Face Recognition Technology Based on Neural Network

Abstract An artificial neural network (ANN) is an information processing system established by simulating the structure and logical thinking of the human brain. It uses the interconnection between a large number of neurons to form a network system that can perform complex calculations, and is widely used. For various complex problems, by choosing different model structures and transfer functions, various neural networks can be formed and different expressions of the relationship between output and input can be obtained. Face recognition is one of the important research directions of ANN. It mainly refers to the automatic inference of identity, expression, age, gender and other attribute information through the analysis of facial images, videos or pictures and video collections of people. Widely used in mobile payment, safe city, criminal investigation and other fields. The origin, types and research progress of ANN are introduced, and the face recognition technology based on neural network are investigated.

1 Introduction

With the advent of computer technology, people have discovered that its computing power far exceeds that of humans. However, computers often cannot be used as effective auxiliary tools for problems involving judgment, classification, and not clearly defined, such as data prediction, image classification and so on. In the summer of 1956, the Artificial Intelligence Symposium was held at Dartmouth College, where McCarthy first proposed the concept of "artificial intelligence (AI, artificial intelligence)". The so-called artificial intelligence is the study of how to make computers do intelligent work that only humans could do in the past, including natural language processing, intelligent search, reasoning, planning, machine learning, neural networks and so on. As an important branch of artificial intelligence, artificial neural network can simulate the human brain to deal with some problems that require high-intensity learning and calculation, so as to solve some complex problems better and faster.

Artificial Neural Network (ANN) is a logical algorithm for information processing by simulating the way of thinking of the human brain. Each connection in the network is similar to a synapse between neurons for information transmission between neurons. The interconnection between neurons forms a neural network to obtain the final feedback [1,2]. The unique structure and information processing method of neural network make it have obvious advantages in many aspects and have a wide range of applications. The main application fields include intelligent driving [3-5], robot control [6], automatic power system control [7], signal processing [8,9], chemical process control and optimization [10-12], image processing [13,14], health care and medical treatment[15,16] and game theory[17]. This article will mainly introduce the origin and types of neural network, and analyze its application research progress in the field of face recognition.

2 The origin of artificial neural network

The structure of ANN The structure of artificial neural network As shown in Figure 1, the structure of artificial neural network includes input layer, hidden layer and output layer. Neurons, also known as perceptrons, are the smallest units that make up a neural network. The composition of the perceptron consists of three parts: input weights, activation function and output. By substituting the output, weight and bias of the neurons in this layer into the activation function, the input of the neurons in the next layer can be obtained, and so on, and finally the output of the neurons in the output layer can be obtained [18,19]. The input layer is responsible for receiving external information and data; the hidden layer is responsible for processing information and continuously adjusting the connection properties between neurons, such as weights, feedback. The output layer is responsible for outputting the calculated results. The weight reflects the connection strength between the units, and the feedback represents the positive and negative correlation between the units.

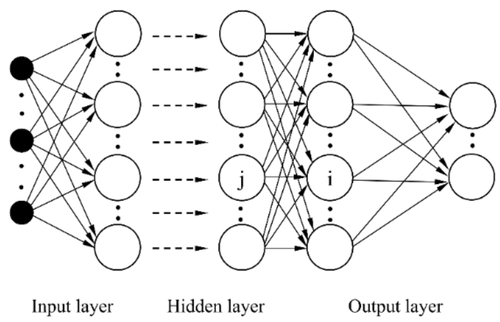

Figure 1 The structure of artificial neural network

Research progress of ANN In 1943, McCulloch and Pitts [20] proposed a research method for mathematical simulation by simulating biological nerve cells, called the M-P model, which marked the birth of artificial neural networks. Then, the Hebb learning rule proposed by Hebb [21] is still a basic principle of neural network learning algorithms; in 1960, Widrow [22] proposed an adaptive (Adaline) linear element model. These models and algorithms enrich the neural network system theory to a great extent. But the development of neural networks stagnated for nearly 20 years due to difficulties encountered with the crossing limits of electronic circuits. In the 1980s, new theories such as ART network, cognitive machine network, Boltzmann machine theory, and parallel distributed processing were continuously proposed, which solved the two problems proposed by Minsky [23]. Marked by the Hopfield model proposed by Hopfield [24], artificial neural networks have entered a new era of development. In 1986, Rumelhart and Hinton [25] proposed a multilayer feedforward network (BP) algorithm. The BP algorithm includes the forward propagation of the signal and the reverse propagation of the error. This bidirectional feedback structure can reduce the error signal to the minimum at that time. In 1998, Vapnik [26] proposed the SVM algorithm, the concept of support vector machine. In 2006, Hinton [27] alleviated the local optimal solution problem of ANN by using pre-training method.

