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Tilted License Plate Correction and Character Segmentation Based on Deep Learning and Hough Transformation

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Abstract: The correction of tilted license plate plays an extremely important role in license plate recognition. Accurate recognition of license plate information can not only strengthen the traffic safety, but also reduce the probability of traffic accidents. Therefore, this paper proposes a tilted license plate correction and character segmentation method based on the deep learning and digital image processing. Firstly, the Faster R-CNN is proposed to detect the location of tilted license plate. Then the images of license plate area are cropped out from the original images according to the vertices coordinates of bounding box detected by Faster R-CNN. The cropped license plate images have a certain tilt angle. Hough transformation is applied to complete the tilted license plate correction. Then, through digital image processing technology, the characters of license plate are segmented. The experimental results show that the characters of license plate are well segmented and the location average precision of the Faster R-CNN is 90.12%.

Keywords: license plate recognition; license plate character segmentation; Hough transformation; tilted license plate correction; Faster R-CNN; deep learning.

1. Introduction

In intelligent transportation system, the accurate recognition of license plate character is conducive to the handling of traffic accidents and driver's awareness of safe driving and it also conducive to reduce the possibility of accidents. However, in actual traffic conditions, due to the different installation positions and angles of the onboard cameras, the license plate images of the vehicles in front of the left and right cameras have a certain tilt angle in both horizontal and vertical directions [1,2].This phenomenon will bring many difficulties to the license plate information recognition. Therefore, the horizontal and vertical correction of the tilted license plate is particularly important. In the past few decades, researchers have conducted research on license plate recognition in various situations [3, 4, 5]. In this section we will briefly review the relevant literature.

A new ALPD (Autonomous License Plate Detection) method is proposed by Samiul *et al.*, which can be able to effectively detect license plate area from an image in the complicated conditions [6]. A new contrast enhancement method with a statistical binarization approach is introduced in the proposed ALPD. For correcting tilted license plate, the Radon transformation is applied based on the tilted license plate correction method for the first time.

Wu *et al*. proposed the license plate location and segmentation based on the Open CV technology and Tensor Flow. Tensor Flow is used to recognize license plate characters. Each link is independent, which can reduce the coupling between the layers and improve the maintainability of the system [7].

Currently, several deep learning methods have been applied widely on vehicle and license plate detection [8].Zhang *et al.* proposed a robust license plate detection system to detect and correct the tilted license plate in the detection stage, and a pre-trained character segmentation network is proposed based on CNN and RNN [9]. Xie *et al.* proposed a CNN-based MD-YOLO framework for multi-directional license plate detection for high-accuracy real-time license plate detection [10].

In summary, significant progress has been achieved in tilted license plate detection and correction about the autonomous vehicle technology. However, these methods generally cannot satisfy the calculation and accuracy requirement. Consequently, from the perspective of the efficiency and accuracy, it is extremely important to locate, classify and correct the tilted license plate. Accordingly, the objective of this study is to construct a network for license plate location and a Hough transformation algorithm for correcting the tilted license plate.

2. Experimental scheme

The connection area outside the license plate has great influence on the segmentation of license plate character information. In order to improve the accuracy of license plate information segmentation, we firstly cut out the license plate area image from the original input images. Then the tilted license plate image is corrected by Hough transformation. To obtain the license plate area images, the Faster RCNN is proposed to locate the license plate area images. After locating the ROI region of the original license plate images, the license plate area image can be cropped according to the four vertices coordinates of the detected bounding box. Then the Hough transformation correction was applied. Therefore, the corrected image still has some areas connected with the license plate. Currently, it is necessary to determine the upper and lower boundary of the license plate, and the license plate area is cropped within the upper and lower boundary. The characters of the license plate are segmented by image morphological processing. The whole process is shown in Figure 1.

