Face recognition based on histogram equalization and convolution neural network

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***Abstract*—In order to improve the recognition rate of face recognition, a face recognition method based on histogram equalization and convolution neural network is proposed, which is used for face recognition. First, the histogram equalization method is used to preprocess the face image. Then, we use Google deep learning framework TensorFlow1.3.0 to build convolution neural network. Its structure is referenced to LeNet-5 model, and trained neural network is trained by pre processed face images. Finally, the test samples are input into the completed convolution neural network, and the recognition rate is obtained. By using the method of histogram equalization and convolution neural network to simulate the face images of ORL face database, it is concluded that the algorithm has a high recognition rate.**

Keywords- face recognition; convolution neural network; deep learning; histogram equalization

I. INTRODUCTION

Face recognition technology has been widely applied in all aspects of social life, such as password service, criminal investigation, human-machine interaction and so on. Because face recognition is of great practical value and wide application range, the improvement of its technology has been a hot topic [1-2]. Face recognition includes four parts: face extraction, face image preprocessing, feature extraction, classification and recognition. Higher recognition rate is the main goal for researchers to improve recognition methods. After the continuous improvement and research of the researchers, a series of classical recognition algorithms have emerged in the field of face recognition, such as the principal component analysis (PCA) [3-5], the feature face, the wavelet transform , the hidden Markov model and so on. In recent years, artificial neural network has shown great advantages in pattern recognition, system identification, image processing and so on. Recently, some smart phones have been successfully applied to face recognition technology to unlock mobile phones, and the technology of human face recognition is based on neural network development.

With the expansion of the application field (such as image processing), the problems needed to be solved are becoming more and more complex, and the amount of data is also increased exponentially. The traditional neural network with full connection structure also shows many problems in the face of these situations, for example, the network needs too much training and the time needed for training is too long. The structure is complex and so on. Therefore, when using traditional neural network as classifier, we often need to reduce the dimension of image data separately.

Convolution neural network is a very classic neural network structure used in the field of deep learning in recent years. It has a great advantage in the field of image processing [6]. The convolution neural network has reduced a lot of parameters compared with the fully connected neural network, and the network structure and training process have been simplified. Convolution neural network extract feature information of image, which can effectively reduce the dimension of image data, and do not need to reduce the dimension [7-8] of image data separately. Histogram equalization is a method of preprocessing the image. After preprocessing the image by histogram equalization, the quality of the image will be improved by [9]. Convolution neural network and histogram equalization are used to solve the problem of face recognition. TensorFlow1.3.0, an open source deep learning framework developed by Google Corporation, is used to build neural network.

II. HISTOGRAM EQUALIZATION

Because the collection of face images will be affected by other factors such as light and other factors, the quality of the collected images will be uneven, and the image contrast will be low. For image histogram equalization, image contrast will be increased, and image quality will be improved. The processed image data are saved as input of neural network.

The process of histogram equalization: First, we obtain the probability distribution of all gray levels in grayscale image in turn. The f_i represents the gray level, n_i represents the number of occurrences of the ith gray level, N represents the total number of pixel pixels, $P(f_i)$ represents the ith gray level of the frequency, then:

$$P(f_i)=\frac{n_i}{N} \quad , i\in(0,1,2,...,255) \tag{1}$$

Then calculate the cumulative distribution function:

$$S_k=\sum_{i=0}^{k}P(f_i) \tag{2}$$

Remember g_i for the histogram equalization after the gray level, then:

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$$g_j = INT\left[\left(g_{\max} - g_{\min}\right)s_k + g_{\min} + 0.5\right] \tag{3}$$

Where INT is the rounding operation. Histogram equalization is a mapping of g_j and f_j The gray scale of the image after the equalization is evenly distributed, thus increasing the contrast of the image and facilitating the processing of the later algorithm of face recognition.

III. Convolution Neural Network

The concept of convolution neural network was put forward by Hubel and Wiesel in the 60s of last century, and its first implementation was completed in 1980 by K.Fukushima. The characteristics of the unique non full connection structure and weight sharing of the convolution neural network completely break through the limitations of the network of the fully connected structure, and have outstanding advantages in dealing with the huge data sets. Convolution layer for feature extraction in convolution neural network structure and pool layer for dimension reduction of matrix are the main parts.

A. Volume layer

The function of convolution layer is to extract features of input data, and it is the most important and significant structure in network. Convolution layer is the feature mapping of input sample matrix through filter (convolution kernel). The filter is a two-dimensional matrix, and its size can be customized. The convolution layer traverses the whole input sample and extracts a feature map of the sample. The more the convolution level is, the more the sample feature is extracted. Each filter traverses the entire input sample and gets the corresponding feature map. The depth of the feature graph depends on the number of the filters. Before training, we need to set the number, size and structure parameter of the filter. The process of training is to learn the value of the filter.

Assuming that the m layer is a volume layer, the formula for m layer to achieve convolution is as follows.

$$x_j^m = f\left\{\sum_{i \in M_j} x_i^{m-1} * k_{ij}^m + b_j^m\right\} \tag{4}$$

x_j^m represents the j feature graph of the convolution layer m, on the right side of the equation is the feature graph x_i^{m-1} of the M-1 layer and the j filter k_{ij}^m of the m layer to realize convolution and sum, plus the bias. $f(\ldots)$ is an excitation function. In this paper, ReLU function is used as an excitation function. The realization of the convolution layer is shown in Figure 1.