Since the advent of the Hopfield network model [24], the artificial neural network has derived hundreds of models to achieve data analysis and utilization by simulating other industries, such as thermodynamics, mathematics, and medicine. The following will introduce the three most used neural networks: Feedforward Neural Network (BP), Radial Basis Neural Network (RBF) and Convolutional Neural Network (CNN).

Feedback Neural Network (BPNN) Rumelhart et al. [25] proposed a feedback neural network (BP) to compensate for the shortcomings of multi-layer neural networks. The basic idea is to provide learning samples to the neural network, and modify the weight according to the error between the actual output value and the expected output value, so that the output value obtained by the modified network is as close to the expected output value as possible. The specific steps are as follows [28,29]:

(1) Take the sum of squared errors of neurons in the output layer as the objective function, as shown in equation (1), to find the weight and bias when the objective function reaches the minimum value:

$$J_d = \sum_{i \in \text{output layer element}} \left(t_i - y_i\right)^2 \qquad (1)$$

where J_d is the error of the sample, and t_i and y_i are the predicted and actual values, respectively.

(2) Using the stochastic gradient descent algorithm, the error is optimized as shown in equation (2):

$$\omega_{j,i+1} = \omega_{ji} - \eta \frac{\partial J_d}{\partial \omega_{ji}} \tag{2}$$

where the partial derivative is calculated by the chain derivation rule, and is treated differently according to the position of the j node (hidden layer or output layer).

The error terms of the output layer, hidden layer and input layer are calculated in turn, and all weights are updated [30]. The weights are adjusted every time a sample is processed. After multiple rounds of iterations (that is, all training data are repeatedly processed for multiple rounds), the weights of the network model can be trained to achieve the objective function.

RBF Neural Network The output value of the RBF Neural Network is no longer 0 or 1, but a set of smooth numbers with the largest output value at a specific input value. RBF network uses radial basis function as transfer function. Compared with BP neural network, there is only one hidden layer, so RBF neural network is superior to BP neural network in function approximation, classification ability and learning speed [31].

Convolutional Neural Networks (CNN) Vaillant et al. [32] applied convolutional neural networks to face detection as early as 1998, but it was not until 2012 that the convolutional neural network AlexNet [33] made a major breakthrough in image recognition. LeCun [34] proposed LeNet-5 with deep structure as a classifier for image recognition. Its basic structure mainly includes input layer, convolution layer, pooling layer, fully connected layer and output layer. The features of the convolutional layer are obtained from the local features of the previous layer through the weights shared by the convolution. The features of the input image are extracted by multiple convolution layers and pooling layers, and gradually change from low-level to high-level. The high-level features are then classified by the fully connected layer and the output layer to generate a one-dimensional vector, representing the category of the current input image. Therefore, according to the function of each layer, the convolutional neural network can be divided into two parts: feature extractor (including input layer, convolutional layer and pooling layer), classifier (including fully connected layer and output layer). CNN simulates biological visual perception: visual perception cells receive light signals from the retina, but a single cell does not receive information from all signals. It can only be activated by sensing the stimulation in the innervated area, and the visual space is generated by the superposition of multiple cells. Krizhevsky et al. [35] proposed AlexNet, which greatly improved the classification accuracy on the Image Net dataset.

3 Research progress of face recognition technology based on ANN

In recent years, with the continuous breakthrough of computer vision technology, the accuracy of object detection and target recognition has been improved by leaps and bounds. Traditional face recognition algorithms such as Principal Component Analysis (PCA) have certain shortcomings in terms of accuracy and characteristics. Face recognition with the help of artificial neural networks has become mainstream. It is generally accepted that face recognition may rely on both compositional information (e.g. eyes, mouth and nose) and non-compositional/holistic information (spatial relationships between these features), although how these cues should be best integrated remains unclear.

Belhumeur, Swets and Barlett et al. [36-38] proposed the Fisherman Face method (FLD) to leverage class information to enhance the discriminative ability. These algorithms are largely based on maximizing the ratio between the "class scatter matrix" to the "within class scatter matrix" to find another subspace that best distinguishes the input data, where LDA is applied to the classification of PCA-transformed face data, that is, "PCA+LDA". In the face recognition process, PCA or LDA is used to extract the face features and is classified by ANN using radial basis function (RBF) network [39,40] or backpropagation (BP) [41-43]. When a back-propagated neural network was used to classify 40 face subjects using facial features provided by PCA and LDA, the face recognition results were shown to be superior to Euclidean distance [44].

