# Research on License Plate Recognition Algorithm Based on ABCNet

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*Abstract*—**In order to improve the accuracy of license plate recognition algorithm, we propose a license plate recognition algorithm based on ABCNet. Firstly, the original images with ABCNet is to locate license plate detection network, secondly, use CRNN - CTC algorithm for license plate character recognition, character recognition algorithm is the main process of the convolution neural network is used to extract image convolution, the cycle of neural network is used to extract image convolution features of sequence, the CTC algorithm is used to solve the problem that training characters cannot be aligned, the license plate recognition's accuracy is 96.4%.With a speed of 9ms, it has a well effect and can play an important role in actual traffic management.**

***Keywords—image processing, license plate detection, artificial intelligence, deep learning***

## I. INTRODUCTION

With the continuous development of intelligent transportation technology, license plate recognition technology has become an indispensable part of intelligent transportation system. License plate is the identity symbol of the vehicle, according to the license plate number, to obtain the vehicle's numerous identity information. License plate recognition technology is widely used, such as vehicle tracking, parking fees and community access control identification.

The previous steps of the whole license plate recognition are: license plate region location, character segmentation, character recognition. The location of the license plate region is the location of the license plate. Character segmentation is the separation of characters from the whole region one by one. Character recognition is the feature extraction and judgment of a single character to obtain recognition results. Niu [1] et al. designed a license plate recognition system, which adopts the edge detection method in the operation of license plate region positioning and adopts the vertical projection method for the segmentation of single characters. The template matching method is used to recognize the characters, and the accuracy of the method is higher. Liu [2] et al. trained AdaBoost classifier with HAAR features, found the license plate region in the image, and then detected the edge of the license plate region. Then, the characters were segmented one by one with threshold segmentation method, and BP neural network was used to recognize the characters. Finally, the license plate information was obtained. This method can recognize license plate information effectively and has strong practicability. The accuracy of license plate recognition can reach more than 80%, and the recognition effect is better. Khan et al. [3] divided license plate recognition into four main steps :(1) extraction of license plate from cie-lab color channel. (2) the license plate region is segmented by color threshold segmentation. (3) get the shape feature of a single character through the feature histogram. (4) the method of Support Vector Machine (SVM) is adopted for character recognition, which can basically meet the technical requirements of license plate recognition.

In the above traditional license plate recognition methods, the result of character segmentation affects the accuracy of character recognition, and the existing method of character segmentation is difficult to meet the precise needs of practical application. Therefore, the end-to-end license plate recognition algorithm came into being. The end - to - end license plate recognition method means no character segmentation is needed, the input end directly inputs the complete license plate image, and the output end outputs the recognition result. Zhu [4] proposed an end-to-end method of LSTM + CTC for license plate sequence recognition, which can achieve a license plate recognition accuracy of more than 80%. Sajed [5] proposed a license plate recognition algorithm based on multi-task learning based on Shared features. The encoder - decoder network is used to extract the characteristics of license plate characters, and 8 parallel classifiers are used for license plate character recognition. The data set used in the training process contains 11,000 license plate images, which are taken by the camera installed on the dual lane. The character recognition accuracy of this method can reach 90%.

Although the end-to-end recognition framework avoids character segmentation, there are still many problems at present, because Chinese license plates include Chinese characters, letters and Numbers, and the combination forms are diverse and complex. In addition, there are often complex situations such as license plate blurring and shielding in images, which require higher robustness of the algorithm. The current license plate recognition algorithm has little research on license plate recognition under the complex background of multi-angle and variable illumination acquisition. Therefore, this paper proposes a license plate recognition algorithm based on ABCNet. The algorithm firstly the original image with ABCNet to locate license plate detection network, reuse CRNN - CTC algorithm for license plate recognition, recognition algorithm is the main process of the first convolution neural network was used to extract image convolution, the cycle of neural network is then used to further extract image convolution features of sequence, finally introduced the CTC solve the problem of training characters cannot align the realization of ultimate license plate recognition. The vehicle license plate recognition technology has a recognition accuracy of 96.4% and a speed of 9ms, which has a good effect and can play an important role in actual traffic management.