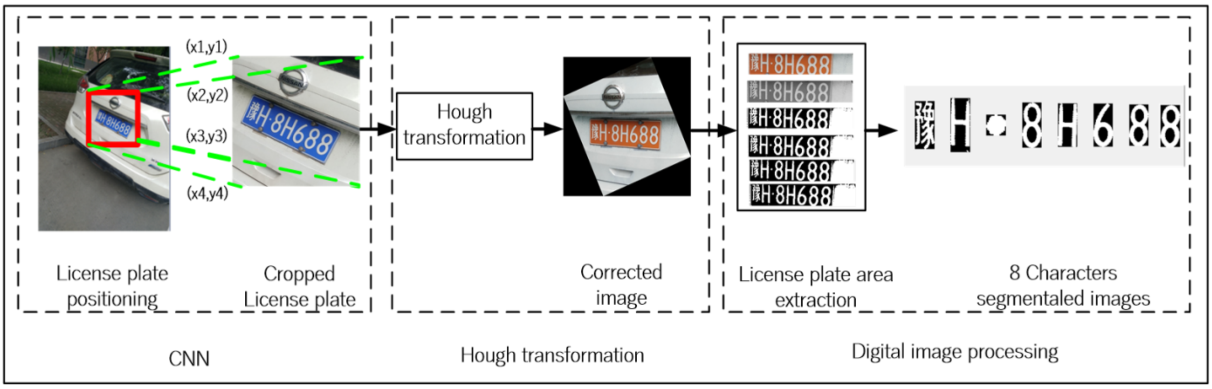

Figure. 1 Location, correction, and segmentation process of tilted license plate

3. Network architecture and Hough transformation

3.1 Faster R-CNN

The Faster R-CNN consists of four parts [11]. CNN is the first part, which is used for extracting Feature Maps from the input images. It includes 13 Conv Layers, 13 ReLU Layers and 4 Pooling Layers. The second part, called RPN, is used for extracting the Region Proposals [12]. The third part is the ROI Pooling Layer, which combines the Region Proposals extracted by RPN and Feature Maps produced by CNN to generate the Proposal Feature Maps. The Classification Layer, the fourth part, carries the Proposal Feature Mapsto the Fully-Connected Layer. Then targets classification and Bounding Box Regression are applied. The Faster RCNN architecture is shown in Figure 2, which can be regarded as the combination of the Fast R-CNN and RPN [13].Firstly, the Conv Layer extracts the Feature Maps from the input images. The ROI Pooling Layer and RPN share the Feature Maps together. RPN extracts the Region Proposals from the Feature Maps, and then sends them into the Roi Pooling Layer. The ROI Pooling Layer generates the Proposal Feature Maps and sends them into the Fully-Connected Layer for classification and Bounding Box Regression to find out the location of the targets and display them in the input image [14].

