_i , after l convolution and pooling operations respectively, g_l facial feature maps (size $\Delta_l \times \nabla_l$) can be obtained. Finally, based on the operation of a fully connected layer composed of a 1×1 convolution kernel, the $\bar{m}$ -dimension facial convolution feature vector $\bar{C}_i = [\bar{c}_{i,1}, \dots, \bar{c}_{i,\bar{m}}]$ of U_i can be obtained, where $\bar{m} = \Delta_l \times \nabla_l \times g_l$.

Here, the selection of l is determined by the dimension n of the training dataset U . Generally, when the depth of CNN network is increased, more detailed image features can be obtained by further convolution and pooling operations, and there are $n \downarrow, l \downarrow$, and vice versa. In addition, for a specific network level l , increasing the number of facial feature maps can also increase the amount of information of each network layer. However, under the finite universe condition, the increasing of the number of feature maps will make the information amount in the network tend to be saturated and cause redundancy. Therefore, the maximum information entropy index can be used to obtain the feature map space of each layer of CNN with sufficiency representation. Let the feature map field of the output of the $l-1^{th}$ layer network be $X^{l-1} = \{X_1^{l-1}, \dots, X_{g_{l-1}}^{l-1}\}$. Then, the minimum facial feature map space $X^l = [X_1^l, \dots, X_{g_l}^l]^T$ with sufficient information amount of the l^{th} layer network can be obtained by the formula (1), where X_μ^l is the feature map vector extracted by the μ^{th} input in X^l , $\mu \in [1, g_l]$.

$$\begin{cases} \max_{g_l} H(R(X^l)) = \max_{g_l} (-\sum_{q=1}^{\delta_l} \frac{|\Phi_q|}{|X^{l-1}|} \log_2 \frac{|\Phi_q|}{|X^{l-1}|}) \\ s. t. \quad 0 < \delta_l < g_l \end{cases} \quad (1)$$

where, $H(R(X^l))$ is the information entropy of X^l , and $R(X^l) = \{\Phi_1, \dots, \Phi_{\delta_l}\}$ is the quotient of X^l based on the equivalence relation.

Thus, for the training face image sample dataset $U = \{U_1, \dots, U_n\}$, a facial convolutional neural network feature set $\bar{C} = \{\bar{C}_1, \dots, \bar{C}_{\bar{m}}\}$ with sufficiency representation can be obtained, where $\bar{C}_j$ is the j -dimensional facial convolutional neural network eigenvector, $j \in [1, \bar{m}]$.

3.1.3. Face recognition decision information system based on feature fusion. Different samples have different degrees of applicability to different features. Therefore, a single type of feature has one-sidedness for the representation of face images. Multi-dimensional feature representation of multi-feature fusion is an effective solution. However, high-dimensional feature space, especially the CNN-based facial feature extraction method used in this paper, inevitably has redundant related information. Therefore, the effective feature selection is beneficial to improve the classifier performance.

In this paper, the variable precision rough set model and the conditional entropy-based feature selection algorithm [6] are used, and the parameter of classification accuracy is introduced to construct the face recognition decision information system $S^{\beta_w} = \{U, B^{\beta_w} \cup D\}$ with the discriminative representation under the condition of determined feature effectiveness, where $B^{\beta_w} = [B_1^{\beta_w}, \dots, B_r^{\beta_w}]$ is the r -dimensional fused and reduced feature space of training face image samples obtained from $C = \tilde{C} + \bar{C}$ via a conditional entropy-based feature selection algorithm. The dimension of C is $\tilde{m} + \bar{m}$,

$B^{\beta_w} \subseteq C$, $r \leq \tilde{m} + \bar{m}$, β_w is the given classified accuracy, and $\mathbf{D} = [D_1, \dots, D_n]^T$ is the class label of the training face image samples.

That is to say, for the known facial feature space C of face images, as long as the classified accuracy β_w is given, the fused and reduced facial feature space with the discriminative optimization representation can be obtained, thereby to achieve the correspondence between the classified quality and the feature effectiveness.