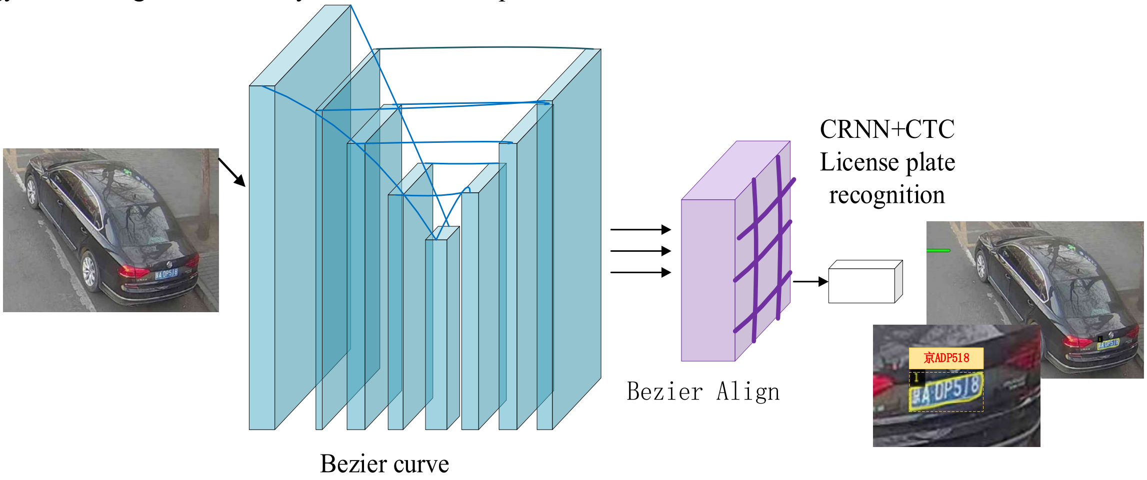



Fig. 1. License plate recognition network structure

## II. LICENSE PLATE RECOGNITION

The method proposed in this paper firstly USES Adaptive bezier-curve Network (ABCNet) for vehicle license plate positioning, and Bezier Align method for feature alignment to prepare for subsequent character recognition. CRNN+CTC method is adopted for character recognition. The overall structure of vehicle license plate recognition Network is shown in Fig, 1.

### *A. ABCNet license plate location network*

Adaptive bezier-curve Network (ABCNet) [6] is an end-to-end scene text positioning Network, whose Network structure is composed of four overlapping convolutional layers, of which the step length is 1, the interval is 1, and the convolution kernel size is 3×3.

The ABCNet network consists of two parts: one is to generate Bezier curves for plate location. Second, the method of Bezier Align is used for feature alignment. Can be used for text recognition of any shape.

Regarding the generation of Bezier curve, Bezier curve is a parameterized curve, which can be represented by c(t). It is a smooth curve with fewer control points. Commonly used types are: first order Bezier line, second order Bezier curve, third order Bezier curve. The curve can be understood as a graphical representation of Bernsteinov Bernstein polynomials. Bezie polynomial definition is shown in equation (1).

$$c(t)=\sum_{i=0}^{n} b_i B_i, n(t), \qquad 0 \le t \le 1 \tag{1}$$

Where, n is the number of times, and bi is the ith control point. Formula (2) is Bernstein polynomial:

$$B_{i,n}(t)=\binom{n}{i} t^i (1-t)^{n-i}, i=0,......,n \tag{2}$$

In order to obtain the optimal value of c(t) in equation (1), the standard least square method is used to realize the formula, such as equation (3).

$$\begin{bmatrix} B_{0,3}(t_0)\cdots B_{3,3}(t_0) \\ B_{0,3}(t_1)\cdots B_{3,3}(t_1) \\ \cdots \\ B_{0,3}(t_m)\cdots B_{3,3}(t_m) \end{bmatrix} \begin{bmatrix} b_{x0} & b_{y0} \\ b_{x1} & b_{y1} \\ b_{x2} & b_{y2} \\ b_{x3} & b_{y3} \end{bmatrix} = \begin{bmatrix} p_{x0} & p_{y0} \\ p_{x1} & p_{y1} \\ p_{x2} & p_{y2} \\ p_{x3} & p_{y3} \end{bmatrix} \tag{3}$$

According to formula 1 and formula 3, the license plate positioning frame in the image can be transformed into a smooth curve.