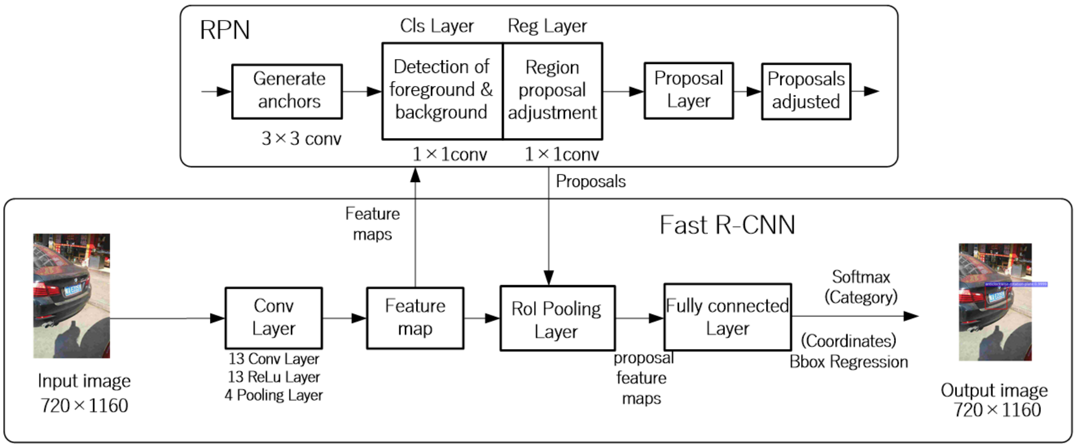

Figure. 2 Faster R-CNN architecture

3.2 Hough transformation

Hough transformation is one of the basic methods to detect geometric shapes from images. The basic principle of Hough transformation is to use the duality of points and lines to change a given curve in the original image space into a point in the parameter space through the curve expression [15].In this way, the problem of detecting the given curve in the original image is transformed into the problem of finding the peak value in the parameter space. The coordinate transformation relation of x-y plane into θ-ρ plane is shown in Figure 3 below [16].

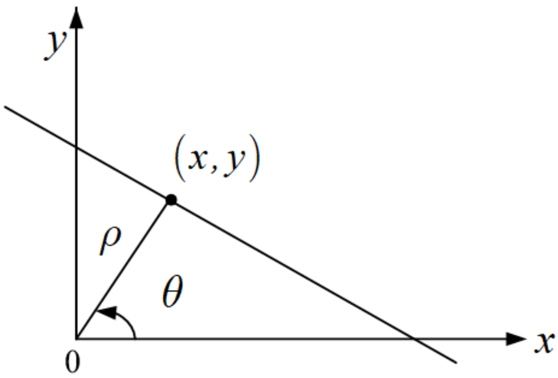

Figure.3. transformation of x-y plane into θ-ρ parameter plane

The image of x-y plane is transformed to the image matrix of θ-ρ plane. The expression of Hough transformation is as follows.

$$x\cos\theta + y\sin\theta = \rho \qquad (1)$$

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4. Training and testing

The training dataset for the Faster RCNN license plate positioning model has1500 images of CCPD [17], and the learning rate is set at 0.001, and the iterations is set at 120K times, the experiment is implemented in Caffe. Experimental hardware configuration includes Intel Core i7 processor with 8G NVIDIA GeForce GTX 1070 GPU. The operating system is Ubantu18.04 and programming language environment is based on Python. Precision-Recall curve of the model is shown in Figure 4, and the detection model obtains an average precision of 90.12%.

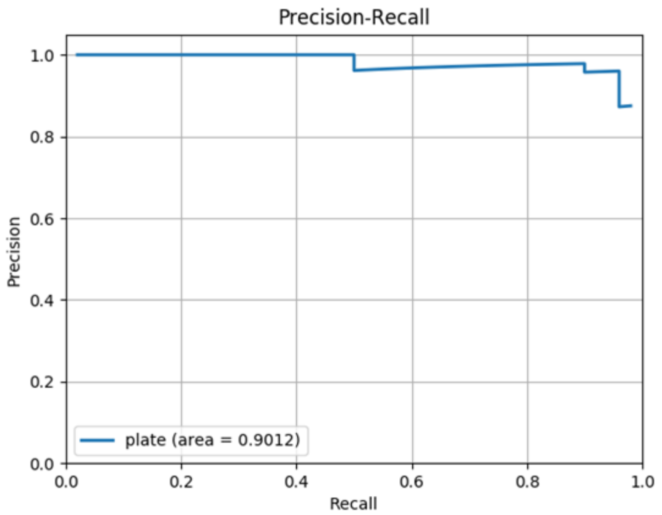

Figure. 4 Precision-Recall curve

In this paper, the average precision (AP) and recall rate are used as the main evaluation indexes to measure the performance of the model. The definitions of AP, precision and Recall are as follows

