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Number Plate Detection of a Car Using Neural Networks

B. Naveen Kumar[1], D. Sashitha[2], E. Alekya[3],L. Anirudh[4]

1-Assistant Professor, Dept of CSE, AITS, Rajampet, AP, India

2,3,4-Student, Dept of CSE, AITS, Rajampet, AP, India

ABSTRACT

This paper introduces a novel convolution semantic network (CNN)-based approach for detecting high-precision real-time car license plate. Most contemporary methods for detecting car license plate are reasonably effective under specific conditions, or only under strong assumptions. We show poor results, however, when the photos of the car license plate evaluated have a degree of rotation, Thanks to traffic police manual recording or video deflection. We are therefore suggesting the multi-directional car license plate identification system for a CNN-based YOLO. Our pro-positioned approach can elegantly handle rotational problems in real-time situations, using precise rotation angle estimation and a quick orthocenter-over-union evaluation strategy. A series of experiments were performed to demonstrate that the proposed method outperforms other current state-of - the-art methods in terms of greater accuracy and lower computational costs.

Keywords— number plate detection, convolutional semantic network, YOLO, ortho- centre over union, multi dentate.

1.INTRODUCTION

Recent years have seen a substantial increase in the number of private cars and this has, in effect, increased the burden of traffic management. The resulting congestion has caused extreme issues,

such as traffic accidents or exposure to violence or terrorist attacks in public spaces. Physical control of this ubiquity of cars is quite difficult and has facilitated this issue, Creation of automated traffic jam management system. Automated license plate recognition, in particular, can effectively control the cars and significantly relieve traffic management burdens; thus, this method has attracted significant researchers interest. Moreover, automatic car license plate identification can also be implemented in many other situations, e.g. for collecting expressway tolls, tracking of speed violations and man-augmenting unattended parking lots.

The problem is solved using both conventional and convolutional semantic network-based approaches. The traditional methods involve hand-crafted features such as color, edge and morphology which are primarily confined by stringent conditions. For example, some of these systems require high-resolution images as inputs, the processing of which requires expensive equipment, while others require strict, translation-and rotation-free mounting. Real-world situations, however, are quite different where car license plate detection becomes very challenging Different types of cars and roads, changing weather conditions, camera-device rotation, and thus dramatically curtail the detection efficiency. Therefore, a reliable system with hand-crafted features is relatively difficult to suggest under the complex situation. Even though people may employ multiple independent features and integrate some models together, it is still difficult to distinguish whether it is sufficient to meet the challenge with such limited features and models as stated in it. Recently, however, these types of detection methods have achieved very impressive results, their time consumption is significantly higher than that of the techniques described above.

Inspired by the frame-work of "you only look once" (YOLO), we suggest a CNN-based approach that can manage the multidirectional problem fairly well. The main contributions of our work are summarized as follows:

1) We propose a new, precise rotation angle prediction method for multi-dentate car license plate detection;

2) We propose an approximate method, namely the angle deviation penalty factor (ADPF) to quickly determine the orthocentre-over-union (IOU) between the two rotational rectangles.

3) To further encourage detection accuracy, we are developing a pre-positive CNN model that is implemented before YOLO, which is used in the overall system to assess the "attendance zone."

4)The proposed method achieves state-of -the-art precision in the identification and can also be tested in real time.

2. RELATED WORK

The computer vision group has carried out groundbreaking work over the past two decades to

address the problem of automatic car license plate detection and recovery. This license plate detection function can be loosely classified as follows: 1) geographic approaches, 2) pixel-to-pixel approaches, and 3) color-based approaches. In regional approaches, input image is segmented into smaller regions, where some of the license plate's pre-specified attributes are located in such subsequent regions. Numerous coherent methods are designed to efficiently perform car license plate identification tasks based on morphological and high-pass filtering. In pixel-to-pixel approach, each pixel among its neighboring pixels is evaluated to form a coarse rectangular box in the image. Pixel-by-pixel scanning of the entire input image is performed using a detection window. The scanning window response is measured at each position of the pixels and the regions with high response to the scanning window are selected as candidate region. In this relation L. Dlagnekov has devised an Ada boost classifier to represent an image pixel-to-pixel. Use pixel-to-pixel method in license plate detection problem. The authors contributed in the later stage by devising the first step Adaboost classifier and then the later stage SVM classifier based on SIFT. Scale-invariant Feature Transform (SIFT) based approach was also exercised by F.A. Silva for license plate detection and recognition. In HOG-features of the segmented license plate were extracted and then a Gentle AdaBoost trained classifier was used for license plate detection. Subsequently, a novel color-based approach was developed by converting the RGB-color images to the HSV-color space. This HSV-image is then segmented into smaller blocks, where each block is inspected for license plate or some portion of the license plate using a carefully designed filtering process. This suggested three stage procedures for detecting and recognizing a car license plate; where first,

