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A New Bank-card Number Identification Algorithm Based on Convolutional Deep Learning Neural Network

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Abstract

Recently bank card number recognition plays an important role in improving payment efficiency. In this paper we propose a new bank-card number identification algorithm. The proposed algorithm consists of three modules which include edge detection, candidate region generation, and recognition. The module of 'edge detection' is used to obtain the possible digital region. The module of 'candidate region generation' has the role to expand the length of the digital region to obtain the candidate card number regions, i.e. to obtain the final bank card number location. And the module of 'recognition' has Convolutional deep learning Neural Network (CNN) to identify the final bank card numbers. Experimental results show that the identification rate of the proposed algorithm is 95% for the card numbers, which shows 20% better than that of conventional algorithm or method.

Keywords: *Bank-card number, Identification Algorithm, CNN, Edge detection, Candidate region generation, Recognition*

1. Introduction

With the development of the mobile Internet and the wide application of mobile devices such as mobile phones, mobile payment has become one of the current main payment methods. Bank card number recognition is one of the very important roles in the payment system, which can quickly solve the complicated card number entry problem [1,2].

In recent years, many scholars have studied end-to-end bank card number recognition algorithms and/or technologies. In 2011, Keshav Datta proposed an algorithm for bank-card number recognition. In this algorithm, they obtain card number area by extracting harris points of interest in the image, then use horizontal and vertical projection method of featuring to localize the characters [3]. In 2016, Han proposed a bank card number intelligent recognition method based on digital image processing. The algorithm uses image preprocessing and binarization technology, and then uses mathematical forms to locate the digital number area[4]. In 2019, Pranav Raka proposed a method that is OCR to read embossed text from credit card. The

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algorithm first detects the edge of the image, and then uses the method which is based on the integral projection of the edge feature points in the horizontal and vertical directions for segmentation to get characters [5]. The above algorithms can obtain the digital area better in a simple background, but those are less robust in complex background cards.

In 2020, Jiawei Ge proposed a bank card number recognition algorithm based on deep learning. This method uses YOLO v3 framework to perform the feature extraction, then it obtains the candidate card number region and select the bounding box with the highest probability [6]. The algorithm uses YOLO v3 network, the structure of the network is too complicated and the training time is so long. For the card-number identification, some researchers have tried to use Multi-layer Perceptron (MLP) which is a simple neural network compared with deep learning networks [7]. The MLP shows good performance for the standard number with noise, but it has lower robustness for the invariance problems such as rotation and scale invariance. And Meng Fei suggested an identification algorithm based on Gabor Feature, and the algorithm structure is simple [8]. But this algorithm also shows insufficient amount of recognition rate for card numbers.

In this paper, we proposed a new algorithm which combines edge detection technology, candidate region generation method, and recognition network. The proposed algorithm has two characteristics in comparison with conventional methods. Firstly, our method combines edge detection technology for cards and card number region generation method (*IoU*: Intersection over Union) to get candidate number regions whose method is very simple in structure. Secondly, the convolutional deep learning neural netork (CNN) is used to recognize the final bank card numbers. The CNN can keep higher character recognition rate.

2. Proposed Algorithm

The basic structure of our proposed algorithm is shown in figure 1, which consists of its key function modules: Edge Detection, Candidate Region Generation, and Recognition modules.

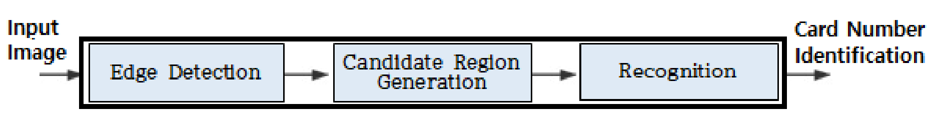


Figure 1. The structure of proposed algorithm

In the Edge Detection module, we use canny operator to detect edges of input image [9]. The Candidate Region Generation module has the function to generate candidate number region, which will produce some possible number regions. The last module functions to recognize card numbers from the generated region. In recognition module, CNN is introduced to recognize the final each card number.

2.1 Edge Detection

Generally, the original card image may be colorful, and the background colors will be rich as in figure 2. The colorful image is not helpful to take position the number string. Therefore, the conversion of original colorful image into a gray-scale image not only reduces the memory but also does not lose useful information. But its conversion makes image processing simple.