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$AP = \int_0^1 P(R)dR \quad (4)$$

where TP (True Positive) is the number of positive samples, which is correctly classified, and FP (False Positive) is the number of negative samples, which is incorrectly labelled. *Recall* represents the correct probability of being predicted in a positive sample. *Recall* can be expressed as (3), where FN (False Negative) is the number of positive samples labelled incorrectly as negative samples. The most common metric is average accuracy (AP), which is calculated based on accuracy and recall rates. AP typically evaluates in a specific category. Calculate separately for each object category. In this paper, there are two object categories for vehicles and pedestrians. In general object detection, the detector is usually tested by detecting some object category. To compare the performance of all object classes, the mean AP (mAP) average of all object classes is used as the final performance metric. In this paper, the average value of license plate AP is used as the final performance evaluation of the detector.

In general-purpose detection, IoU is called Intersection over Union, which is a standard for measuring the accuracy of detecting corresponding license plate in a specific dataset. The IoU calculates the ratio of the intersection and union of the predicted border and the actual border, which can be expressed as

$$IOU\left(b,b^{g}\right)=\frac{\text{area}\left(b\bigcap b^{g}\right)}{\text{area}\left(b\bigcup b^{g}\right)} \qquad (5)$$

where b is the detection prediction bounding box (Detection Truth Box), and b^{g} is the Ground Truth Box; $\text{area}\left(b\bigcap b^{g}\right)$ is the intersection of the predicted bounding box and the ground truth bounding box labeled manually, and $\text{area}\left(b\bigcap b^{g}\right)$ is the combination of the predicted boundary box and the ground truth bounding box.

5. Experiment results and discussion

5.1 Detection results of tilted license plate

It can be seen from the result of license plate positioning that the license plate area is well positioned.The average positioning accuracy reached 90.12%. In order not to lose the license plate angle information, the positioning bounding box is close to the square. Figure 5 shows the effects of 5 experimental samples.

a	b	c	d	e

Figure. 5 Detection results of tilted license plate of Faster R-CNN

5.2 Hough transformation correction results of tilted license plate

According to the four verities coordinates of the located license plate bounding box, the license plate area is cropped out.There is a certain tiltangle in the cropped license plate, and the Hough transformation can be used to correct the license plate image.The results in Figure 6demonstrate that the license plate image is well corrected,and the license plate area is shown in orange, which is conducive to the next step of license plate character segmentation.

Original image

Hough transformation	

Figure 6. Hough transformation correction results

5.3 Character segmentation of license plate

The character segmentation of license plate is based on image morphology. Firstly, Canny operator is used to detect the edges of license plate image. Then,the edges of the license plate image are smoothed. The image after smoothing the edges has many small areas of interference. This affects the detection of the upper and lower boundaries of the license plate area, so the small areas need to be removed. Thirdly, the license plate area is cropped according to the upper and lower boundary of the license plate. After image processing such as binarization and corrosion expansion, the license plate characters are separated from the background.After image processing such as binarization and corrosion expansion, the license plate characters are separated from the background.After distinguishing license plate characters from license plate background, license plate characters are well segmented. The process of the above steps can be shown in Figure 7.