In order to achieve end-to-end training, feature alignment is needed, and ABCNet proposed the method of Bezier Align for feature alignment. Bezier Align is sampled with a grid instead of a rectangle. Each column of the grid is orthogonal to the Bezier curve boundary of the text. The sampling points have equidistant intervals in width and height, and then the coordinates are bilinear interpolated.

This method is mainly based on the Bezier curve boundary generated in the previous step, and then the Bezier Align algorithm is used to distort the text of the curve to the horizontal without any obvious deformation. Therefore, the text of the license plate can be positioned at any oblique Angle.

The specific implementation of the Bezier Align feature alignment algorithm is, when the size of the input rectangular image is, and the coordinates of the pixel points are, the calculation formula of point t on the Bezie curve is shown in equation (4).

$$t=\frac{g_{iw}}{W_{out}} \tag{4}$$

According to formula 1 and formula 4, calculate the upper boundary point tp of Bezie curve and the lower boundary point bp of Bezie curve, and then index the sample point op according to formula (5).

$$op = bp \cdot \frac{g_{ih}}{h_{out}} + tp \cdot (1 - \frac{g_{ih}}{h_{out}}) \tag{5}$$

By using the index position of the sampling point op, the feature alignment can be performed by bilinear interpolation, and the slanted and curved text can be twisted horizontally.

*B. CRNN network*

Convolutional ciRculatory Neural Network (CRNN) [7] is mainly divided into three parts: Convolutional layer, ciRculatory layer and transcriptional layer.

Convolutional layer: it is a convolutional neural network with the full connection layer removed. All images need to be compressed to the same size before entering the convolutional layer.Among them, the convolution layer and the maximum pooling layer are used to extract feature vectors from the input image, and these feature vector sequences are used as the input of the cyclic layer.

Circular layer: a deep bidirectional memory network structure. Each bidirectional memory network structure consists of a forward-propagating memory network and a forward-propagating memory network. These bidirectional structures are then stacked on top of each other. The function of the deep structure is to make predictions based on the characteristics obtained from the convolution layer in the previous step.

Transcriptional layer: the predicted value obtained from the previous cyclic layer is converted into the license plate tag sequence. The function is to convert the predicted value obtained from the loop layer into the final character recognition result.

In this paper, the convolutional neural network part of CRNN USES the structure of VGG-16 convolutional network. In order to adapt to the vgg-16 feature extraction network, the size of all input pictures containing license plate information was compressed to 224*224.The network structure diagram of CRNN is shown in Fig.3.

*C. Sequence decoding module*

Connectionist Temporal Classification (CTC) [8] is widely used in character recognition, and alignment of character input and output is not required. The application of this method in license plate recognition can further improve the efficiency of license plate recognition.

CTC mainly includes three parts:

(1) Extended the output layer of the cyclic neural network, and added many-to-one spatial mapping between the output sequence and the final label, and defined the CTC loss function on this basis. To calculate the probability of a tag, the probability of all output sequences corresponding to that tag can be accumulated.Fig. 2 shows the structure of many-to-one spatial mapping.

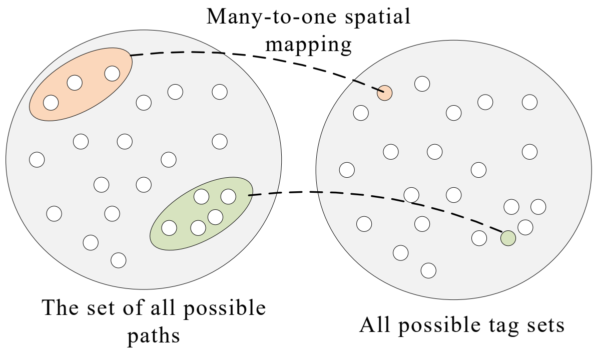



Fig. 2. Map of many-to-one spatial mapping structure

(2) Based on the algorithm idea of forward and backward propagation of Hidden Markov Model (HMM), CTC loss function and its derivative are calculated by dynamic programming.

