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A YOLO-Based Method for Oblique Car License Plate Detection and Recognition

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***Abstract*— In recent years, automatic license plate recognition (ALPR) system is applied in some traffic-related applications based on deep learning. However, the new ALPR is very difficult to obtain high detection and recognition rates for oblique car license plate (LP). Recently, Silva et al. [5] proposed a warped planar object detection (WPOD) based on deep convolutional neural network (CNN) to overcome the oblique views of LP. Although the WPOD network can achieve the location and rectification of LPs, the loss function of WPOD renders the confidence parameter due to high computational complexity. This also leads to WPOD network cannot locate the optimal LP bounding box. In order to further improve the accuracy of ALPR system, we develop a simple intersection over union (IOU) algorithm to speed up the calculating process of confidence. In this paper, the four-vertex coordinates of the label bounding box and prediction bounding box of oblique LP are used to generate two rectangular boxes, and then a simple IOU algorithm is used to fast calculate the approximate value of IOU. Simulation results show that the proposed ALPR system can arrive a high accuracy of LP recognition about 95.7% on an average. In addition, the proposed system also can achieve higher recognition rate about 1% when compared to the Silva's ALPR system.**

Keywords*—*license plate recognition, deep learning, YOLO

I. Introduction

In recent years, automatic license plate recognition (ALPR) system is applied in some traffic-related applications based on deep convolutional neural network (CNN). However, most ALPR systems capture a mostly frontal view of the vehicle and license plate (LP) to obtain high LP recognition rates. This is because the traditional ALPR cannot capture the correct area of oblique LP which results in an error in character recognition or missing characters [1-4]. As a result, the traditional ALPR will largely reduce the accuracy of recognition for oblique LP. Recently, Silva et al. [5] proposed a warped planar object detection (WPOD) based on convolutional neural network (CNN) to overcome the oblique views of LP. In order to achieve an ALPR system of high accuracy, they divided ALPR into three stages. The first stage is to locate vehicles through YOLOv2 [6]. And then, the second stage locates the oblique LPs and allows a rectification of the LPs area to a rectangle which resembles a frontal view through the WPOD network. Finally, the rectified LPs are fed to an optical character recognition (OCR) in the third stage.

Although the WPOD network can achieve the location and rectification of LPs, the loss function of WPOD renders the confidence parameter due to high computational complexity. This also leads to WPOD network cannot locate the optimal LP bounding box. In order to further improve the accuracy of bounding box. In order to further improve the accuracy of ALPR system, we proposed a modified WPOD network to get a more precise loss function. The proposed method develops a simple intersection over union (IOU) algorithm to speed up the calculating process of confidence. Therefore, the modified WPOD network can obtain higher LP recognition rate since it considers the confidence parameter in the loss function.

In this paper, the four-vertex coordinates of the label bounding box and prediction bounding box of oblique LP are used to generate two rectangular boxes, and then a simple IOU algorithm is used to fast estimate the approximate value of IOU. As a result, a more exact loss function can be finished. In order to compare the performance of LP recognition rate, we train and test the WPOD and the proposed modified WPOD in databases including OpenALPR EU [8], AOLP RP [9] and Car Dataset Hard (CD-HARD) [10]. The proposed method can achieve a very high accuracy of oblique LP recognition.

II. Overview of WPOD

Figure 1 shows the proposed ALPR system by Silva's method in [5], including three main steps: vehicle detection, LP detection and OCR. When given an input image, the first module detects vehicles in the scene. And then, the LP detection module searches for LPs and performs a rectification of the LP area to a rectangle resembling a frontal view. In the third step, these positive and rectified detections are fed to the OCR module for final character recognition. Finally, ALPR system demonstrates the results of output character.

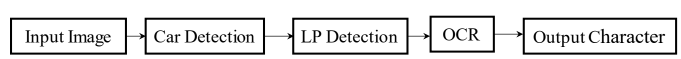


Fig.1 Modules of the Silva's ALPR system.

The WPOD network [5] is the most important step in Silva's ALPR system since it can detect the oblique LPs and rectified LPs by using affine transformation. For an input image with height H and width W, the CNN network output feature map consists of an $m \times n$. For each point cell (m, n) in the feature map, there are eight parameters to be estimated, which include two class probabilities of object/non-object, and the six parameters ($v1$ to $v6$) of bounding box are used to build the local affine transformation T_{mn} as follows:

TABLE I: Computational complexity of warped IOU.