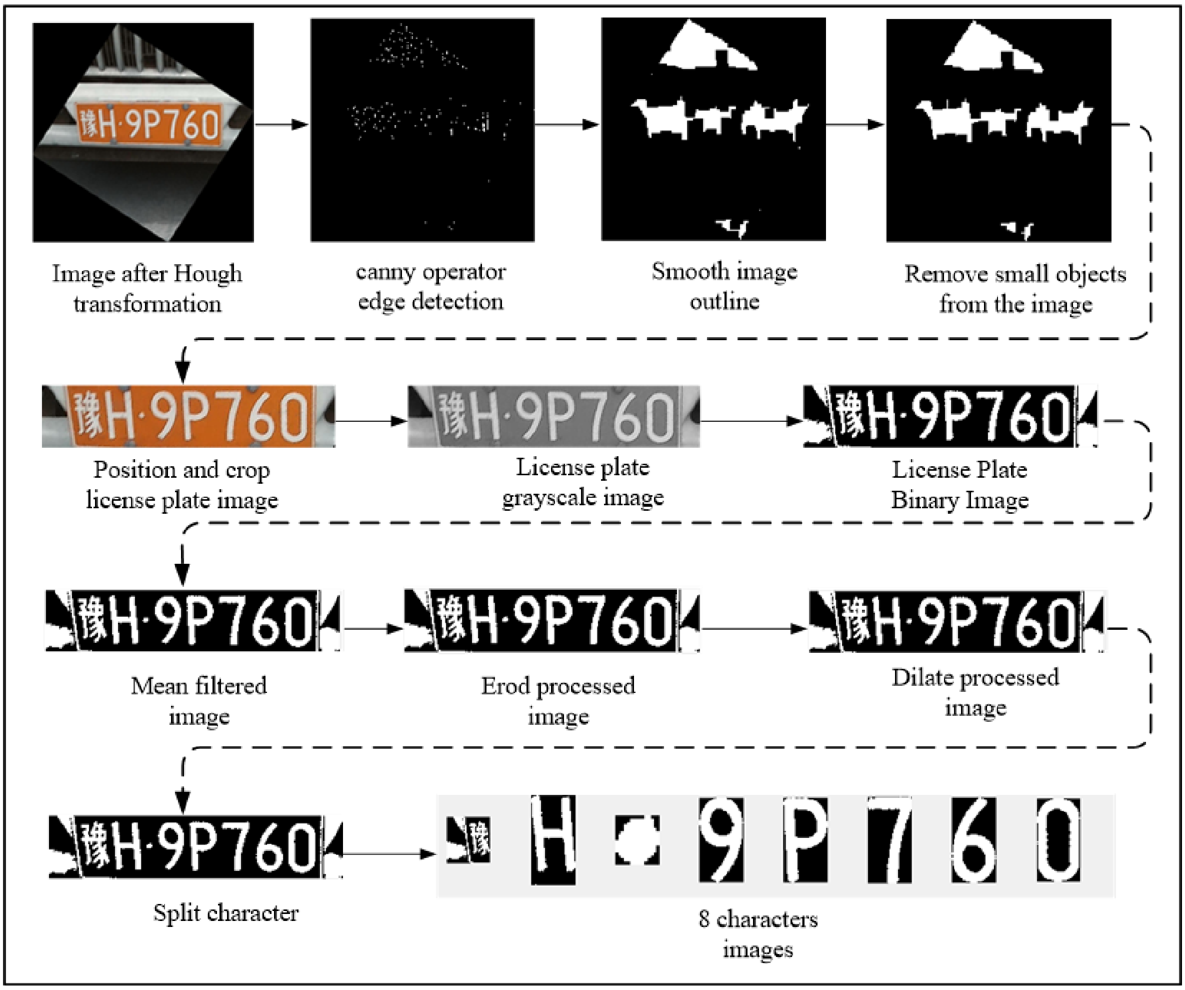

Figure. 7 Character segmentation process of license plate

Conclusion

Based on deep learning and image processing technology, the license plate correction and license plate character segmentation method proposed in this paper can not only correct the deflection of license plates well, but also segment the tilted license plate characters according to the corrected images.First, faster RCNN detects the location of the license plate, and then the image of the license plate area is cropped from original image according to the four vertices coordinates of the detection bounding box of Faster RCNN.In the image of the license plate area after cropping, the license plate still has the tilt angle, and then Hough correction is used to correct the tilted license plate, the license plate image is segmented and extracted based on image processing technology.In the future, in order to further improve the accuracy of license plate correction, we will consider introducing regression convolutional neural network.The regression convolutional neural network will be used to calculate the license plate tilt angle, and then the license plate tilt angle will be corrected by image transformation processing such as rotation and shearing.

Reference

[1] Wang Weihong, Tu Jiaoyang, "Research on License Plate Recognition Algorithms Based on Deep Learning in Complex Environment", Access IEEE, vol. 8, pp. 91661-91675, 2020.