For any time t, using forward probability $\alpha_t(s)$ and backward probability, $\beta_t(s)$ the loss function of CTC $-In(p(l|s))$ is:

$$p(l|x) = \sum_{s=1}^{|l'|} \frac{\alpha_t(s)\beta_t(s)}{y^t_{l'_s}} \tag{6}$$

$$-In(p(l|s)) = -In(\beta_1(1) + \beta_1(2)) \tag{7}$$

(3) The combination with cyclic neural network can effectively predict the sequence data from end to end.

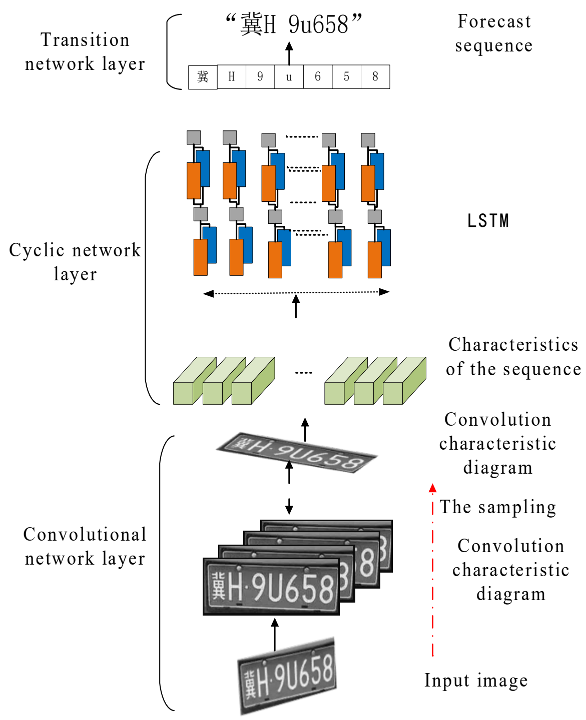


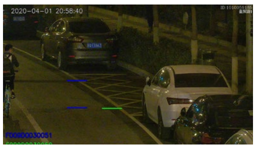

Fig. 3. CRNN network structure diagram

## III. Analysis and discussion

*A. The data set*

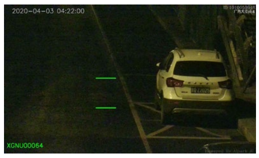
In order to verify the validity of the vehicle license plate recognition network proposed in this paper, the vehicle license plate recognition network was verified in day and night scenes, respectively. The self-built data sets were used for the verification in four scenes. All the image data were taken in changping district, Beijing from June to November, 2019 by intelligent communication technology co., LTD. The data set covers images of four types of scenes: large Angle tilt during the day, large Angle tilt during the night, day standard and night standard. The data set contains 200,000 images, among which the ratio of the number value of the image training set to the number value of the verification set is 3:1, that is, 150,000 images in the training set and 50,000 images in the verification set. For r the entire dataset, picture in the normal environment: picture in the complex environment = 2:1. The experiment was carried out on a PC. The hardware configuration of the PC was as follows: CPU core-i7, GeForce RTX2080, and 16 GB of memory. The environment is configured as: pytorch1.3.0, python 3.6, Linux Ubuntu 18.04

(a) Tilt at a wide Angle during the day



(b) The night tilted at a wide Angle

(c) Standard during the day



(d) Evening standard

Fig. 4. Partial data set sample

### *B. The evaluation index*

The evaluation index of license plate localization is represented by Intersection Over Union (IOU). When the value is 1, it means that the prediction box of the algorithm and the manual annotation box completely overlap, and the IOU is represented by formula (8).

$$IOU = \frac{B}{A} \times 100\% \tag{8}$$

Where, B represents the target box predicted by the algorithm, and A represents the target box marked manually.

The evaluation index of Character Recognition is indicated by the Recognition Accuracy (RA) and Character Recognition Accuracy (CRA).

$$RA = \frac{TS}{AS} \tag{9}$$

$$CRA = \frac{TC}{AC} \tag{10}$$

Where, TS represents the number of correct sequences, AS represents the number of all sequences, TC represents the number of correct characters, and AC represents the number of all characters.

