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Container Number Recognition Method Based on Deep Learning

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Abstract: In Container number recognition is the key technology to realize the intelligent management of container entering and leaving the port. Character detection and recognition are common methods. Aiming at the problem of locating the container number in the picture, we propose to use FastCNN detector to determine the location of the container number and revolutionary recurrent neural network to identify the 11 digit container number at one time. In addition, aiming at the problem of low recognition accuracy caused by the inclination of container number in the captured picture, the method of picture randon transformation is used to preprocess and correct the container number picture. The implementation shows that our method has the advantages of simple implementation, high detection accuracy, fast recognition speed and better application value.

Keywords: container; Text recognition; Smart port; Deep learning; Randon transform.

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1. INTRODUCTION

At present, China is the world's largest importer and exporter of goods. International import and export trade depends on the port for storage and transportation through containers. Container management is the key component of port intelligent management, and the realization of container intelligent management first needs to effectively identify the container number. In a large port, it is unrealistic to rely on manual container number identification. With the application of deep learning in text recognition, using deep learning to realize the automatic recognition of container number has become the mainstream [1]. Using deep learning technology to realize container number recognition can not only reduce labor cost, but also realize effective recognition all day. Container number recognition involves character positioning, character segmentation and character recognition. Character positioning is the process of cutting the container number from the picture containing the container number. Common character location methods include edge based location method, texture based location method and region based location method. Character segmentation technology is usually needed to realize container number recognition by 36 kinds of methods. Character segmentation is the process of further dividing the container number into a single character in the cut container number picture. Projection method, continuous domain analysis method and region growth method are commonly used in character segmentation. Character recognition is the process of recognizing characters in pictures. Common methods include character recognition based on character features, character recognition based on template matching, and character recognition based on neural network.

Although the existing schemes can realize the recognition of container number through several steps of character positioning, character segmentation and character recognition, the existing schemes also face the following problems: (1) the container pictures captured in the port environment are usually affected by environmental factors such as light. In addition, the containers that have been transported by sea for a long time also have broken and incomplete container numbers; (2) The captured container number pictures are deformed and tilted, and the spacing of container numbers in different arrangement forms is inconsistent, which will increase the difficulty of character segmentation; (3) The incomplete or incomplete container number displayed on the container and the poor capture angle will lead to poor quality pictures. In this case, the recognition rate of the method based on character feature recognition or template matching will be significantly reduced. However, the 11 bit character recognition scheme using neural network needs to train multiple models, which faces the problem of low efficiency.

In order to solve the above problems, this paper proposes to use the efficiency of deeping learing target recognition to locate the container number and cut the picture containing the container number. In order to improve the efficiency of recognition and reduce the influence of character spacing on the recognition results, this paper proposes a method of using revolutionary recurrent neural network to directly recognize the box number picture cut by FastCNN. In addition, this paper also proposes to use randon transform to correct the inclined container number picture in order to improve the text recognition accuracy of revolutionary recurrent neural network . Compared with the traditional container number recognition method, the scheme proposed in this paper has a simpler structure, can effectively reduce the impact of external factors on the container number recognition results, and can recognize the container number contained in the picture at one time. The innovations of the scheme proposed in this paper can be summarized as follows: (1) this paper proposes a container number recognition structure with simpler steps; (2) This paper proposes a more efficient method to resist the influence of environmental factors; (3) This paper presents a one-time recognition mechanism suitable for both vertical and horizontal distribution of packing numbers.

2. ALGORITHM IN THIS PAPER

This paper proposes a scheme to realize container number recognition by using two deep neural networks: FastCNN and revolutionary recurrent neural network..Specifically,

(1) For a given container picture captured by the camera, the scheme first uses the trained

FastCNN to locate the position of the container number and cut it out of the captured picture; (2) After the cut image is obtained, the randon transform is used to correct the tilt of the tilted container image; (3) The corrected container image is input into the trained revolutionary recurrent neural network, and the revolutionary recurrent neural outputs the identification result of container number.

2.1 Container number positioning

Because the painting position of container number is not fixed, the pixel cutting method of prefixed position is not realistic. In order to detect the position of the container number flexibly, conveniently and universally, we use the deep target detection network FastCNN, which is widely used in industry. It first divides the whole image into S × S network image block, each network is responsible for detecting targets in its area. In order to detect compatible small target object detection and large target object detection, FastCNN performs down sampling and up sampling on the extracted feature map to form three scale feature maps. In each characteristic diagram, each network predicts B prediction targets, and FastCNN defines the confidence as: Where is the probability value of the predicted object and the intersection ratio IOU between the predicted bounding boxes and the real box. The organization of each prediction target is composed of four position outputs (x, y, W, H), one object probability value and C category probability values. After a large number of labeled container number data training, the network model parameters can well fit the distribution space of the container number, and generalize to the unseen container number data, so it is not limited to the container number in the fixed position.

2.2 Tilt correction of container number

Due to the camera shooting angle and the printing of truck container number, the container number selected and cut by FastCNN is sometimes not vertical or horizontal (Fig. 1), and the inclined text will affect the subsequent revolutionary recurrent neural network identification of container number, such as missing words or multiple words. Therefore, it is necessary to change the inclined text into horizontal or vertical by some correction means before character recognition.