[2] Chen, Y., Ding, X.: The method of car license localization and character division in complex vehicles image. Infrared and Laser Engineering 33(1), 29–33 (2004).

[3] Yang, Dingding; Zhou, Hongbo, Tang, Liming; Chen, Shiqiang; Liu, Song. A License Plate Tilt Correction Algorithm Based on the Character Median Line Algorithme de correction d'inclinaison de plaque d'immatriculationbasé sur la lignemédiane du caractère [J]Canadian Journal of Electrical and Computer Engineering, v 41, n 3, p 145-150, Summer 2018; ISSN: 08408688; DOI: 10.1109/CJECE.2018.2867591; Article number: 8526360; Publisher: IEEE Canada.

[4] P. Li, M. Nguyen and W. Q. Yan, "Rotation correction for license plate recognition," 2018 4th International Conference on Control, Automation and Robotics (ICCAR), Auckland, 2018, pp. 400-404.

[5] Piyuan Li, Minh Nguyen, Wei Qi Yan, "Rotation correction for license plate recognition", Control Automation and Robotics (ICCAR) 2018 4th International Conference on, pp. 400-404, 2018.

[6] Samiul Azam, Md Monirul Islam Automatic license plate detection in hazardous condition[J] Journal of Visual Communication and Image Representation, 2016, 36.

[7] Wu Linhui, Yang Chenyao, Zhang Wenlong, Jiang Weixiang. Design and development of license plate recognition software based on OpenCV and deep learning [J]. Computer Knowledge and Technology, 2020,16(01):203-204+212.

[8] Hui Li, Peng Wang, Mingyu You et al. Reading car license plates using deep neural networks[J] Image and Vision Computing, 2018, 72.

[9] Y. Zhang and C. Huang, "A Robust Chinese License Plate Detection and Recognition Systemin Natural Scenes," 2019 IEEE 4th International Conference on Signal and Image Processing (ICSIP), Wuxi, China, 2019, pp. 137-142, doi: 10.1109/SIPROCESS.2019.8868545.

[10] L. Xie, T. Ahmad, L. Jin, Y. Liu and S. Zhang, "A New CNN-Based Method for Multi-Directional Car License Plate Detection," in IEEE Transactions on Intelligent Transportation Systems, vol. 19, no. 2, pp. 507-517, Feb. 2018, doi: 10.1109/TITS.2017.2784093.

[11] Ren, S., He, K., Girshick, R., et al.: Faster R-CNN: towards real-time object detection with region proposal networks. In: Advances in Neural Information Processing Systems, pp. 91–99 (2015).

[12] X. Yu, Y. Si and L. Li, "Pedestrian detection based on improved Faster RCNN algorithm," 2019 IEEE/CIC International Conference on Communications in China (ICCC), Changchun, China, 2019, pp. 346-351, doi: 10.1109/ICCChina.2019.8855960.

[13] R. Girshick, "Fast R-CNN", Computer Science, 2015.

[14] S Ren, K He, R Girshick et al., "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", Proceedings of IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 6, pp. 1137-1149, 2017.

[15] J. C. Cexus, A. O. Boudraa and A. Bouchikhi, "A combined Teager-Huang and Hough Transforms for LFM signals detection," 2010 4th International Symposium on Communications, Control and Signal Processing (ISCCSP), Limassol, 2010, pp. 1-5, doi: 10.1109/ISCCSP.2010.5463482.

[16] R. O. Duda and P. E. Hart, "Use of the Hough transformation to detect lines and curves in pictures", Commun. ACM, vol. 15, no. 1, pp. 11-15, 1972.

[17] Xu Z, Yang W, Meng A, et al. Towards end-to-end license plate detection and recognition: A large dataset and baseline[C]//Proceedings of the European conference on computer vision (ECCV). 2018: 255-271.