Signature handwriting identification based on generative adversarial networks

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Abstract. Handwritten signature has been an important identity-verification method since ancient times. Compared with manual handwriting verification, the use of computer image recognition technology for handwriting verification is faster and avoids subjectivity. However, there are still some challenges in traditional image recognition methods, such as feature selection, lack of a standard basis, and low accuracy. For the first time, generative adversarial nets (GAN) technology is adopted to study the task of handwritten signature identification. A special network SIGAN (Signature Identification GAN, SIGAN) is proposed based on the idea of dual learning. The loss value of the trained discriminator of SIGAN is used as the identification threshold. The authenticity of the test handwritten signature is determined by comparing the threshold and loss value of the test image obtained through the network. The experimental data set in this study consists of five hard pen-type signatures, which include some real signatures and some deliberate imitations. The experimental results show that the average accuracy of the SIGAN-based signature identification model is 91.2%, which is 3.6% higher than that of the traditional image classification method.

1. Introduction

Handwriting identification[1] is a special technology to identify the writer's identity according to the characteristics of people's writing habits. Signature identification is an important part of handwriting identification. It is widely used in social life, such as signing contracts, document confirmation, written documents and so on. In criminal investigation, the result of signature identification can be used as an important clue to break the case, and the results of signature identification can also be used as court evidence.

The characteristics of the handwriting are behavioural. For each writer, his handwriting is relatively stable in general, while the local variation of handwriting is the inherent characteristic of each writer's handwriting. The traditional handwriting identification is made by artificial determination of the same characteristics and different features between the handwriting and the sample handwriting. Finally, they make a comprehensive evaluation. such as the comparative test method[3], the auxiliary portable video microscope identification method[3] and so on. These methods are professional, but time-consuming, laborious and costly. The study of handwriting identification using computers began in the Soviet Union in the 60s of the last century. The initial method was to use the different feature extraction methods to extract the features of the handwriting and to classify them with the minimum Euclidean distance and L1 distance. The common feature extraction methods include Fourier transform and autocorrelation[4], range histogram[5], run length analysis method[6], independent component analysis method[7], multi-channel Gabor filter decomposition method[8], etc. These methods
need to extract features first, and feature extraction often lacks standard basis, which leads to insufficient accuracy. With the rise of deep learning, a handwriting study based on deep convolution neural network \((9)\)\(^{12}\) has been developed. The deep convolution neural network can automatically learn the characteristics of the sample and help to improve the accuracy of the identification. The above method is an important part of handwriting identification for general handwriting identification. The representative methods include: signature identification based on information entropy\(^{10}\), signature identification of Ferryman chain code\(^{11}\), handwriting signature recognition algorithm based on LBP and depth learning\(^{12}\).

In this paper, the problem of signature handwriting identification is studied by using Generative Adversarial Nets for the first time. By using the idea of dual learning, a special SIGAN network is designed to realize the task of signature identification. The experimental results show that the SIGAN algorithm can achieve better handwriting identification than the traditional method, and is far higher than the average accuracy of the subjective test.

2. SIGAN

2.1. GAN
In 2014, Ian J.Goodfellow proposed an Generative Adversarial Nets\(^{14}\). The Generative Adversarial Nets is a deep learning model, and its problem is how to learn new samples from the training samples, which is one of the most promising methods of unsupervised learning in the complex distribution in recent years. GAN generally consists of two modules: the data generation model (G) and the discriminant model (D) for estimating the true and false probability of the generated samples. In the training process, the goal of G is to generate realistic samples to deceive D, while the goal of D is to separate the G generated samples from the real samples as much as possible. In this way, G and D form a mutual "game" process, and the optimization of GAN is a minimax game\(^{15}\) problem, as shown in Figure 1.

![Image of the game process of generator and discriminator.](image)

2.2. The network structure of SIGAN
The overall architecture and data flow of the SIGAN network are shown in Figure 2.

![Image of the overall architecture of the network and the flow of data.](image)
(1) The generator $G_A$ translates the standard Chinese character (Song font) image into a handwritten signature image, and its corresponding discriminator $D_A$ is used to distinguish a handwritten signature image from a real image or a image translated by a $G_A$.