Figure1 Inclined text

There are many methods for skew text correction, such as radon transform and spatial transform network. This paper uses the method of Radon transform. Radon transform is an integral transform, which integrates the function defined on the two-dimensional plane along a straight line and applies it to the binary image, that is, sum the pixel values of all pixels passing through a straight line, and perform the same operation on all straight lines parallel to the straight line and passing through the image to obtain the projection of the binary image along a specific angle (Fig. 2).

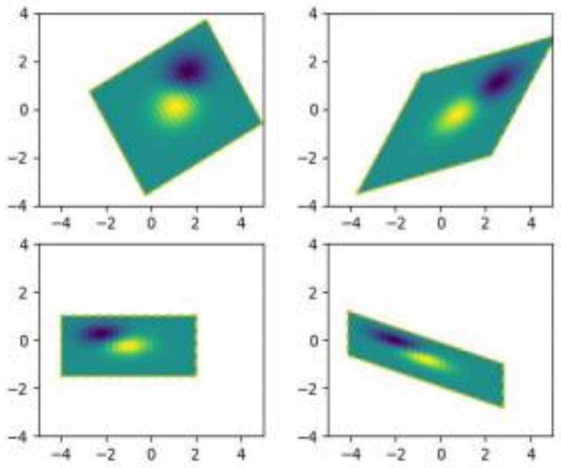

Figure 2 Radon transform

After finding the tilt angle, rotate the image to obtain the corrected image. You can also further use radon matrix to determine the four vertices that can frame the text, and use rotation transformation to correct the image。

2.3 Container number identification

Compared with the segmentation of a single font, considering the limited number of container number characters, revolutionary recurrent neural can sample the whole container number information well, so as to recognize all the characters in the image in sequence instead of one character at a time, which reduces a lot of time consumption of network processing.

The processing of image data by revolutionary recurrent neural is shown in the figure below. Firstly, the image is preprocessed to form the required input size, and then the c * h * W feature map is generated through the full convolution layer. After the full convolution layer specially designed by us, the final generated h is 1 (that is, the image height we require to input is fixed). Finally, each channel is input into the bidirectional long-term and short-term memory network (LSTM) as a sequence node, so that the network can automatically explore the context relationship between image features, Finally, the feature with timing information is generated, and then the corresponding text information is decoded through a predefined dictionary, and then the final result is generated after a correction.

3. EXPERIMENTAL RESULTS AND ANALYSIS

The experiment runs on a window 10 enterprise machine

configured with Intel (R) core (TM) i7-7700k CPU @ 4.20ghz processor, 16GB memory and nvidi geforce GTX 1660 Ti graphics card.

Data set: in order to compare the ability of model recognition under different lighting conditions, this paper collected a test set of 1000 photos, recorded as s, including

500 photos under normal light and 500 photos under backlight. And even the illumination degree of the photos in the same group is also different, which takes into account the shooting conditions in various cases.

3.1 Container number positioning experiment

Accurate positioning of container number is the basis of the whole recognition scheme. Here, we detect the container number in different scenarios. Here, the target evaluation index we use is mean average accuracy (map).

As shown in Table 1, we can find that the target detector trained in a specific data set has a higher detection effect on the box number in the case of forward light, and can effectively detect the location of the box number in most cases in the case of backlight . The reason is that there is an obvious pixel edge between the box number as a white font and the box, It can also be detected effectively under the multi-scale detection characteristics of deep network.

Table 1 Target detection results

Environment	training set	mAP (%)
Smooth	500	97. 14
Backlight	500	96.54

3.2 Container number identification

In order to more fully illustrate the advantages of our method, we compared different single character recognition methods. The experimental results are shown in Table 2.

Table 2 Comparison of case number identification results

Environment	Smooth	Backlight	All
M^{36}	85.80	81.80	83.80
$Ours^{w/o\ R}$	87.8	83.20	85.80
Ours	91. 10	89.60	90.60

In Table 2, we can see that our complete method has the best recognition effect, and there is a large gap between the effect of the method and that of the method. Through our visual recognition results, it is found that because the method is to recognize a single character, if a character is wrong, the whole recognition result will be wrong, and there is the shortest board problem. Our method can analyze the text in the whole picture at one time and find the standard law. Therefore, we can learn the ability to correct and rarely make mistakes. The result without randon correction affects the recognition effect. Because without correction, the detected box number image is directly input into the revolutionary recurrent neural network. When scaling, in order to ensure a certain height, but the image length is pulled and deformed, and the information is damaged, resulting in the decline of recognition accuracy.

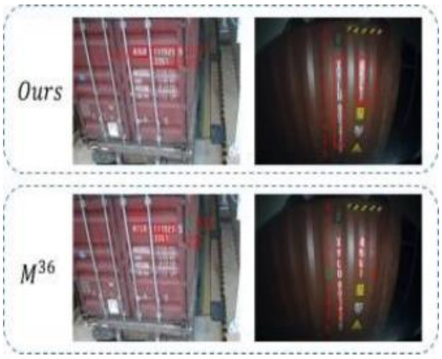

Figure 3 Comparison of methods

4. CONCLUSION

Aiming at the problems of complex identification process of existing container schemes and too many networks to be trained, a container number identification scheme using FastCNN and revolutionary recurrent neural network is proposed in this paper. The experimental results show that the scheme has the advantages of simple recognition process, strong adaptability to complex environment, fast recognition speed and strong practicability. In the future, we will study a scheme to realize container number recognition without tilt correction.

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