3.2. Face recognition classifier construction based on SCN

The methods of neural network are widely used in face recognition because of their greater adaptability in complex pattern expression. In order to overcome the randomness of neural network parameters, this paper uses a SCN network [10] to construct the face recognition classifier to improve the classifier performance. For the input fused and compacted face recognition decision information system $S^{\beta_w} = \{U, B^{\beta_w}UD\}$, the supervised learning-based SCN equivalent network can be defined as:

$$\varphi(B^{\beta_w}, \boldsymbol{\theta}) = \sum_{s=1}^{n_b} \vartheta_s \hbar_s(\omega_s \cdot B^{\beta_w} + b_s) \quad (2)$$

where, $\boldsymbol{\theta}$ is the output layer weight vector of SCN network, ω_s and b_s are the input layer weight and the hidden layer offset of SCN network, respectively, $\omega_s, b_s \in [-\lambda, \lambda]$, $\hbar_s(\cdot)$ is the basis function, and n_b is the number of base functions.

The constraints of the network parameters ω_s and b_s are:

$$\zeta_b = \frac{(e_{b-1}^T(U_i) \cdot A_b(U_i))^2}{A_b^T(U_i) \cdot A_b(U_i)} - (1 - v - \xi_b) e_{b-1}^T(U_i) e_{b-1}(U_i) > 0 \quad (3)$$

where, $A_b = \hbar_s(\omega_s \cdot B^{\beta_w} + b_s)$, $e_{b-1}^T(U_i)$ is the output error obtained by the $b - 1^{th}$ basis function. See [10] for details on SCN.

4. Face recognition mechanism based on error feedback

4.1. Representation of face recognition error

From section 3.1.3, the classified criteria of the training face image dataset U can be obtained with the limited domain under the condition of specific feature effectiveness β_w . Then, for the input testing samples, the recognition result can be obtained through the same facial feature extraction and classified process. However, the result has a certain degree of uncertainty, that is to say, the current feature effectiveness condition cannot fully meet the adaptation needs of all testing samples. In order to increase the credibility of recognition results, human cognition thinking is simulated in this paper, which measures the uncertainty of face recognition results under certain feature effectiveness condition, to provide the heuristic knowledge for the feature effectiveness optimization at feedback layer, to improve the system performance. In the process of the w^{th} feedback recognition, based on the given feature effectiveness parameter β_w , for the testing face image dataset $Y = \{Y_1, \dots, Y_d\}$, the uncertain recognition result $P_t^{\beta_w}$ of the t^{th} ($t \in d$) testing sample Y_t can be obtained. For consistency, the parameter w is used as the system feedback number. S^{β_w} and B^{β_w} respectively represent the constructed face recognition decision information system and the fused and reduced feature space of the training face image dataset by the w^{th} feedback recognition.

Therefore, in order to obtain the error information of the testing face image recognition result, this paper uses the method in Ref [6] to construct the error semantic information system of the testing sample Y_t :

$$\Pi_{t,w} = (U_{t,w}, M(t, w)) \quad (4)$$

where, $U_{t,w}$ represents the semantic error field of the recognition results for Y_t and training face images with the same class, and $M(t, w)$ represents the semantic error matrix obtained of Y_t in the current feedback recognition process.

Therefore, based on the equivalence relation, the measure index in the form of entropy function can be used to represent the face recognition error of the current recognition process, namely, the latent semantic entropy of the recognition error of Y_t in the w^{th} feedback recognition process is

$$H_{t,w} = - \frac{\sum_{\sigma=1}^p \frac{|E_{\sigma}|}{|U_{t,w}|} \log_2 \frac{|E_{\sigma}|}{|U_{t,w}|}}{\log_2 n_w} \quad (5)$$

where, $E_{\sigma}(\sigma \in [1, p])$ is the σ^{th} equivalence class in the p -dimensional quotient obtained by dividing $U_{t,w}$ with respect to $M(t, w)$. The smaller $H_{t,w}$, the smaller the recognition error of Y_t , and vice versa.