Method	10^3 iterations	10^6 iterations
CGAL	5.15s	>1h

$$T_{mn}(\boldsymbol{q}) = \begin{bmatrix} \max(v1\,,\,0) & v2 \\ v4 & \max(v5\,,0) \end{bmatrix} \boldsymbol{q} + \begin{bmatrix} v3 \\ v6 \end{bmatrix} \quad (1)$$

where the max function of scaling parameters used for $v1$ and $v5$ was adopted to ensure that the diagonal is positive. $v2$ and $v4$ represent the rotation parameters, $v2$ and $v4$ represent the shifting parameters, respectively. The matrix q denotes the corresponding vertices of a canonical unit square centred at the origin. To extract the oblique LP, WPOD first utilize an imaginary square of fixed size around the center of a cell (m, n). If the object probability for this cell is above a given detection threshold, part of the regressed parameters is used to build an affine matrix that transforms the fictional square into an LP region. Thus, WPOD can easily rectify the oblique LP into a horizontally and vertically aligned object to locate bounding box (bbox).

The loss function of WPOD is defined as follows

$$loss = \sum_{m=1}^{M} \sum_{n=1}^{N} \left[\mathbb{I}_{obj} f_{affine}(m,n) + f_{probs}(m,n) \right] \quad (2)$$

where $\mathbb{I}_{obj}$ is the object indicator function that returns 1 if there is an object at point (m, n) or 0 otherwise, and $f_{affine}(m,n)$ is the error between a warped version of the canonical square and the normalized annotated points of the LP. The second part of the loss function $f_{probs}(m,n)$ is given by the sum of two log-loss functions, which is the probability of having/not having an object at (m, n).

From Eq. (2), we can find that although the WPOD is based on YOLOv2 [6], the defined loss function ignores confidence parameters. This is because it has a very huge computational load to calculate the values of IOU for the warped LP. Therefore, this also leads to WPOD network cannot locate the optimal LP bounding box for oblique LP.

III. Proposed Method

From the observation of WPOD, we can find that the calculation process of IOU is an obstacle for oblique LP. Therefore, how to find a simple and fast calculation method for IOU is an important topic. In order to analyze the overlapping relationship between two oblique LPs, we make use of the computational geometry algorithms library (CGAL) algorithm to calculate the values of IOU, which is an open source software library [7]. The CGAL provides an efficient and reliable geometric algorithms to calculate the areas of arbitrary geometry. However, it needs a high computational complexity to find IOU of oblique LP such that it can not be directly applied to loss function in the WPOD network. Table 1 shows that the computational complexity of oblique IOU by Xie et al. in [10].

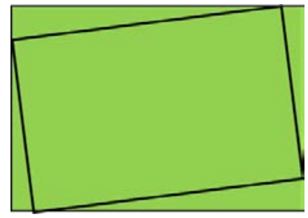
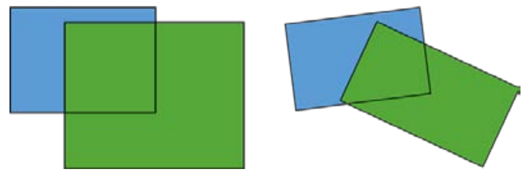


Fig.2 A circumscribed rectangle.



(a) IOU=0.17 (b) IOU=0.38

Fig.3 The value of IOU (a) proposed method, (b) CGAL.

As shown in Table I, we can find it is very time-consuming in this work.

In order to reduce computational complexity of oblique IOU, we propose a simple IOU algorithm by connecting four-vertex coordinates of oblique LP to obtain a circumscribed rectangle, as shown in Fig. 2. After getting the circumscribed rectangle, we can easily estimate the IOU value of the oblique LP.

However, using the circumscribed rectangle to calculate the IOU will produce an error with the precise IOU calculated by CGAL. Figure 3 shows the values of IOU from a simple IOU algorithm and CGAL, respectively. We can find there is an error of 0.21 occurred by proposed method and CGAL.

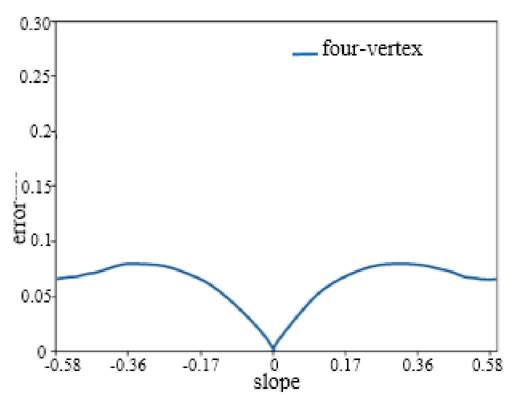


Fig.4 A statistic analysis of error vs. slope.