I) sliding concentrated windows based approach is used to detect candidate regions, (ii) HSI-color dependent verification is made to classify candidate regions, and (iii) candidate regions are decomposed using histogram location to segment alphanumeric characters in the plate. Over the past couple of years, many computer vision issues have been solved through the use of profoundly convolutionary semantine networks (CNNs); in line with that, other researchers have been exercising to solve the problems of detecting and identifying car license plate using CNNs. Current state-of - the-art CNN based models may not be directly used to achieve good enough efficiency, particularly in the challenging situation of multi-dentate car plate detection. Although the multi-directional car license plate detection problem was well established and has been tackled by some researchers, the performance using traditional method is still far from promising in practice. Work on computer vision tasks in transportation system has recently made significant progress. Many new methods prefer to use the features derived by CNN instead of hand-crafted applications, under high demand for robustness. Furthermore, other data augmentation approaches need to enrich the dataset. The work of balancing the proportion of various objects in the dataset with hierarchical increase obviously has increased the accuracy. In addition, several researchers have tried to use previous knowledge to improve the results, e.g. position symmetry. In this paper our proposed method also follows these patterns to achieve high precision detection.

3. Methodology

In this section, we introduce our YOLO method and discuss a further refinement of the proposed design.

A . Multi-dentate number plate detection With YOLO

3.1Gyration Angle*:*

YOLO is a unified CNN-based detection system which views detection as a problem of retro gradation. With some significant improvements in the original design, our proposed YOLO will tackle multidirectional problems with high precision detection. The configuration of the YOLO network is shown at Fig

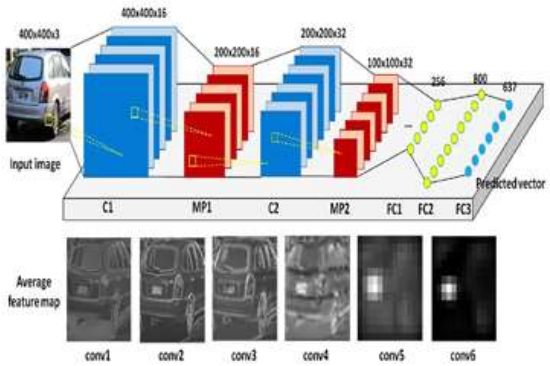

Fig: the model graph of YOLO for number plate detection

Remember that in the training set the average rotation angle should be much greater than the one in the test set to match the actual situation, which

can be ensured by a random rotation strategy as stated later. Unlike the other parameters considered in this process, we choose to preserve the negative value for the angle variable so that direction can be calculated.

3.1 Evaluating IOU With ADPF*:*

We wish to predict the rotation angle, which involves evaluation of the IOU between two rotational rectangles during forward propagation of the CNN. We attempt to evaluate the IOU using the Computational Geometry Algorithms Library (CGAL) directly.

3.2Retro gradation and Recognition:

In the retro gradation process, we wish to find a non-linear function F(I) that accepts image I as input and produces a specific target t. However, it is extremely difficult to determine F(I) exactly; therefore, we employ CNN to allow the algorithm to learn an approximate function FI. Further, we use the back propagation algorithm (BP) to approach F(I*)*. YOLO executes direct retro gradation to detect a car license plate. This retro gradation is schematically illustrated in Fig. 2. Each input image is divided into regular S×S grid cells, and the cell in which the car plate center is located is used to detect the car license plate. B bounding boxes and a confidence score P(object) are predicted for each grid cell.

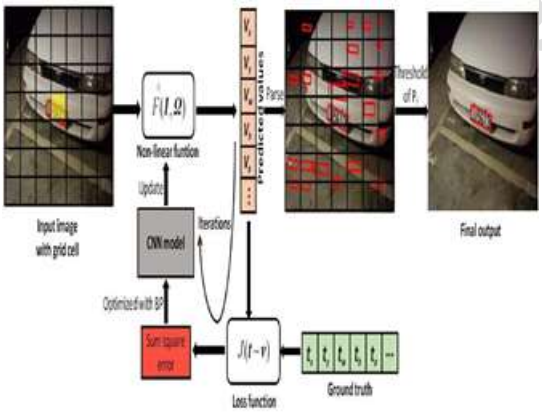

Fig: yolo retrogradation procedure

3.4 Network Design and Training :

As illustrated Fig. 1, Our YOLO network is composed of seven convolution layers and three fully connected layers. All layers of convolution use a kernel size of 3 / 3 and a padding size of 1. Max-Pooling (MP) follows the first five convolution layers with a 2-2 window size and a 2-step step. The final three fully connected (FC) layers have 256, 800, and 637 channels, respectively. To ensure that our CNN model can identify negative rotation angle values, leaky and identity functions are chosen as the activation functions, rather than ReLU function. We first pre-train our model using the Image Net dataset . Then, the model is trained to detect car license plates.