The edge detection is main step for identifying the numbers on the bank card, thus this step is very important. Here Canny operator is used to suppress background noise while extracting the edges of objects [9]. In this step, Gaussian filter is used to smooth the image by removing noise. And then the first-order partial derivative to calculate the gradient amplitude and direction is used. After then the Non-maximum suppression method of gradient amplitude is adopted. Finally, dual threshold method is introduced to detect and connect edge.

(a) **(b)**

Figure 2. The example of edge detection: (a) Source image, (b) Edge image

The dual threshold method, which is based on the chord line tangent one, acquires the threshold by using a long chord line and a short chord line which can represents an integral shape feature of the histogram and are stable based on the integral shape feature of the histogram.

2.2 Candidate Region Generation

At present, the commonly used algorithms for candidate regions are based on sliding window method, segmentation method, and deep learning. In the sliding window method, a fixed-size window is specified in advance and the window is used to slide in the original image to each position, then the overlapping part of the window and the image is considered as a candidate area, and the candidate area is used for subsequent detection tasks [10]. This algorithm has very low efficiency and poor performance, such as EdgeBoxes. In the segmentation-based algorithm, the candidate region algorithm segments different regions to identify potential objects [11]. Compared with the exhaustive list of different positions and sizes of the sliding window method, the candidate region algorithm generates a much smaller number of regions than the sliding window method, and the range selected by the candidate region algorithm naturally takes into account different sizes and aspect ratios such as selective search.

In this paper, we introduced a simple and high-performance method for obtaining candidate areas based on the location characteristics of the card number. In target recognition, we usually locate the target and then identify the target. The acquisition of the candidate area is used as a preliminary estimation of the target position, and then the information of relatively accurate target position is obtained.

After edge detection, we can obtain the edge contour of some card number numbers. As long as we find a certain number of the card, we can get the corresponding card number region according to its position. Therefore, we need to find the potential card number from the edge image. To do this, we mark the connected edges, and obtain the length of each edge and the information of the outer rectangle of the edge.

From here we find Max length of all edges:

$$L_M = \max(L_i) \tag{1}$$

where the L_i is the length of *i*th edge, the L_M is the maximum length.

Consider figure 3 and calculate the width ratio and length factors of the rectangle surrounding each edge. Here the *w* and *l* are the height and width of bounding box of each candidate character respectively. Let us assume that *m* and *n* are the height and width of total card image respectively.

And we let the a as the ratio of height to width as following:

$$a = w / l \tag{2}$$

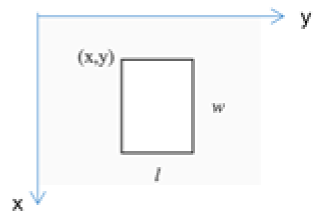
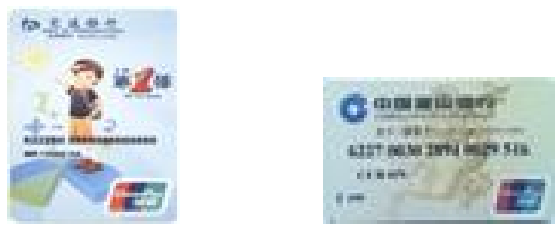


Figure 3. Bounding box illustration

Another thing we think is that there are two kinds of bank cars types as in figure 4.



(a) **(b)**

Figure 4. Two types of cards : (a) *m*>*n* type, (b) *m*<*n* type

Here we can also assume that most of the bank cards satisfy the following conditions for $m>n$, i. e. the edge condition of the card number meets the following conditions:

$$\begin{cases} 1 < a < 22 \\ \frac{m}{10} < w < m/4 \\ L_i < 0.5L_M \end{cases} \tag{3}$$

The Eq. (3) means that the height of the number should be greater than m/10 and less than m/4, this condition can excludes the line segments that are not digital.

The result of applying of Eq. (3) to the figure 2(a) is shown in figure 5.

Figure 5. The result of applying of Eq. (3) to figure 2(a)

For another card type with $m<n$, we also assume a restriction as following:

$$\begin{cases} 1 < a < 2 \\ L_i < 0.5L_M \end{cases} \tag{4}$$

where the L_i denotes the length of the character edge segment.