In order to analyze the error produced between using proposed fast method and CGAL, we perform a large of IOU test by using two oblique rectangles from slope = ± 0.58 ($i.e.\ \pm 30^{\circ}$). A statistic analysis of our simple IOU for error vs.

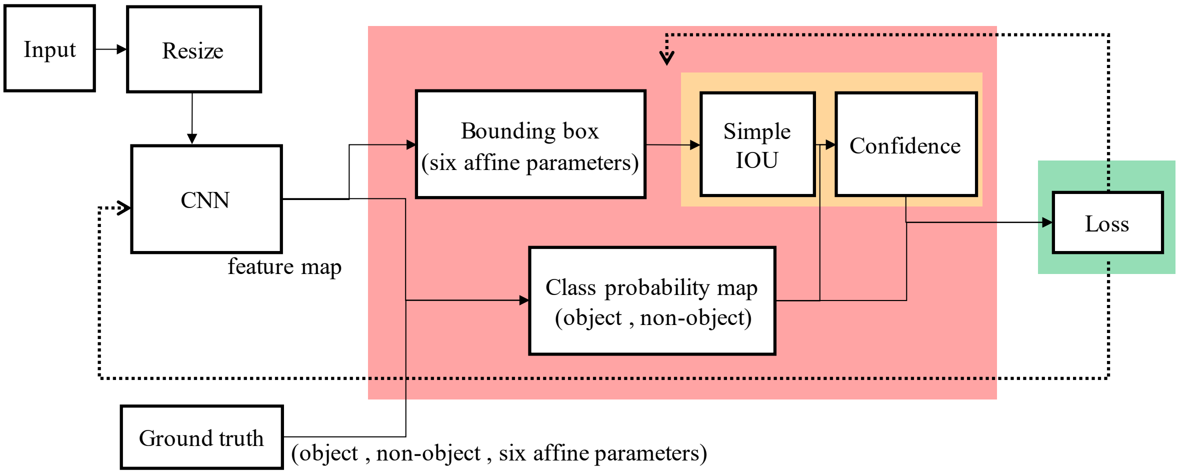


Fig.5 The architecture of the proposed modified WPOD network.

slope between two methods is shown in Fig. 4. From Fig. 4, we can find the average error is lower than 0.1. Therefore, the estimated IOU values of the proposed fast method is very approximate to those of CGAL.

Since the proposed simple IOU algorithm can fast estimate an approximate IOU value for oblique LP, we easily embed the confidence parameter into loss function. The new loss function of the proposed method is written as follows:

$$loss = \sum_{m=1}^{M}\sum_{n=1}^{N}\left[\mathbb{I}_{obj} f_{affine}(m,n) + f_{probs}(m,n) + \mathbb{I}_{obj} f_{iou}(m,n)\right] \tag{3}$$

In Eq. (3), the loss $f_{iou}(m,n)$ of the confidence is defined as follows

$$f_{iou}(m,n) = (C_t - C_p)^2 \tag{4}$$

where C_t and C_p are the confidence of truth label LP and predicted LP, respectively. And, the confidence parameter is defined as

$$C = p_{object} \times IOU'^{label}_{pred} \tag{5}$$

where the p_{object} is the probability of predicted object and IOU'^{label}_{pred} is an IOU value of the proposed simple IOU algorithm.

Therefore, we proposed a modified WPOD network by embedding the new loss of confidence into loss function of WPOD using the proposed fast IOU estimating method. Figure 5 shows the architecture of the proposed modified WPOD network.

IV. Experimental Results

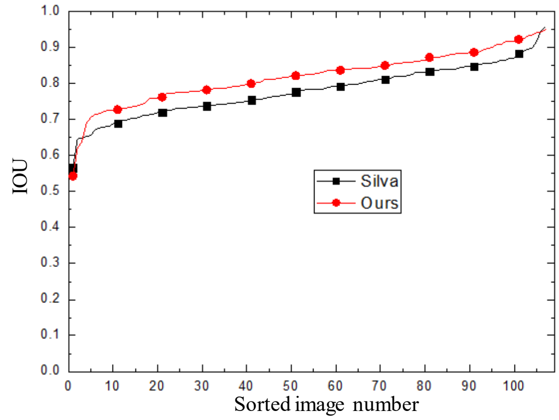
In this work, we adopted three independent datasets to evaluate the accuracy of the proposed method in different scenarios and region layouts. In order to get a fair comparison for the ALPR system, we set up an experimental condition and chose three car datasets available online as follows:

(a) Experimental condition
- CPU：Intel(R) Core(TM) i7-7700 3.6GHz
- GPU：NVIDIA GTX1060 6GB
- RAM： 16GB
- OS：Ubuntu 16.04 LTS 64bit
- Software ： Tensorflow 1.5.0、Python 2.7
- CUDA Toolkit： CUDA Toolkit 9.1

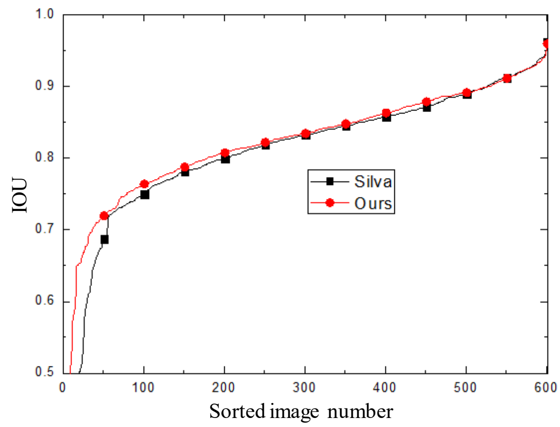
(b) Test dataset
- A. OpenALPR [8]：
  - EU (European Union: 104 images)
- B. AOLP [9]：
  - RP (Road Patrol: 611 images)
- C. Cars Dataset [10]：
  - CD-HARD(Car Dataset Hard: 102 images)

In test dataset [8-10], we selected mostly images with oblique LP distortion but still readable for humans. In order to evaluate the ability of the YOLO-based ALPR systems, we calculate the IOU score and the accuracy rate of character recognition, respectively. Figure 6 shows the comparisons of IOU values between the proposed method and Silva's WPOD network by using three car datasets: EU, RP and CD-HARD. For convenient observation and analysis, these images in Fig.6 are resorted according to their IOU score from low to high. From Fig.6, we can find that all IOU scores of our method are higher than Silva's WPOD in different scenarios. This is because that our method consider the confidence parameter for oblique LPs in the loss function.

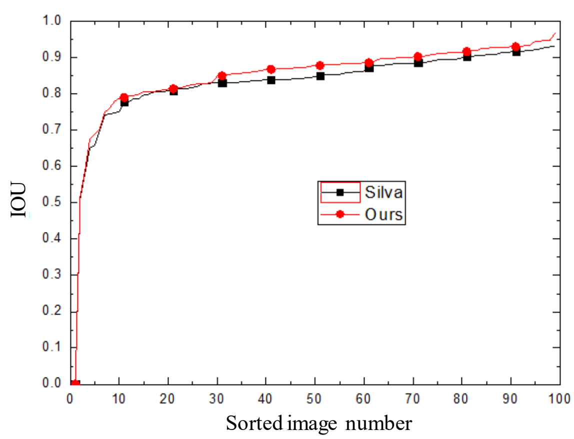
Table II indicates the comparisons of full ALPR results between the proposed and WPOD in terms of average IOU, accuracy and improvement. From Table II, we can find that the proposed ALPR system can achieve better accuracy rate of character recognition. In addition, the proposed system also can arrive a high accuracy of LP recognition about 95.7% on an



(a) EU



(b) RP



(c) CD-HARD

Fig. 6 Comparisons of IOU between ours and Silva using three car datasets (a) EU, (b) RP, (c) CD-HARD

Table II: Comparisons of full ALPR results.

Dataset	Method	Avg IOU	Avg accuracy	Improve
EU[8]	Proposed	0.777	96.30%	1.852%
	WPOD	0.746	94.44%	
RP[9]	Proposed	0.805	95.25%	0.163%
	WPOD	0.797	95.09%	
CD-HARD[10]	Proposed	0.862	78.79%	1.01%
	WPOD	0.819	77.78%	

average. In addition, the proposed system also can achieve higher recognition rate about 1% when compared to the Silva's ALPR system. It is very obvious when the larger the IOU value is, the more the improvement of accuracy rate is.

On the other hand, we also find that our system slightly outperform Silva's method by a small IOU score in the challenging scenarios (CD-HARD dataset) in Fig.6(c). However, our system can outperform Silva's ALPR system by a significant margin over 1% accuracy gain.

V. Conclusions

In this paper, we presented a YOLO-based ALPR system for oblique LP scenarios. Our results indicate that the proposed approach outperforms Silva's method in challenging datasets, containing LPs captured at strongly oblique views. The main contribution of this work is to design a simple IOU algorithm to speed up the calculating process of confidence. Therefore, we can finish a more exact loss function such that a higher oblique LP recognition can be obtained.

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