### *C. License plate location experiment*

In order to comprehensively analyze the accuracy of the localization algorithm, ABCNet's license plate localization algorithm (the algorithm in this paper) was compared with reference[9] algorithm (contour and color), reference[10] algorithm (HSV color space and image texture), reference[11] algorithm (support vector machine), reference [12] algorithm (YOLO) and reference [13] algorithm (Faster r-cnn) for experimental results. It can be seen from the data in table I.

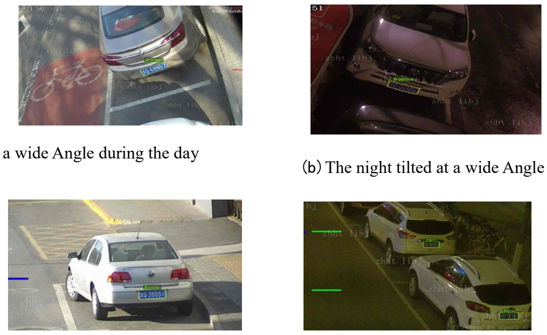
TABLE I. ACCURACY COMPARISON OF LICENSE PLATE LOCATION ALGORITHMS ON DIFFERENT DATA SETS

| **model** | **accuracy/%** | | | |
|---|---|---|---|---|
| | **day** | | **The dark night** | |
| | **standard** | **Large Angle dip** | **standard** | **Large Angle dip** |
| Literature 9 | 95.95 | 90.21 | 92.30 | 83.29 |
| Literature10 | 90.57 | 88.35 | 86.12 | 81.40 |
| Literature11 | 96.96 | 92.11 | 94.75 | 90.20 |
| Literature12 | 96.54 | 94.25 | 93.16 | 89.20 |
| Literature13 | 96.75 | 95.33 | 94.52 | 92.03 |
| The algorithm used in this article | 96.88 | 95.46 | 95.12 | 93.26 |

To sum up, vehicle license plate positioning was compared on four types of data sets: large Angle tilt in the day, large Angle tilt in the night, standard in the day and standard in the night. The experimental results showed that the vehicle license plate positioning effect and accuracy adopted by the algorithm in this paper were better than other algorithms.

### *D. Character recognition experiment performance comparison*

In this paper, using 2000 different situations (license plate large inclined Angle and night environment, etc.) of the vehicle images as test data sets, testing training good license plate recognition model, finally can accurately identify 1920 license plate images, recognition rate is 96%, in which different scenarios of test images as shown in figure 6, in the end the license plate character recognition results as shown in figure 5.In order to verify the validity of the license plate recognition network proposed in this paper, the license plate recognition network was verified under day and night scenes, and license plate detection was performed on images of four types of scenes: large Angle tilt during the day, large Angle tilt during the night, daytime standard and night standard.



(a)Tilt at a wide Angle during the day

(b) The night tilted at a wide Angle

(c)Standard during the day

(d)Evening standard

Fig. 5. Partial sample test results

The detection effect of this paper is shown in Fig. 5.

In order to compare the performance of the neural network described in this paper, a comparative experiment method is used. A standard CRNN+CTC neural network was built, and the training set and data set in this paper were used for network training and testing. EasyPR was compared with EasyPR character recognition network. EasyPR is an open source LPR framework based on support vector machine, which belongs to supervised segmentation method. As can be seen from table II, compared with EasyPR character recognition network, the algorithm in this paper has improved the recognition accuracy of Chinese characters, Numbers and letters.

TABLE II. ACCURACY COMPARISON

| model | accuracy/% | | time/ms |
|---|---|---|---|
| | License plate recognition | Character recognition | |
| EasyPR | 93% | 94.5% | 11.ms |
| The algorithm used in this article | 96% | 96.4% | 9ms |

## IV. CONCLUSION

This paper proposes a license plate recognition algorithm based on ABCNet network. The algorithm first USES ABCNet network to locate the license plate in the original image, which is more accurate than the traditional method to locate the license plate in the large Angle position. Then, crnn-ctc is used to extract the character features of the license plate, and then it is matched with the training samples in the database. The euclide distance is used to judge the similarity of the characters, and finally the license plate recognition is realized. This simple method can greatly improve the accuracy of license plate recognition and will play an important role in the actual traffic management.

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