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Research on Evolutionary Neural Network Method Based on Multi-feature Fusion

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Abstract

Evolutionary neural network is an information processing method combining artificial neural network and evolutionary algorithm, which uses evolutionary algorithm to learn the topological structure and weights of neural network at the same time. The problem of fast detection and recognition of targets by machines has always been a hot spot in the field of machine vision. Feature extraction is one of the core steps in face recognition, and accurate and complete description of face information is the key to improve recognition accuracy. The evolution of neural network includes the evolution of network structure and the evolution of network connection weights. The starting point of network evolution is to regard the learning process of network as the process of searching the optimal structure in the structure space. Because evolutionary computation is a kind of global random search algorithm, they can quickly and effectively find the global optimal value in complex, multi-peak and nondifferentiable large vector space. Based on artificial neural network and training methods, this paper proposes an evolutionary neural network and face recognition algorithm based on multi-feature fusion.

Keywords

Neural network, evolutionary algorithm, information processing, multi feature fusion, face recognition.

1. Introduction

Neural network is a parallel information processing system composed of a large number of nonlinear processing units connected closely. Because of its powerful learning ability and information representation ability, it is widely used in pattern recognition, automatic control and system decision-making [1]. Target comprehensive recognition is a process of obtaining target identity information by fusing target information detected by various sensors and making full use of mutual complementarity and redundancy [2]. Network evolution is composed of two parts: evolutionary learning of basic network modules and integration based on module network [3]. Evolutionary neural network is an information processing method combining artificial neural network and evolutionary algorithm. It uses evolutionary algorithm to learn the topological structure and weights of neural network at the same time [4]. When the current global optimum cannot be found due to the algorithm problem of evolutionary algorithm, the network structure will be expanded, that is, the problem will be converted into a more complex structural topological complexity of neural network, and the topological complexity of network will in turn cause the algorithm difficulty of evolutionary algorithm [5]. Because evolutionary computation is a kind of global random search algorithm, they can quickly and effectively find the global optimal value in the complex, multi peak, non differentiable large vector space, so as to make up for the shortcomings of traditional neural network learning algorithm [6].

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At present, with the rapid development of artificial intelligence technology, it can be used in many fields. The problem of machine rapid detection and recognition of targets has always been a hot spot in the field of machine vision [7]. Compared with other recognition methods, face recognition has the advantages of convenience, high security, easy implementation and installation. Two dimensional face recognition has many limitations under the conditions of illumination, posture, expression, occlusion and aging [8]. This is mainly because the essence of two-dimensional image is the projection of three-dimensional objects on two-dimensional plane, and it is the simplification of three-dimensional information in two-dimensional space. For the evolutionary learning algorithm of neural network, as long as the correct fitness function can be established, it can implement effective learning for the network of various structures, thus breaking the limitations of network structure and neuron type on the learning algorithm [9]. Feature extraction is one of the core steps of face recognition, and accurate and complete description of face information is the key to improve recognition accuracy [10]. The research in the field of evolutionary neural network is more difficult, mainly because it contains two complex fields of evolutionary computing and neural network, which have not yet been solved [11]. If we can make full use of the multiple features provided by the image and realize the complementarity between different features, we are expected to obtain more reliable change detection results [12]. In this paper, based on artificial neural network and training methods, an evolutionary neural network and face recognition algorithm based on multi feature fusion is proposed.