(2) The generator $G_B$ translates the handwritten signature to a standard Chinese character (Song font) name, and its corresponding discriminator $D_B$ is used to distinguish a standard Chinese character (Song font) image as a real image or a image translated by $G_B$.

(3) The result of the generator $G_A$ translation is sent to the generator $G_B$. The result is a reconfiguration of the standard Chinese character (Song font) image; the result of the translation of the generator $G_B$ is given to the generator $G_A$. The result is a reconfiguration of the handwritten signature image. The network minimizes the reconstruction error by continuous iteration.

3. Experiment and analysis of result

3.1. The setting of the experiment

The software and hardware configuration used in this experiment is as follows: the operating system is Ubuntu14.04, the processor is Intel (R) Core (TM) i7, the main frequency is 2.27 GHz, the memory is 16.0GB, the graphics card is GTX1080, and the GPU accelerates. The deep learning platform used in this paper is TensorFlow1.0.0, and the programming language uses Python2.7.6.

The experimental image library contains 640 signed images, of which 320 of the positive samples are written by Liu Yanjiao herself with 5 kinds of pen (neutral pen, ballpoint pen, pencil, blue pen, black pen) and 64 own signatures respectively. The number of negative sample is 320, and the other 4 students in the laboratory imitate Liu Yanjiao with 5 kinds of pen respectively. Each type of pen is modeled on 16, as shown in Figure 3. The ratio of the training set, validation set and test set in this paper is 4:1:5, in which the test set contains 320 signature images, which are composed of 160 random sample signature images and randomly selected 160 negative samples, and all the remaining images form a training set and a validation set. In this paper, the training of SIGAN is used only in the positive samples, while the AlexNet used in the contrast experiment uses all the positive and negative samples in the training center.

![Figure 3. The display of the image's library.](image-url)

3.2. Experiment

3.2.1. SIGAN. (1) All type of pen. The experimental training set contains all the pen types, and the training set of 160, 80, 40, 20, 10 and 5 are randomly selected for training (the number of each type of
pens are the same). Figure 4 gives a comparison of the accuracy of handwriting identification using data enhancement and non data enhancement training. The training time of the mixed pen is shown in Figure 5, and the testing time is 0.27s for each image. Table 2 is the result of models by 160 training set.

![Figure 4](image1.png)

**Figure 4.** Accuracy of handwriting identification based on mixed pen training.

![Figure 5](image2.png)

**Figure 5.** training time of the mixed pen.

Through the above experimental results, we can draw the following conclusions:

1. The accuracy of the model trained with all 160 signature handwriting images is the highest, reaching 90%. However, with the reduction of the number of training sets, the accuracy of the model is gradually reduced. When the number of training sets is less than 10 (no data enhancement), the accuracy drops to below 80%. This indicates that the more the training set is, the better the accuracy of model identification will be.

2. As can be seen from Figure 5, the use of data enhancement can effectively improve the accuracy of the model identification; the less the number of original training samples, the more obvious effect of data enhancement; when the number of original training samples is only 5, the accuracy of the identification can be raised by 17% by the data enhancement.

4. Conclusion

In this paper, the method of signature identification based on SIGAN is studied. By combining the Generative Adversarial Nets with dual learning, the mutual game of the generator and the discriminator is fully utilized to realize the identification task of the signature handwriting. The discriminator identifies the validity of the signature up to 91.2%, which greatly reduces the time and cost of the manual handwriting identification. This paper also needs to further improve the following aspects: (1) How to train handwriting identification model with few training samples; (2) How to improve the performance of SIGAN with the prior knowledge of handwriting identification; (3) In this paper, the image library and algorithm only involve Chinese handwriting in stiff brush. In the future, we will collect samples of brush and various foreign handwriting and test the algorithm.

4. References

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