An Automatic Recognition Method for Bank Card Number

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Abstract. With the development of mobile internet, mobile payment has become one of the most popular payment methods. In order to improve work efficiency, reduce labor costs and enhance user experience, the intelligent identification of bank cards is widely used in mobile payment. Conventional optical character recognition (OCR) technology has the problems of low recognition rate when dealing with bank card text with complex background. Thus, a bank card number identification method based on deep learning is proposed. Firstly, the data set is expanded. Then the CRNN algorithms is used and optimized to identify the card number. Some experimental results show that the method have a high recognition rate.

1. Introduction

Bank card number identification is widely used in many fields such as finance, mobile software and financial management. For mobile payment methods such as WeChat and Alipay, people need to enter the card number to bind the bank card in advance. Before the bank conducts business, it needs to provide a bank card and type the card number to identify bank card. The import of bank card number is mostly done manually. However, manually entering has the risk of mis-recording and missing which is easy to cause transaction failure and financial loss.

The bank card number identification belongs to the field of natural scene text detection and recognition. Since the form of text in the natural scene image is extremely rich, its recognition is more difficult than the text recognition in scanned document images. The above OCR technology is a common method for text recognition in natural scenes. Cai et al. [1] proposed a bank card and ID card number recognition method which consists of image preprocessing, numeral segmentation and numeral recognition. Zhou et al. [2] proposed a novel method for identifying banknote serial numbers, which consists of a hybrid binarization algorithm (HybridB) and an adaptive character extraction algorithm (ACE). Yanhua et al. [3] proposed an improved feature matching algorithm and applied it to bank card number identification. The deep learning continuously unleashes its power in a wide range of applications [4]. Compared with OCR technology, deep learning can better meet the precise identification requirements for complex scene text. It can learn experience based on the data given and then predict the outcome. Today, the combination of deep learning and text recognition is getting closer. Liu et al. [5] has comprehensively investigated the performance of LSTM (long-term short-term memory) on clinical entity recognition and protected health information recognition. Zhang et al. [6] proposed a handwritten Kazakh letter recognition method based on deep convolutional neural networks, using the advantages of convolutional neural networks in image recognition. Liu et al. [7] proposed a method using Normalization-Cooperated Gradient Feature (NCGF) and Recurrent Neural Network (RNN) based on Long Short-Term Memory (LSTM) for serial number identification.

In order to solve the problem of intelligent identification of bank card number, a novel bank card number identification method based on deep learning is proposed in this paper. In the proposed
approach, digital image processing methods are used to augment data sets, the CRNN algorithms [8] is optimized and applied to identify the card number. The experimental results verify the effectiveness of the method.

2. Bank card number recognition based on deep learning
This section introduces the detailed information of the bank card number identification method based on deep learning. It includes three core work: data set processing, establishment of card number location model and establishment of card number recognition model. The overall network framework is shown in figure 1.

\[ \text{Input image (normalized to } h:32, w:600, c:3) \]

\[ \text{Convolution network layer 1} \]
\[ \text{Convolution network layer 2} \]
\[ \text{Convolution network layer 3} \]
\[ \text{Convolution network layer 4} \]

\[ \text{Sequence segmentation} \]
\[ \text{Hidden unit} \]
\[ \text{Hidden unit} \]
\[ \text{Hidden unit} \]
\[ \text{Sequence identification} \]
\[ \text{Transcription layer} \]
\[ \text{Circulating layer} \]

2.1. Data set processing
In order to implement the bank card number identification method proposed in this paper, we will expand the image data we have. In terms of data expansion, we mainly call the third-party library opencv-python.

2.2. Establishment of card number identification model
The most important part of the bank card number identification is the CRNN algorithm. In this paper, the CRNN algorithm’s input is a card number sequence image which the size is normalized to 32×600. First, extracting feature map through the 4-layer CNN, and the feature map is divided by columns. Then the 128-dimensional features of each column are input to two bidirectional LSTMs of two 128-unit units. At last, bidirectional LSTM gives classification results. During the training process, the approximate soft alignment of the character position is achieved through the guidance of the CTC loss function.
2.3. Training of network models
The CRNN network is mainly used to identify the detected sequence of bank card texts. The training details are as follows: First, collect data and label the data set, the training label is the bank card number text. With the expansion of the data set, the total data set used by the system to identify bank card number was 78,836, of which 80% were used as training sets and 20% were used as test sets. The training was also carried out in batches with a fixed number of 128 per small batch. The initial learning rate was set to 0.001, the momentum was 0.9, and the attenuation was repeated every 1000 steps with a decay rate of 0.98.

3. Experimental results
The experimental environment used in this article is Windows 10, the running memory is 64GB, the programming language is python, and the development software is pycharm. At the same time, GPU was used to accelerate computing in the development, using the graphics card version Nvidia Quadro M2000, cuda version 9.0.

The performance of the method proposed in this paper is given below. Finally, the loss of our recognition model is stable at around 0.05 on the training set. After training, the accuracy of our method is stable at 98% on the verification set.

This paper selects 280 bank card images collected from the network and life as the test set to conduct experiments, the experiment achieved 95.6% precision. Table 1 shows the recognition results of some bank card test pictures.

Because the background of bank card is complicated, and there is a certain similarity between different texts, it is normal to cause missing and wrong in the recognition. From the experimental data, it can be seen that the training loss and accuracy are within the normal range. Therefore, there is not much impact in the actual application. Compared with other methods, the method proposed in this paper is relatively stable and achieves high precision.

| Positioned bank card | Recognition result | Judge  |
|-----------------------|-------------------|--------|
| ![Bank Card Image 1](image1.png) | 6222601310012850053 | correct |
| ![Bank Card Image 2](image2.png) | 6226190602392981 | correct |
| ![Bank Card Image 3](image3.png) | 62284180330341640515 | correct |
| ![Bank Card Image 4](image4.png) | 6216697600000020025 | correct |
| ![Bank Card Image 5](image5.png) | 62299111640006609 | correct |
| ![Bank Card Image 6](image6.png) | 6217002940000410265 | correct |
| ![Bank Card Image 7](image7.png) | 621226171102447002 | correct |
| ![Bank Card Image 8](image8.png) | 4695920347081597 | correct |
| ![Bank Card Image 9](image9.png) | 6221682231920344 | correct |
| ![Bank Card Image 10](image10.png) | 621992610010672517 | correct |
| | | Error (missing a 7) |

4. The conclusion
This paper studies the intelligent identification of bank card numbers. Aiming at this problem, a bank card number identification method based on deep learning is proposed. In the proposed method, the CRNN algorithm is applied to bank card number recognition. The proposed method can optimize the detection capability and recognition efficiency of bank card number. The simulation results show that
the proposed method can significantly improve the detection and recognition ability of card number in the bank cards with complex and diverse background. Moreover, by using the end-to-end training method, the complexity of the annotation work before the network model training is greatly reduced.

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