2. Modeling idea of evolutionary neural network method

Evolutionary neural network method not only makes use of the nonlinear mapping, network reasoning and prediction functions of neural network, but also makes use of the global optimization characteristics of genetic algorithm, which has high application significance in dealing with complex engineering problems without obvious mathematical expression between variables and objective function values. In the process of face recognition, feature extraction directly affects the recognition results. There are many features used in 3D face recognition, among which the common ones are based on geometric information of face surface and neighborhood information. After the mapping relationship between rock mass mechanical parameters and rock mass displacement is established by neural network, the corresponding displacement value can be obtained for any given group of rock mass mechanical parameters through the generalization and prediction ability of the network. If the error of a certain displacement value is the smallest compared with the actual displacement value, the rock mass mechanical parameter corresponding to this displacement value is obtained. In order to complete the mapping from input to output, we first consider the problem from a statistical point of view. The input and output vectors are analyzed by statistical clustering, and the input and output vector samples representing class features are extracted as training samples. The initial network designed according to its statistical characteristics can evolve into the initial optimal network reflecting the statistical characteristics of input and output through less steps of adaptive adjustment. With the increase of the scale of the problem, the solution search space of the evolutionary neural network becomes larger and more complex, and the evolutionary learning becomes more difficult, and the original problem of long evolution time worsens [13]. The reason is that the whole evolutionary method ignores the regularity of solving the problem itself, and whenever the same problem of different scales is encountered, evolutionary learning should start from scratch. Genetic operations such as replication, hybridization, mutation, etc. are carried out on chromosomes with each parameter value, and a possible parameter value population of offspring is generated.

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All the input data are introduced into the initial network. After a period of training due to the rapid increase of sample size, there will be a big error in the forward network, that is, the current network structure is not the best structure. At present, people always give a network topology according to experience, and then use a given learning algorithm to learn. If the learning result is satisfactory, it will be successful. Assume that the digital image histogram with gray level is represented by discrete function, as follows:

$$t_{\max} = \frac{1}{\lambda}\ln(\frac{1}{i_0} - 1) \tag{1}$$

a is the total number of pixels. Then the probability of R_t appearing is:

$$dR_t = \chi \cdot a(t) \cdot dt + \delta \cdot a(t) \cdot dw_t \tag{2}$$

The resulting curve is the grayscale image of the image. To normalize the gray level, its transformation function is:

$$H(x,\pi) = E\left[\left(\int_0^{\pi} e^{-cs} \cdot dL_s^{\pi}\right)\right] \tag{3}$$

The gender recognition process based on face sub-regions is shown in Figure 1.

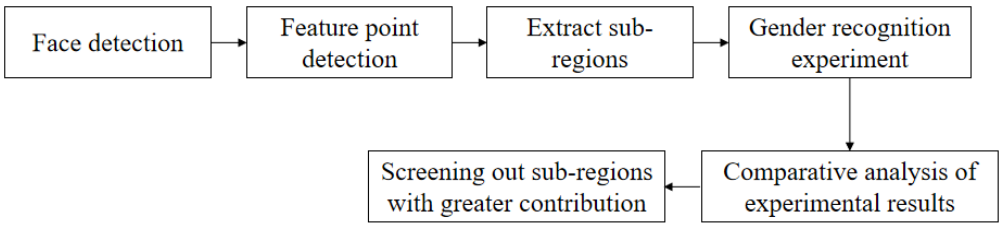

Figure 1 Gender recognition structure diagram based on face subregions

The basic training data is mainly composed of two types of data. The first type of data includes all kinds of face open data sets, and the face images are collected on the spot. These pictures are characterized by clutter, covering high-resolution and low-resolution pictures. Various scenes, such as illumination conditions, facial pose and expression changes, facial obstructions, age changes and other attributes of face images, have large categories of image data samples, thus meeting the requirements for robustness of various low-quality images in the training process. While deepening the depth of the network, it keeps the simplicity of the network, and adopts the internal evolution mechanism to filter the responses of neurons, adds residual modules in the network, and introduces weight factors to give different weights to the output single features, and finally weights and fuses multiple features to improve the recognition [14]. Firstly, the original image is convolved with the filter in the convolution layer to obtain several feature images, and then the features are blurred by the down-sampling layer. After extracting the features layer by layer, the features used to identify the image are output through the full connection layer. Convolutional neural network is mainly composed of three parts, which are input layer, hidden layer and output layer. The hidden layer contains a repetitive structure composed of multiple convolution layers and sub-sampling layers.