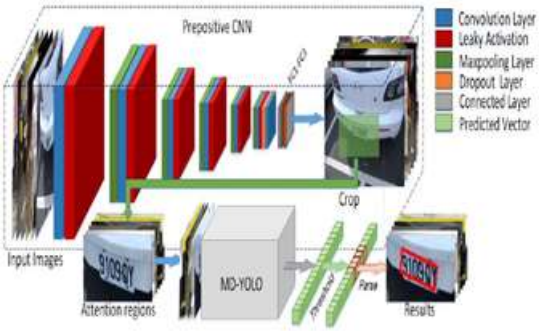

Fig: All- Inclusive YOLO structure

B. Further Refinement of Proposed Design

The image area proportion of the car license plate is usually very small for car license plate detection using an acquired image. When using the YOLO method, global image features are extracted, and small portions of the image, such as the car license plate, may be considered to introduce some redundant information. However, this problem is alleviated by introducing a prepositive CNN attention model, which is used before YOLO is implemented. Such models of attention can remove redundant information, and can significantly exceed performance.

TABLE

DETAILS OF REDESIGNED CNN MODEL FORYOLO

Layer Type	Parameters
Fully connected	#neurons:637
Dropout	Prop:0.3
Fully connected+Leaky	#neurons:985
Fully connected+Linear	#neurons:384
Convolution+Leaky	#filters:256, k: 3×3, p:1
Dropout	Prop:0.2
Convolution+Leaky	#filters:256, k: 3×3, p:1
Convolution+Leaky	#filters:164, k: 3×3, p:1
Convolution+Leaky	#filters:128, k: 3×3, p:1
Max pooling	k: 2×2, s:2
Convolution+Leaky	#filters:64, k: 3×3, p:1
Max pooling	k: 2×2, s:2
Convolution+Leaky	#filters:32, k: 3×3, p:1
Max pooling	k: 2×2, s:2
Convolution+Leaky	#filters:16, k: 3×3, p:1
Input	100×100

4 EXPERIMENTS

4.1 Dataset

The Application Oriented License Plate (AOLP) dataset was used in the car license plate detection experiment, which contains 2049 images of Taiwanese auto plates. This dataset is divided into

three sub-sets: access control (AC): 681 samples; traffic law enforcement (LE): 757 samples; and road patroll (RP): 611 samples. AC refers to cases where a car crosses a fixed passage at a significantly lower speed than normal, or comes to a complete stop. LE refers to cases where a car is in violation of traffic laws, with a roadside camera capturing this behavior. In this scenario, the background can be heavily cluttered in a single image, with road signs, pedestrians or multiple plates. Finally, RP refers to cases where the camera is attached to a patrol car, and the images are acquired from arbitrary viewpoints and distances.

TABLE
COMPARISON BETWEEN HORIZONTAL AND ROTATIONAL DATASETS. THE VALUES ARE EXPRESSED IN REC/PREC/F-MEASURE FORMAT

Data \ IoU	0.5	0.6	0.7
Horizontal	96.6/97.3/97.0	89.0/89.7/89.3	72.0/72.6/72.3
Rotational	92.6/94.4/93.5	80.5/82.1/81.3	60.0/61.2/60.6

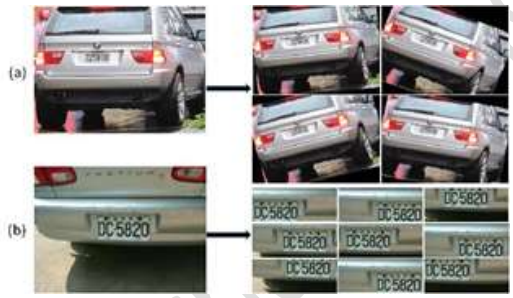

Fig. 5 Random rotation strategy. Each image is randomly rotated within [−30°, +30°].

4.2 Evaluation Criterion and Quantitative Comparison

In this subsection we report comparisons of both our proposed method's performance and computational complexity with those of other state-of - the-art methods. Since there is no uniform criterion for assessing the performance of different methods of detecting car license plate, we adopted the evaluation rule for general text detection, i.e. we used precision, recall, and F-score measurements.