4.2. Feedback adjustment index based on recognition error

The purpose of the error feedback adjustment proposed in this paper is to repeatedly recognize within the feasible domain of the classified accuracy parameter β to obtain the optimal recognition performance. Therefore, based on $H_{t,w}$, the incremental calculation model of classified accuracy β_w is constructed, which provides a quantitative standard for the optimal feedback adjustment with the constraint of entropy measure index.

Based on human cognition thinking from whole to local, the classified accuracy β_w of non-uniform transformation is more in line with human sensory characteristics. Therefore, in the w^{th} feedback recognition process, based on β_w and the latent semantic entropy $H_{t,w}$ of the recognition error of Y_t , the classified accuracy β_{w+1} in the $w + 1^{th}$ feedback recognition process can be defined as:

$$\begin{cases} \beta_{w+1} \leftarrow \beta_w + \Delta\beta_{w+1} \\ \beta_1 \leftarrow 0.5, \beta_w \in (0.5, 1] \\ \Delta\beta_{w+1} = \frac{\alpha \times \min_{t \in [1, d]}(H_{t,w})}{w(2^{\alpha}-1)} \end{cases} \quad (6)$$

where, α is a real number and $\alpha \neq 1$. Thus, there are $w \uparrow$ and $\Delta\beta_{w+1} \downarrow$, namely, the feedback adjustment is iteratively performed from coarse to fine.

4.3. Face recognition algorithm based on feature fusion and error feedback

From the above analysis, this paper presents a face recognition algorithm based on feature fusion and error feedback, as shown in Algorithm 1.

Algorithm 1: Face Recognition Algorithm Based on Feature Fusion and Error Feedback

Input: U, Y, expected error ε , maximum $n_b^{\max}$ of base functions.

Output: Cognitive result η_{opt} .

1. **Begin;**
2. $\beta \leftarrow 0.5, w \leftarrow 1;$
3. **While** $\beta_w \leq 1$
4. **While** $n_b \leq n_b^{\max}$
5. Obtain the best ω and b based on Eq. (2) and (3);
6. **End While;**
7. Obtain $P_t^{\beta_w}$, and Calculate $H_{t,w}$,
8. **If** $H_{t,w} < \varepsilon$, **Then**
9. $\eta_{opt} \leftarrow P_t^{\beta_w};$
10. **Else** $w \leftarrow w + 1$, regulate β_{w+1} based on Eq. (6);
11. **End If;**
12. **End While;**
13. Get the best cognitive results of the testing samples η_{opt} .
14. **End**

5. Experiment and result analysis

In order to verify the effectiveness of the method, the LFW face image database was used for testing

and comparison experiments, which contains 5000 people and 13000 face images in total. In this experiment, 70% face images were randomly selected as the training dataset U , and the remaining 30% as the testing dataset Y . 500 random sampling experiments are used to obtain the average recognition rate to verify system performance. All face images participating in the experiment were with the size of 250×250 , and some LFW face images are shown in Figure 2. Based on empirical analysis [8-10], the following parameters were selected for testing comparison experiments. The direction and scale parameters of the two-dimensional Gabor wavelet kernel function are chosen to be $u \in \{0,1,2,3,4\}$ and $v \in \{0,1,2,3,4,5,6,7\}$. The number of CNN network layer is selected as $l = 11$, the feasible domain of SCN network parameter n_b is selected as $\{5, 10, 15, \dots, 80\}$ (step size is 5), and the search range λ of ω and b is $\{1, 15, 30, 45\}$. All experiments were run on Intel Core i5 CPU 3.0GHz, 16G memory, GTX1080Ti.



Fig.2 Parts of face image samples

Fig. 3 shows that in a certain experiment, when the facial image feature extraction parameters are selected, the parameters ω and b are selected based on the optimal λ , and the classified accuracy $\beta = 0.8$, the changing curve of the recognition rate of the testing samples is with respect to the number of basis functions n_b of the SCN classifier. It can be seen from Fig. 3 that increasing n_b can improve the system performance within a certain range. However if the selection range of n_b is too large, it will lead to the over-fitting of the mapping relationship before input features and output labels, to affect the recognition rate of the testing samples.