Rama Linga Reddy et al. [45] proposed a new algorithm using multi-scale face components and Eigen/Fisher features of artificial neural networks. The basic idea of this method is to downsample the face components of different resolutions such as eyes, nose, mouth and full face according to the saliency of the face components, and perform subspace principal component analysis (PCA) or linear analysis to construct face feature vector. They studied the face recognition performance of PCA+BP, PCA+RBF, LDA+BP and LDA+RBF for the multi-scale features of the ORL face database. 200 Faces of 40 subjects were used for training, and another 200 faces are used for testing. The results showed that the LDA+RBF method achieves a recognition rate of 98.40% for 40 objects with an image size of 112×92 with a 40:50:40 ANN structure.

Ouyang et al. [46] proposed a joint convolutional neural network based pedestrian detection model. The model integrates feature extraction, deformation processing, occlusion processing, and feature classification in a single convolutional neural network, and automatically establishes the interrelationships between pedestrian components through end-to-end training, enhancing the separability of features. Chen et al. [47] proposed the concept of face candidate regions, and used the Adboost face detector to prejudge all candidate regions and reserve the candidate regions that may be faces. Then, a small-scale convolutional neural network was used to judge whether the candidate area is a face, and a medium-scale convolutional neural network was used to complete the classification of all candidate areas.

Gao et al. [48] proposed an image matching method with rotation and scale invariance. The model first established sparse keypoint matching based on local invariant features, and then used the sparse matching result as a reference to complete dense matching. Finally, the dense matching relationship of the wide baseline image is obtained. According to the matching correspondence, the depth information in the two-dimensional image can be recovered, and the three-dimensional reconstruction of the target scene can be realized. Shi et al. [49] made the method affine-invariant by extracting affine-invariant features in the image, which improved the robustness of the model.

Existing face recognition algorithms are vulnerable to various face presentation attacks (face-PA), such as printing paper, video playback, and silicone masks. To deal with the above problems optimally, Zhao et al. [50] constructed a novel deep neural network to deeply encode facial regions and utilized PCA to reduce the dimensionality of deep features while removing redundant and polluted visual feature. A joint Bayesian framework is then used to evaluate the similarity of feature vectors, and finally a face recognition performance of 98.52% was achieved. Zangeneh et al. [51] proposed a novel coupled mapping method for low-resolution face recognition using deep convolutional neural networks (DCNNs). Its architecture consists of two branches of DCNN that map high- and low-resolution face images into a common space with nonlinear transformations. The distances between the features of the corresponding high-resolution and low-resolution images are back-propagated to train the network. The method is evaluated on the FERET, LFW, and MBGC datasets and compared to state-of-the-art competing methods, achieving a 5% improvement in recognition accuracy. Moghadam et al. [52] proposed a novel dynamic deep bottleneck neural network for analyzing and extracting three main features of videos about facial expressions. The proposed model has the advantages of recurrent networks and can be used to analyze the sequence and dynamics of information in videos. The model achieved an average accuracy of 97.77% in identifying the six salient emotions (fear, surprise, sadness, anger, disgust, and happiness) and 78.17% accuracy in identifying emotions. Soni et al.[53] proposed a simple and effective face recognition system using deep learning concepts. It consists of four main steps: preprocessing, cascade feature extraction, optimal feature selection, and identification. The preprocessing of face images mainly focuses on the face detection of the Viola-Jones algorithm. Local Diagonal Extremal Number Pattern (LDENP) is applied to cascade feature extraction. A hybrid meta-heuristic concept, Multi-Verse with Colliding Bodies Optimization (MV-CBO), is used to perform optimal feature selection. Face recognition is performed by an optimized deep neural network (DNN) based on the optimally selected features. Extensive experiments on several benchmark databases demonstrate that the proposed model outperforms existing face recognition methods. Yu et al. [54] constructed a face recognition system based on neural computing models and neural network principles. The experimental results showed that the detection rate of the method is higher and the processing time is shorter.

4 Conclusion

As a paradigm for solving fuzzy problems in the era of intelligence, artificial neural networks have provided many application examples for the era of intelligence. In the future, with the development of hardware technology, the fragmentation and marginalization of cloud services, the intelligence and informatization of cities, and the application of artificial neural networks will increase. Facial recognition is becoming increasingly important in developing a secure environment for organizations and also enhances the use of artificial intelligence in security. For many years, people have been studying face recognition to accurately identify complete face images. Although a lot of research has been done on handling occluded and noisy images, more refinement is still required to achieve high accuracy.

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