3. Target feature fusion

The features extracted by a single sensor can't get a complete description of the target because of its own detection characteristics, and it is often beneficial to reduce the false recognition rate by using independent and complementary features extracted by various heterogeneous sensors. Some traditional genetic algorithms can obtain the global optimal solution by simulating the biological evolution process of natural selection and genetic mechanism. The evolutionary learning process starts from a randomly generated initial solution group, and

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generates a new solution by applying various genetic operators to the solution group. Then, the fitness function is used to calculate the fitness of each individual. Then, according to the principle of "survival of the fittest", the winning individuals are selected by certain selection operators to form the next generation solution group. Set design of base classifiers, which builds a group of base classifiers independently on a given data set, requires that this group of base classifiers can achieve the best classification performance after fusion. The recognition accuracy of the fusion classifier derived from lifting and bagging is higher than that of the single classifier derived from the original training data set. Although lifting can often get higher accuracy than bagging, there is a risk of over-fitting because lifting pays attention to misclassified samples.

Deep belief network is similar to other deep learning models, which can learn by inputting low-level feature description and get more abstract and effective feature description. A number of structural layers are connected in series to form a deep convolution neural network for feature extraction. The deep convolution neural network designed in this way is more abundant in feature extraction, which greatly improves the recognition accuracy. In the same experiment, although the recognition accuracy of fusion classifier is not improved much compared with the best BP neural network, the recognition accuracy is still higher than that of the best BP neural network. In addition, the fluctuation of recognition accuracy of fusion classifier is obviously smaller than that of any BP neural network. Then, based on image segmentation, spectral features, texture features and spatial features are extracted and normalized to prepare for the subsequent multi-feature fusion. If the network error has not yet reached the requirements, carry out the third stage of network design and consider adding a new hidden layer. The new network structure should further reduce the total network error. Displacement back analysis method based on evolutionary neural network is a general back analysis method of rock mechanics parameters and original rock stress. As long as the model training sample data set is changed according to specific problems, the corresponding rock mechanics parameters and original rock stress values can be obtained. Although the training samples are sufficient, better recognition accuracy can be obtained, but it is easily affected by over-fitting.

Fixed fusion algorithm gives voting rights to each BP neural network and fuses their results to make the final decision. Under the condition of reasonable distribution of voting rights, it can obtain better recognition accuracy and is not easily affected by over-fitting. Compared with other face recognition algorithms, the deep convolution neural network based on internal evolution mechanism and the model weighted face recognition algorithm have higher recognition rate in both standard face and low-quality face data. Five groups of face images are selected from the face database, and the feature points are located by the average location method and EBGM location algorithm respectively, and different recognition rates are obtained. As shown in Table 1.

Table 1 Comparison of recognition rates of different algorithms for different face images

Algorithm	Graph group 1	Graph group 2	Graph group 3	Graph group 4	Graph group 5
Average positioning method	76.4%	68.2%	63.0%	75.5%	77.4%
EBGM positioning algorithm	83.9%	86.6%	84.0%	82.2%	80.7%

Because the evolutionary learning algorithm performs random global search, the possibility of falling into local minimum is greatly reduced. In addition, the fitness function does not need to be differentiable, so the evolutionary learning algorithm can be applied to a wider range of

neuron types. Because in the evolutionary learning process of neural network, variation plays a leading role and crossover plays an auxiliary role, the crossover auxiliary role of GA is more obvious in the learning of simple network, while in the learning of complex network, the crossover auxiliary role is easily covered by the dominant role of mutation, so it is not obvious [15]. With the evolution process, the network output error will gradually reduce, when the error is less than a predetermined threshold, the evolution ends. The local contour curves of these regions are selected as recognition features, which not only can distinguish but also greatly reduce the impact of face aging, and are not easy to be affected by glasses and masks. Usually, the first mock exam model is better than the other models, because it is smooth and highlighting the best performance of each basic model, and it also discards every basic model that is not performing well. As long as the number of experiments is enough, the optimal weight combination can be approximated, which can not only effectively avoid the optimization process falling into local optimum, but also quickly obtain the approximate optimal weight combination, and the method is easy to implement. All the connections and parameters in the network are arranged in a series in a certain order. If the hidden layer neuron is added successfully, the optimized coding string will be added to the original network coding.