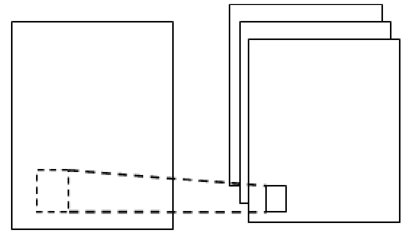

Figure 1. the implementation of the convolution layer

B. Pooled layer

Usually, after every volume layer, there will be a pool layer. The role of the pool layer is to speed up the dimension of the feature map output from the convolution layer. The number of feature maps remains unchanged, and only important information is retained. The common way of pooling is the average pooling of the average value in the neighborhood and the maximum pooling of the maximum value in the neighborhood. The maximum pooling process is shown in Figure 2.

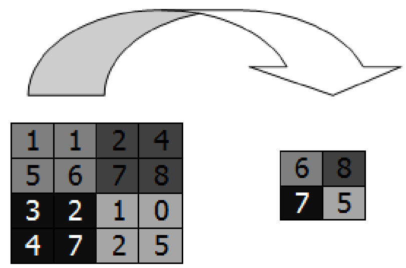

Figure 2. maximum pooling process

C. Classical convolution neural network model LeNet-5

The LeNet-5 model is a classic convolution neural network model, which is proposed by Professor Yann LeCun and has been successfully applied to solve the problem of digital recognition. The LeNet-5 convolution model contains seven layers of structure. The first four layers are convolution layer, pool layer, convolution layer, pool layer, and the last three layers are all connected layers. In this paper, we use TensorFlow1.3.0, a deep learning framework developed by Google Corporation, to build a neural network model. According to the LeNet-5 model, a seven layer convolution neural network model suitable for face recognition is built. The first four layers of the seven layer convolution neural network model in this paper are the coiling layer, the pool layer, the convolution layer, the pool layer, the fifth, sixth layer using the full connection layer, and the last Softmax layer. The main purpose of Softmax layer is to solve classification problems. In TensorFlow1.3.0, the Softmax layer is an extra processing layer, which makes the output of the network become a probability distribution.

IV. Simulation And Algorithm Process

A. Simulation environment

The software used includes Python3.5.2 and TensorFlow1.3.0 developed by Google Corporation. In the field of deep learning, TensorFlow is an open source framework with excellent performance. Its 1.3.0 upgrade version was released in July 2017. The hardware is AMD Athlon (TM) X4 840 processor, the main frequency 3.10GHz desktop computer, the 64 bit operation system. In this paper, we choose the 400 face images of ORL database as 112*92, as the simulation samples. (Each group contains 10 pictures of one person, a total of 40 groups.) In each group of pictures, facial expression and posture varied in varying degrees, and the scale of image was about 10%. The sample set is widely used in published face recognition articles. The results obtained using this sample are pertinent and reasonable to verify the validation of the method used in this paper.

B. Algorithm process

(1) image preprocessing

First, we need to read the face images needed for the simulation, and then we pre treat and save the sample images by histogram equalization. Histogram equalization is applied to improve the quality of the image and highlight the characteristics of the face.

(2) training convolution neural network

First, we use TensorFlow1.3.0 to build the convolution neural network designed in this paper. Then, we extract the pre-processed training sample data and input the convoluted neural network to train.

(3) classification recognition

The pre-processing test set is input into the trained network to classify face images, and then the recognition rate is calculated.

Figure 3. face image comparison of original (left)

TABLE I. THE RECOGNITION RESULTS CORRESPONDING TO THE NUMBER OF TRAINING SAMPLES.

Sample numbers	1	3	5	7	8
Recognition rate(%)	76.1	89.2	94	100	100

C. Simulation results

(1) after histogram equalization, the feature of face sample is enhanced, and the dynamic range of gray scale is expanded. After equalization, the image contrast with the original image is shown in Figure 3.

(2) the 200 pictures of 20 people are simulated. Each group of faces is selected as a training sample. All the images in each group are used as a test except the training samples. The results of the recognition are shown in Table 1.In the simulation results, the lowest recognition rate is 76%, and the number of training samples used is 1. When the training samples of each group are 7, the recognition rate reaches 100%. It can be concluded that the proposed face recognition algorithm based on histogram equalization and convolution neural network has good performance in face recognition.

(3) when the training sample is taken as the test sample, the first layer of the coiling filter size is 7*7, the second layer coiling layer filter is 3*3, the pool layer uses the maximum pool, the algorithm compared with the PCA+BP and PCA+KNN face recognition algorithm is shown in Figure 4. From the simulation results, it can be concluded that the recognition rate obtained by this algorithm is higher than that of the other two algorithms. All the 40 groups of face samples are used for simulation, and the recognition rate is 98.25%. When the number of samples is 100, 200, and 300, the recognition rate of this algorithm is 100%.

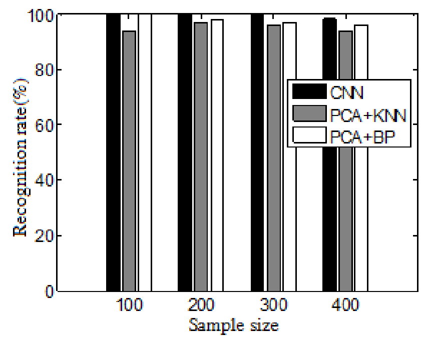

Figure 4. the recognition rate of our algorithm (CNN) and PCA+KNN and PCA+BP algorithm is compared.

V. Conclusion

In this paper, the histogram equalization is used to preprocess the face images. Then, the CNN convolution neural network based on TensorFlow1.3.0 is used to classify the pre processed face samples. The simulation results show that histogram equalization can effectively improve the quality of the images. By comparing with other algorithms, the recognition method of face recognition using histogram equalization and convolution neural network is better than other algorithms. Meanwhile, the face recognition method adopted in this paper has the advantages of simple operation and strong transplantation.

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