Although we do not give them a clear justification for the criteria of equations (3) and (4), the criteria were set from the survey of about 100 bank cards that are actually in circulation.

Usually bank card numbers are distributed in the same row, so we extend the length of each candidate box. Assume that the coordinate position of the original candidate for a character is

$$PR = I(x, y, w, l) \tag{5}$$

where the (x, y) represents the rectangular coordinates for the upper left vertex of bounding box, the w and l are the width and length of bounding box for the each edge respectively. Here we can also assume that the coordinate position of the expanded candidate is indicated as

$$PR1 = I(x, 20, w, n - 20) \tag{6}$$

The coordinate position of the expanded candidate in Eq. (6) means the usually used position. Even though the Eq. (6) does not applied to all the bank cards, but it is applied to most of general bank cards. In other case we have to exchange the '20' and 'n-20' by proper corrected numbers.

In general there will be a lot of overlapping candidate regions, so we need to perform regional deduplication. Here we perform deduplication process by calculating IoU(Intersection over Union) defined in the following Eq. (7). Assume that the two target boxes are A and B as in figure 6 respectively.

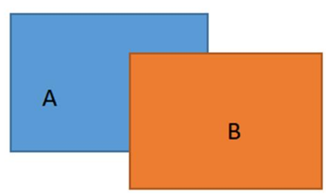


Figure 6. The example of calculating IoU

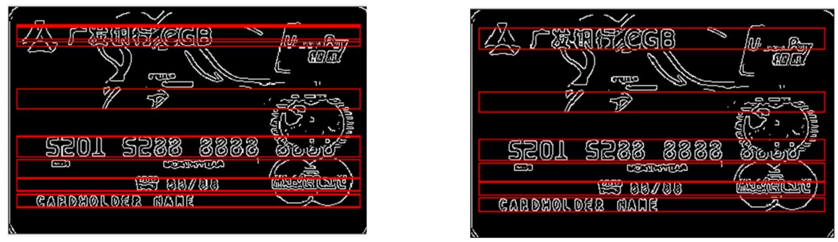
If we can find the location of a certain bank card number, then the line where the number is located may be the bank card number area, so we just define IoU and expand to get candidate number region as following:

$$IoU = \frac{A \cap B}{A \cup B} \tag{7}$$

The IoU is expressed as the degree of coincidence of the two regions. If $IoU > 0.8$, then let's indicates that the two regions have a high degree of coincidence, we can only keep a larger region. In the Eq. (7), we calculate the IoU between all candidate regions separately. Deduplication conditions are as follows:

if $IoU > C$ and area A > area B, keep A and delete B,
if $IoU > C$ and area A < area B, keep B and delete A,

where the C is constant and is given by users. The degree of deduplication depends on C value. The IoU has the range from 0 to 1. A value C less than 0.1 means that the two cards barely overlap. And a common value of C could be set to a value 0.5.



(a) (b)

Figure 7. The example of region deduplication: (a) Before deduplication, (b) after deduplication

Figure 7 shows the example of region before and after deduplication for figure 5. In figure 7(b), ambiguous candidate regions are eliminated.

2.3 Recognition

For the recognition of bank card numbers, we introduced a CNN which extracts feature and locates bank-card number position. The CNN to be used here is the standard model of the CNN, which consists of two stages and FC layer. Each stage has convolution, ReLu(Rectified Linear Unit), and pooling layers [12]. The CNN structure to be used shows in figure 8.