4. Conclusion

Evolutionary neural network method uses genetic algorithm to search the neural network structure, and uses the best generalized predictive learning algorithm to train the network structure, so as to find the most ideal neural network model. Effective sample support is the key to the implementation of this method, which constructs the basic criteria to distinguish the changed class from the unchanged class in the multi feature set. Parameter identification is a large space search problem. Genetic algorithm is once again used to search the value of parameters to be inversed in the global space, so that the back analysis results are globally optimal. The follow-up work can start from increasing the number of sub convolution neural network and reducing the effective range of the number of neurons in each layer to get the accurate number, so as to further improve the recognition rate of the network model. Mutation is the main genetic operator in the process of neural network evolutionary learning, which has a positive significance to design a better neural network evolutionary learning algorithm. Evolutionary neural network provides a new way for neural network structure design and weight learning. With the further study of evolutionary neural network, the advantages of artificial neural network will be better reflected in more complex applications. In order to improve the intelligent degree of the method and reduce the manual participation, the follow-up research can focus on the unsupervised multi feature fusion method.

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References

[1]. Wang Rujiao, Ji Donghong. Twitter sentiment classification method based on convolutional neural network and multi-feature fusion[J]. Computer Engineering, 2018, 044(002):210-219.
[2]. Shi Xuechao, Zhou Yatong, Chi Yue. Face gender recognition based on multi-layer feature fusion adjustable supervision function convolutional neural network[J]. Computer Application Research, 2019, 036(003):940-944.
[3]. Lan Hongyu, Yao Xifan, Lei Yi. Workpiece recognition and detection based on multi-feature fusion of convolutional neural network[J]. Modular Machine Tool and Automatic Manufacturing Technology, 2019, 546(08):49-53.

[4]. Ma Dongmei, He Sansan, Yang Caifeng, et al. Semantic segmentation of feature fusion convolutional neural network[J]. Computer Engineering and Applications, 2020, 056(010):193-198.
[5]. Wang Zengrong. Traffic signal recognition based on single-stage neural network and feature fusion method[J]. Image and Signal Processing, 2020, 009(002):79-85.
[6]. Wang Weibo, Zhang Bin, Zeng Wenlu, et al. Power quality disturbance classification based on feature fusion one-dimensional convolutional neural network [J]. Power System Protection and Control, 2020, 048(006): 53-60.
[7]. LIU Mingtong, ZHANG Yujie, XU Jin'an, et al. Neural network dependency syntactic analysis model based on multi-feature fusion coding[J]. Journal of Chinese Information Processing, 2018, 032(012):41-47.
[8]. [8] Wen Yu. Motion video shot conversion detection based on multi-feature fusion and improved neural network [J]. Modern Electronic Technology, 2021, 576(01): 82-85.
[9]. Zhou Yongdong, Zhang Yun, Cao Yanrong, et al. Sentiment analysis based on feature fusion segmented convolutional neural network[J]. Computer Engineering and Design, 2019, 040(010):3009-3013+3029.
[10]. Wang Jianxia, Chen Huiping, Li Jiaze, et al. Facial expression recognition based on multi-feature fusion convolutional neural network[J]. Journal of Hebei University of Science and Technology, 2019, 40(6):540-547.
[11]. Li Zhijin, Zhang Liang, Wu Peng, et al. Car model fine recognition based on feature fusion convolutional neural network[J]. Computer Engineering and Design, 2020, 041(001):226-230.
[12]. Yao Lisha, Xu Guoming, Zhao Feng. Facial expression recognition based on local feature fusion of convolutional neural network[J]. Progress in Laser and Optoelectronics, 2020, 663(04):338-345.
[13]. Sun Jinguang, Meng Fanyu. Feature weighted fusion face recognition method based on deep neural network [J]. Computer Applications, 2016, 36(002):437-443.
[14]. Wang Weimin, Tang Yang, Zhang Jian, et al. Face recognition algorithm based on feature fusion of convolutional neural network[J]. Computer and Digital Engineering, 2020, 363(01):93-97+110.
[15]. Wang Jiaxin, Lei Zhichun. A Convolutional Neural Network Face Recognition Algorithm Based on Feature Fusion[J]. Progress in Laser and Optoelectronics, 2020, 669(10):339-345.