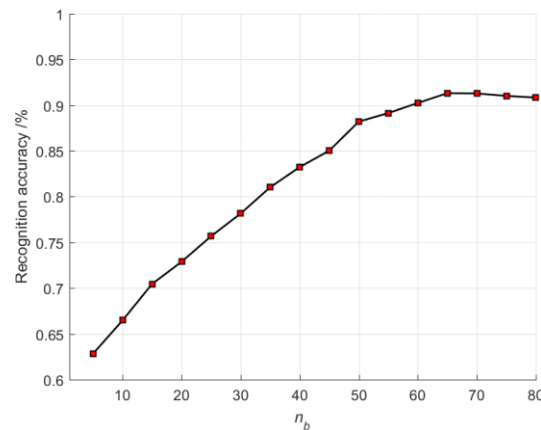


Fig. 3 Recognition accuracy of testing samples vs. various base function sizes n_b

Fig. 4 shows the changing curve of the recognition rate of the testing dataset with respect to different classified accuracy β after the facial image feature extraction and classified parameters are selected in a certain experiment. It can be seen from Fig. 4 that when β changes from 0.5 to 1, the recognition rate of the testing dataset tends to a slight decline after rising first, which indicates that the classified quality of the variable precision rough set model is lower when β is small, and the extracted features based on the model are rough. When β is adjusted according to the recognition error, the features used are better. Therefore, some testing samples with higher similarity or poorer quality can be further analyzed and recognize to improve the system performance. However, when β tends to 1, the fault-tolerant performance of the classified model decreases gradually. With $\beta = 1$, the variable precision rough set

model degenerates into the classical rough set model, which also affects the system performance to some extent.

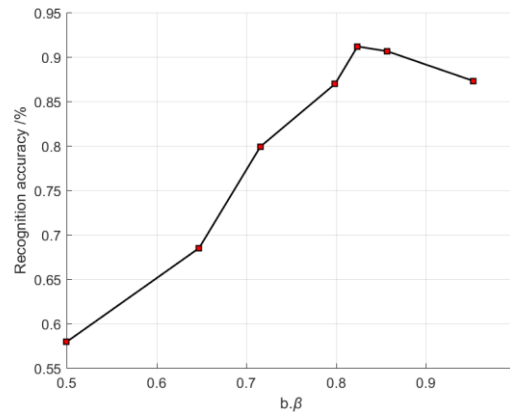


Fig. 4 Recognition accuracy of testing samples vs. various classified accuracy β

In order to verify the effectiveness of the proposed method, the same face image samples as the input database are used, respectively. Using 500 random sampling experiments, in the same computer performance environment, the recognition performance of the proposed algorithm and other open-loop recognition methods are compared, including PCA[11]+SCN, Gabor wavelet [12]+SCN, Gabor+PCA+SCN, geometric Gabor texture feature[8]+SCN, CNN+SCN, geometric Gabor texture feature+CNN+RVFL, and geometric Gabor texture feature+CNN+SVM. The experimental results are shown in Table 1. All data were expressed as mean $\pm$ standard deviation.

Table 1. Performance comparison for various recognition methods

Different methods	Average recognition accuracy /%	Average testing time /s
Our method	91.26 ± 0.6	6.8 ± 0.6
Our method (open-loop)	90.33 ± 0.8	6.6 ± 0.9
PCA+SCN	86.35 ± 0.8	5.0 ± 1.0
Gabor+SCN	85.47 ± 1.2	4.9 ± 0.7
Gabor+PCA+SCN	87.04 ± 0.8	5.4 ± 1.1
Geometric Gabor texture feature+SCN	85.62 ± 0.7	4.2 ± 1.5
CNN+SCN	88.38 ± 0.8	5.6 ± 1.2
Geometric Gabor texture feature+CNN+RVFL	89.54 ± 0.9	6.3 ± 0.7
Geometric Gabor texture feature+CNN+SVM	89.01 ± 0.7	6.5 ± 0.9