TABLE
F-MEASURE OF EACH METHOD ON UCSD AND PKU DATASETS. THE RESULTS WERE EVALUATED UNDER THE IOU THRESHOLDOF 0.5. OUR ALYOLO METHOD HAS EMPLOYED THE SAME MODEL MENTIONED IN SECTION III WITH SAME DATA AUGMENTATION STRATEGY

Method \ Dataset	UCSD [17]	PKU [43]
ACF [7]	76.56	75.17
Faster-rcnn [28] (VGG16)	85.54	83.61
SSD [19]	85.32	86.63
R-FCN [4]	89.78	84.40
ALMD-YOLO (ours)	98.32	97.38

4.3 Analysis:

The foregoing quantitative results show that our proposed method outperforms previous literature methods significantly. In general terms, such improved performance has been achieved due to the precise prediction of multi-dentate rotation angle. The task of multi-dentate detection is considered to be more challenging than the general objects detection. Once the predicted angle deviates from the true one, the overlap between predicted bounding box.

TABLE

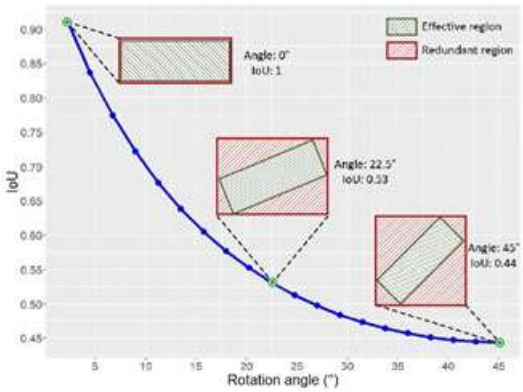

Fig. The decreasing curve of IOU w.r.t. rotation angle.

4.4 Comparison Between ALYOLO and an End-to-End Model:

To prove our two-stage training strategy model outperforms the corresponding end-to-end one, we build an end-to-end model according to the same rules as ALYOLO.

5.CONCLUSION:

We introduced a new YOLO model for multi-directional plate detection of car licences in this

paper. The proposed model can elegantly solve the problem of multi-directional car license plate detection, and can also be easily deployed in real-time conditions due to its reduced computational complexity compared to previous CNN-based methods. With the introduction of a care-like prepositive CNN model, the ALYOLO framework delivers new, state-of - the-art precision. In addition, the multi-directional car license plate detection method presented in this paper can handle challenging real-world scenarios reasonably well, even when there are only limited computational resources available, such as CPUs. There are however still a few issues that need to be addressed in the future for robust license plate detection. Firstly, the lack of adequate data on multidirectional car license plates limits the performance of our method, which will force us to collect more data or use some advanced techniques to synthesize data. In addition, although we are focusing on multi-directional car license plate detection in this paper, the detection still aims at the subsequent recognition. So it deserves further exploration as to whether we can propose an end-to-end model to deal simultaneously with multidirectional detection and recognition. Last but not least, the tasks of multi-dented car license plate detection remain great challenges waiting to be solved under poor conditions such as low resolution, terrible illumination, accidental occlusion and so forth.

6. REFERENCES

[1] A. H. Ashtari, M. J. Nordin, and M. Fathy, "An iranian license plate recognition system based on color features," *IEEE Trans. Intell. Transp. Syst.*, vol. 15, no. 4, pp. 1690–1705, Aug. 2014.

[2] R. Azad, F. Davami, and B. Azad, "A novel and robust method for automatic license plate recognition system based on pattern recognition," *Adv. Comput. Sci., Int. J.*, vol. 2, no. 3, pp. 64–70, 2013.

[3] F. A. da Silva, A. O. Artero, M. S. V. de Paiva, and R. L. Barbosa. (2013). "ALPRS—A new approach for license plate recognition using the sift algorithm." [Online]. Available: https://arxiv.org/abs/1303.1667

[4] J. Dai, Y. Li, K. He, and J. Sun, "R-FCN: Object detection via region-based fully convolutional networks," in *Proc. Adv. Neural Inf. Process. Syst.*, 2016, pp. 379–387.

[5] K. Deb, H.-U. Chae, and K.-H. Jo, "Vehicle license plate detection method based on sliding concentric windows and histogram," *JCP*, vol. 4, no. 8, pp. 771–777, 2009.

[6] L. Dlagnekov, "License plate detection using adaboost," Dept. Comput. Sci. Eng., San Diego, CA, USA, Tech. Rep., 2004. [Online]. Available: https://cseweb.ucsd.edu/classes/fa04/cse252c/projects/louka.pdf

[7] P. Dollár, R. Appel, S. Belongie, and P. Perona, "Fast feature pyramids for object detection," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 36, no. 8, pp. 1532–1545, Aug. 2014.

[8] S. Du, M. Ibrahim, M. Shehata, and W. Badawy, "Automatic license plate recognition (ALPR): A state-of-the-art review," *IEEE Trans. Cir-cuits Syst. Video Technol.*, vol. 23, no. 2, pp. 311–325, Feb. 2013.

[9] R. Girshick, "Fast R-CNN," in *Proc. Int. Conf. Comput. Vis. (ICCV)*, 2015, pp. 1440–1448.