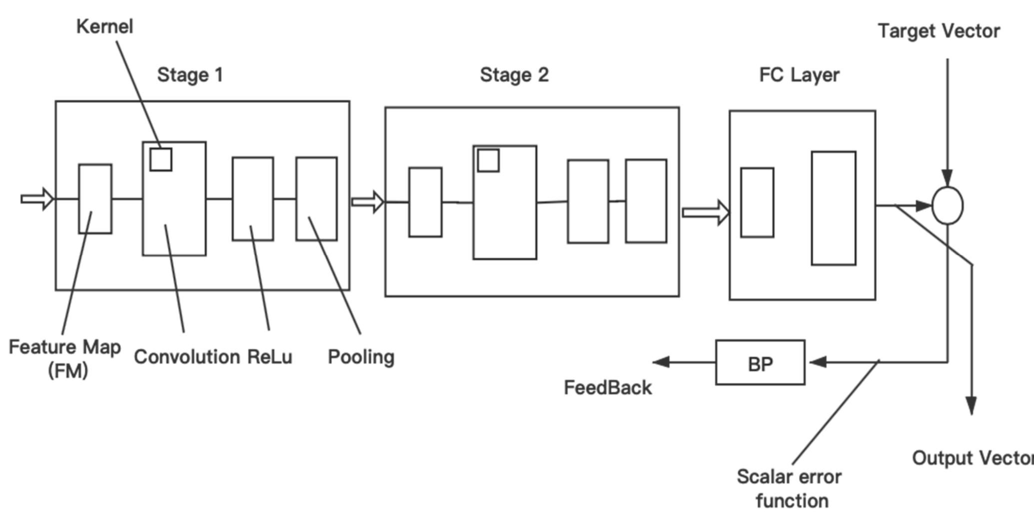


Figure 8. The Structure of the CNN in Proposed Algorithm

In the figure 8, the Feature Map (FM) layer has the function to extract the features of input images. The FM layer has the gray-scale image whose size is 20×100. And the Convolution layer does the convolution of the input feature over regions of a feature map and kernel function, which is transfer function in the sense of classical control theory. In this layer, we used a kernel function, whose size is $5 \times 5 \times 5$. The ReLu (Rectified Linear Unit) usually follows each convolution layer and is repeated. The ReLu has the function satisfying :

$$F(x) = \max\,(0, x) \tag{8}$$

The function of LeLu is a hardMax function, which serves to enhance the nonlinear properties of the decision function without affecting the receptive fields of the convolution layer. The Pooling Operators follows LeLu and has the roles to speed-up computation in CNN for complex deep-learning problems. Here we adopted "max pooling". The Fully Connected (FC) Layer is a single and fully-connected output layer for classification and/or decision.

All weight training in CNN is done by BP(Back Propagation) algorithm. The error is propagated from the output layer through all layers of the CNN network. The error at the output layer is defined as following:

$$E = \frac{1}{NM}\sum_{p=1}^{M}\sum_{k=1}^{N}(d_k^p - y_k^p)^2 \tag{9}$$

where the M and N are the numbers of training patterns and the number of neurons at the FC(output) layer respectively, and the d_k^p and y_k^p are the desired output and real output respectively. And the division by $M \times N$ in Eq. (8) means normalized or averaged error.

3. Simulation Results

To test the performance of the proposed algorithm, we had tried computer simulation for 'the computational speed to the candidate region generation of bank card numbers,' and 'identification rates of bank card numbers'.

3.1 Candidate card number region generation

In this simulations, the card number candidate regions generation of the proposed method is compared with that of conventional selective search method. In this simulation, our experiment platform consists of Intel(R) computer, which has i5-6400 CPU with 2.7GHz and 16 GB memory. The used software is MATLAB R2018b.

Figure 9(a) shows the source card image of a Chinese bank card, and figure 9(b) and figure 9(c) indicate the images by selective search method and our proposed algorithm respectively after simulation.

(a) (b) (c)

Figure 9. The results of the candidate region generation for different methods : (a) Source image, (b) Selective search method, (c) Proposed algorithm

The Selective Search is a region proposal algorithm for object detection tasks. It starts by over-segmenting the image based on intensity of the pixels using a graph-based segmentation method by Felzenszwalb and Huttenlocher[13].

Figure 10 shows the simulation results for the run time in seconds to generate candidate card number regions. In the figure 10, 'Ours' means the result of our proposed algorithm. Here we can see from the experimental results that the time of candidate regions generated by the proposed algorithm is much less than that by the selective search method. And there is always a certain area in the candidate region that is the card number region.