It can be seen from Table 1 that the proposed method is effective and feasible. The feedback adjustment mechanism based on the recognition error effectively simulates human cognitive thinking of repetitive deliberation and comparison. When other conditions are fixed, the feedback adjustment of the error entropy for uncertain recognition results is used to repeatedly extract more detailed facial image features, to establish a multi-level classified model with full view, which has better system performance than the open-loop recognition mode. In addition, under the open-loop recognition model with the same classifier, the feature fusion method in this paper has certain advantages compared with geometric features and statistical feature-based methods, which has sufficient data mining ability in feature extraction and considers the structural characteristics of facial features. Finally, the SCN classifier used in this paper has better classified performance than RVFL and SVM classifiers. SCN has a good universal approximation ability, especially compared with RVFL, which gives the selection range of the network parameters ω and b , and has better generalization performance.

6. Conclusions

This paper explores a face recognition method based on feature fusion and error feedback. Firstly, a

feedback recognition model based on recognition error is proposed to simulate human cognitive thinking. Through the error feedback mechanism, the multi-view and multi-level dynamic facial feature space and classified criteria can be built to realize the intelligent recognition process from whole to local and from coarse to fine. In addition, the feature fusion method increases the information amount of the feature space and effectively removes the redundant information. The SCN classifier fully exploits the classified information contained in the complex feature space, which effectively improves the system performance.

However, the method in this paper is currently based on the testing comparison experiment of supervised learning and the limited face database. However, there are often a large number of unlabeled samples in the actual production life. Therefore, the method in this paper could be appropriately modified to adapt to the open set and the unsupervised learning process with unlabeled samples, which is the focus of our next work.

Acknowledgments

This work was supported by National Natural Science Foundation of China (51877060), Special funds for basic scientific research business fees of central colleges and universities (PA2019GDQT0006), State Grid Corporation Headquarters Technology Project (52110418001L).

References

- [1] Li W J, Wang C J, Zhang W, Chen S F, Survey of human face recognition [J]. Pattern Recognition and Artificial Intelligence, 2006, 19(1): 58-66.
- [2] Zhang Y, Wang Y N, Gabor filter envelopes-based face recognition algorithm [J]. Journal of Image and Graphics, 2018, 13(12): 2314-2320.
- [3] Zhang B P, Research on automatic recognition of color multi-dimensional face images under variable illumination [J]. Microelectronics & Computer, 2017, 34(5): 128-136.
- [4] Chen K Q, Wang J P, Li W T, et al. Variable Granularity and Simulated Feedback Mechanism Based Burning State Intelligent Cognitive Method of Rotary Kiln Sintering Process [J]. Pattern Recognition and Artificial Intelligence, 2015, 28(11): 1013-1022.
- [5] Li W T, Cao Z D, Zhu C H, et al. Intelligent feedback cognition of greengage grade based on deep ensemble learning [J]. Transactions of the Chinese Society of Agricultural Engineering, 2017, 23: 276-283.
- [6] Chen K, Wang J, Li W, et al. An Intelligent Cognition Method of Human Health States Based on a Variant Knowledge Granularity Feedback Mechanism [J]. IEEE Access, 2017, 5(1):19570-19580.
- [7] Yang Z G, Ai H Z. Cluster-based face image retrieval and its relevance feedback [J]. ACTA AUTOMATICA SINICA, 2008, 34(9): 1033-1039.
- [8] Yang F, Su J B. Face recognition based on explicit facial features by fusion construction method [J]. Acta Electronica Sinica, 2012, 40(3): 466-471.
- [9] Lecun Y, Bengio Y, Hinton G. Deep learning [J]. Nature, 2015, 521(7553):436-444.
- [10] Wang D H, Li M. Stochastic configuration networks: fundamentals and algorithms [J]. IEEE Transactions on Cybernetics, 2017, 47(10):3466-3479.
- [11] Turk M, Pentland A. Eigenfaces for recognition [J]. Journal of Cognitive Neuroscience, 1991, 3(1):71- 86.
- [12] Liu C, Wechsler H. Gabor feature based classification using the enhanced fisher linear discriminant model for face recognition [J]. IEEE Trans. on Image Processing, 2002, 11(4): 467-476.