Offline Chinese Signature Verification Based on AlexNet

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Abstract. In order to break the limitation of traditional pattern recognition in offline Chinese signature verification, the method of applying machine learning is put forward. First, the offline Chinese signature data set is pre-processed, include removing noises, binarization and normalization. Then the architecture and implementation methods of AlexNet are proposed. The experimental results show the average accuracy of classification has been up to 99.77%, and verification rate is 87.5%.

Keywords: AlexNet · Convolution neural network
Offline signature verification · Writer-dependent

1 Introduction

Biological characteristics of the human body is inherent in the physiological characteristics or behavioral characteristics, physiological characteristics including fingerprints, palm, face, iris, finger vein, etc., behavioral characteristics including gait, sound, handwriting and so on. Signature has a long history as a representative of the individual's identity, and has been widely used in financial and legal industries. Offline signature verification is for static image recognition.

In 2012, Khalajzadeh used convolution neural network (CNN) to verify signatures for Persian [1]. Based on the LeNet-5 architecture, a total of 176 real signatures and a certain number of forged signatures were trained and tested. There were 22 signers. The experimental results showed the accuracy was 99.86%.

Our paper puts forward a method of applying the convolution neural network algorithm AlexNet to recognize offline Chinese signature. Based on the AlexNet, we designed the experimental program. First, preprocessing the signature image, and then, train the writer-dependent classification of real signatures and forged signatures for each signer [2]. Finally, the trained network is used to identify the test set.

2 Pre-processing

The phrase "garbage in, garbage out" is the best summary of data mining and machine learning projects. Data pre-processing is important for image processing. The pre-processing methods include median filtering, OTSU binarization and normalization.

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The median filter is a nonlinear smoothing technique, often used to remove noise from an image or signal. It replaces the gray value of each pixel with the median value in its adjacent region. The binarized operation of the filtered signature image is aimed at changing the original image to a purely 'black and white' image with only the pixel value of 0 or 255. The binarization process can significantly reduce the amount of data processing. The size normalization principle is to identity the upper and lower, left and right boundaries of the signature image, and then delete the blanks outside the border and set all images sizes to 227 × 227. Figure 1 is the final pre-processing signature image.

Fig. 1. Final pre-processing signature image.

3 CNN and AlexNet Architecture

In machine learning, a CNN is a feedforward neural network. It performs excellently in large image processing. It is inspired by the cat's cortical structure. The special structure of the convolutional neural network is shared by its weight. It has excellent performance in speech recognition and image processing, and its layout is closer to the actual biological neural network. Their error rate only got 0.23% on the MNIST (Modified National Institute of Standards and Technology) database [3].

AlexNet is designed by Alex Krizhevsky to participate in the 2012 ImageNet Large Scale Visual Recognition Challenge. AlexNet contained only 8 layers, first 5 were convolutional layers, and the next three were fully connected layers. It is trained to classify the LSVRC-2010 ImageNet training set which included 1.3 million high-resolution images, the set are classified into 1000 classes. The structure of AlexNet is shown in Table 1. The first convolutional layer filters the N × 227 × 227 × 3 input image, it has 96 kernels, the kernel size is 11 × 11 × 3 size and with a 4 pixels stride. LRN means Local Response Normalization, pool size is 3 × 3 with a strides of 2 pixels. The second convolutional layer has 256 kernels, its kernel size is 5 × 5 × 48. The third and fourth convolutional layers behind without LRN. The third convolutional layer has 384 kernels, the kernel size is 3 × 3 × 256. While the fourth convolutional layer has 384 kernels, its kernel size is 3 × 3 × 192, and the fifth convolutional layer has 256 kernels, its kernel size also is 3 × 3 × 192. However, the fifth convolutional layer behind with LRN. The first two fully-connected layers have 4096 neurons. Dropout can be more effective to prevent the neural network over-fitting. The last fully-connected layer plus the classifier softmax, the input signature images are divided into two categories [4]. In our experiments, there are a total of 40 signers, each signer has 36 real and 36 forged signature images. Experiments are divided into training and test. Each participant in the training set has 25 real and 25 forged

Table 1. AlexNet structure.

Structure	Size	Other parameters
Input	N × 227 × 227 × 3	–
Convolution1	11 × 11 × 3	96 kernels, Strides = 4
LRN	3 × 3	Strides = 2
Convolution2	5 × 5 × 48	256 kernels, Strides = 1
LRN	3 × 3	Strides = 2
Convolution3	3 × 3 × 256	384 kernels, Strides = 1
Convolution4	3 × 3 × 192	384 kernels, Strides = 1
Convolution5	3 × 3 × 192	256 kernels, Strides = 1
LRN	3 × 3	Strides = 2^3
Fully-connected1 + dropout	4096	P = 0.5
Fully-connected2 + dropout	4096	P = 0.5
Fully-connected3 + softmax	M	–

signatures. Test set for each signer has 11 real and 11 forged signatures. For each signer, we have a writer-dependent network training, so in the training phase, N in Table 1 is 50 and the test phase N is 22. Whether the test or training, M is 2.

4 Experiment

4.1 Data Set

Domestic researchers are building their own data sets, because there is no public Chinese signature data set. We convene 20 volunteers with stable mentality to set up signature dataset. At the same time, an open Chinese offline signature data set SigComp2011 was provided at the International Document Analysis and Recognition Conference (ICDAR) in 2011 [5], it includes 20 Chinese signers. Together with the SigComp2011, a total of 2880 Chinese signature images are available for experiment.

4.2 Offline Chinese Signature Verification Based on AlexNet

The experimental equipment of this paper is our laboratory equipped desktop, equipped with ubuntu 16.04 system, the Linux configuration of the CPU version of Tensorflow 1.0.0. The machine's CPU parameters are 8-core Intel i7-7700K, 4.2 GHz. Based on the structure of AlexNet, TensorFlow is used to train real signature and forged signature classification. For each signer, the writer-dependent network training took about 40 min, the average accuracy of classification for 40 signers has been up to 99.77%.

After the network training is completed, the trained network is called to identify test set. Each time a signature image is input for network identification, and the network recognizes the authenticity of the image, and respectively output 'yes' or 'no', 'yes' on behalf the real signature, while 'no' stands for forged signature. Table 2 is the result of accuracy (ACC), false accept rate (FAR) and false rejection rate (FRR) of offline Chinese signature verification based on AlexNet.

Table 2. AlexNet verification result.

ACC	FAR	FRR
87.5%	7.5%	5.0%

4.3 Comparison of Offline Signature Verification Methods

We compare the performance of AlexNet with traditional pattern recognition method using in offline Chinese signature verification. The results are shown in Table 3, it includes accuracy and error rate (ERR).

5 Conclusion

The problem to be solved of this paper is how to apply AlexNet to recognize offline Chinese signature. We have done the offline Chinese signature verification experiment on Tensorflow, its Google's open source machine learning library.

The experimental results show that AlexNet's network training classification average accuracy is 99.77%. Through Table 3, offline Chinese signature verification based on AlexNet is better than SVM methods. The accuracy of AlexNet's verification is 87.5%. Compared with the pattern recognition method, although the accuracy is no better than other traditional methods, but this is a new method. The next step is to test the algorithm on the Caltech (foreign) signature dataset and continue to optimize the approach to improve the accuracy.

Table 3. Comparison offline Chinese signature verification methods.

Method	ACC	ERR
Bayesian [6]	89%	11%
KNN [6]	92.5%	7.5%
SVM [7]	83.7%	16.3%
BP Neural Network [8]	90.0%	10.0%
This article proposed AlexNet	87.5%	12.5%

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