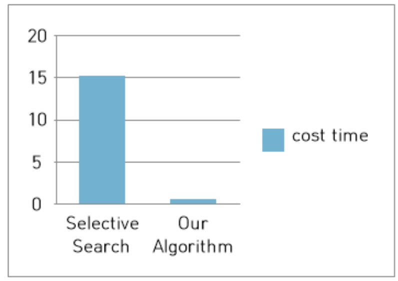


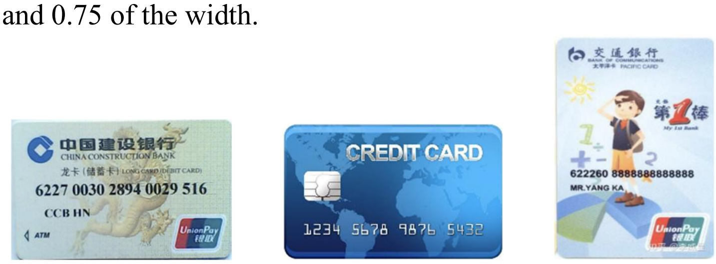
Figure 10. The cost time of candidate region generation for conventional method and proposed algorithm

The generation time of the candidate region by proposed algorithm is much less than that of the selective search method.

3.2 Identification rate as a performance

In this computer simulation, we used 125 bank card types with pictures, and the pictures include different font types of card numbers with printing and burning. Among them, we selected 85 bank card types. Each type has two other different types, which are positive and negative numbers. Thus the total number of cards for training CNN was 170. And then we made another 170 numbers of the cards mixed with 20 % Gaussian noise. Thus total number of training cards are 340.

To test the trained network, we randomly elected 40 bank card images downloaded from Internet. As shown in figure 11, the 30 images were the ones with the card numbers, which are located at the middle of the image, and another 5 other images were the ones with the card numbers located at the non-central image, and the other 5 images were new type of bank card images. Here we used the cards with the number area, which are located at position between 0.5 and 0.75 of the width.



(a) (b) (c)

Figure 11. Types of bank cards and number of test images: (a) type of 'numbers located at middle', (b) type of 'numbers not located at middle, (c) new type

In order to certify the identification rate of the proposed algorithm, we have simulated the proposed algorithm as well as the two conventional algorithms. The first algorithm is based on experience and digital image processing algorithms, which is Meng's algorithm [8]. The second algorithm is based on the algorithm which is composed of the card number candidate method plus the BP neural network known as Multi-layer Perceptron [7][14]. The test data are composed of three kinds of card images, which include 30 horizontal cards with numbers in the center, 5 horizontal cards with card numbers off the center, and 5 vertical cards written on the horizontal axis. That is, the total number of cards for test are 50.

The computer simulation results are shown in figure 12. Here the identification rate is defined as the ratio of successful recognition card numbers to total test cards. Here the identification rate 1 means 100%

recognition.

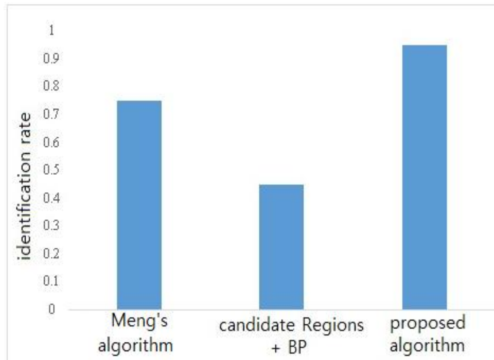


Figure 12. Identification rates according to different methods and/or algorithms

From the experimental results of figure 12, it can be seen that the Meng's algorithm [8] can obtain the recognition rate better than that of 'candidate regions with the BP network', but it shows the poor recognition rate than that of our proposed algorithm. The algorithm based on the method with 'candidate regions with the BP network' can identify the card numbers with the low recognition rate due to the limitations of network characteristics. Finally, the recognition rate of our proposed algorithm has been proven to be more tha n 20% higher than that of the basic methods.

4. Conclusion

In this paper, we proposed a new bank-card number identification algorithm. The proposed algorithm consists of three modules, which are composed of edge detection, candidate region generation, and recognition modules. The recognition module has Convolutional deep learning Neural Network (CNN). The proposed algorithm uses edge detection technology. This method has simple structure, accurate performance, and fast for getting region generation. Experimental results showed that the identification rate of the proposed algorithm is 95% for the card numbers, which shows 20% better than that conventional algorithm or method.

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