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Automatic Number Plate Recognition by Using WPOD Network

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Abstract - Despite the abundance of commercial and academic techniques for Automatic Number Plate Recognition (ANPR) [1], the majority of current algorithms concentrate on a particular region of the number plate (NP) and frequently examine data sets with roughly frontal images. To identify the car, we use a modified version of YOLO, and after that, we localize the license plate. Additionally, we enhance an optical character recognition network (OCR-Net) [1] to recognize the numbers and letters on license plate [2] by CNN techniques. Our approach works well with various vehicle kinds. Images captured by a variety of cameras show vehicle license plates from various nations, automobiles at various distances, and more.

Keywords: Number Plate, Convolutional Neural Networks, Optical Character Recognition.

I. INTRODUCTION

Automatic Number Plate Recognition (ANPR) [1] systems are used to identify automobiles in a number of traffic-related applications, including the detection of stolen vehicles, toll control, and parking lot access validation. To advance numerous vision-related activities, including Object Detection/Recognition and Optical Character Recognition (OCR) [1], which distinctly aid ANPR [1] systems. In fact, deep convolutional neural networks (CNNs) [7] have been the most widely used machine learning method for detecting vehicles and license plates (NP) [2].

Additionally, this system can assist law enforcement in locating criminals who use vehicles as a means of escape and assist in catching and fining those who attempt to violate traffic laws. The number plate of a stolen car can be located using CCTV feeds. System ANPR [1] offers secure parking control in homes. While non-registered vehicles must first be added to a guest list before being assigned a parking spot, registered resident vehicles are immediately permitted entry and parking in their designated spaces.

Our primary contribution is the detection of the license plate in a variety of positions and the estimation of its distortion, enabling rectification before to OCR [1]. A flexible ANPR system that was able to reliably detect and identify the number plate in independent test datasets using the same system parameterization was also made possible by the suggested network and data augmentation method.

II. RELATED WORK

ANPR [1] is the process of locating and recognizing license plates in photos. Some of the primary subtasks that make up a sequential pipeline include character segmentation, vehicle detection, number plate detection, and character recognition. Numerous ANPR systems or related subtasks have already been proposed. Typically, picture binarization or grayscale are used to find candidate suggestions, which are then followed by specialized extraction methods and conventional machine learning classifiers. We begin this section by examining DL [7] based ways for these particular tasks, as well as a few STS methods that can be handled and distorted text, as the fundamental contribution of this study is a novel NP detection network.

A. YOLO MODEL

Many recent works that aim for real-time performance for LP detection were inspired by YOLO networks' success [2]. The YOLO networks were employed by Hsu et al. in a slightly modified form, with the authors increasing the output granularity to increase the number of detections and set the possibilities for two classes (LP and background). There is considerable literature on license plate detectors that employ sliding window techniques or candidate filtering in conjunction with CNNs [3]. They do not share calculations like contemporary meta-architectures for object detection like YOLO, SDD, and Faster R-CNN, hence they are typically computationally inefficient.

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III. EXISTING MODEL

YOLO - (You Only Look Once) It is a very quick multi-object detection system that detects and recognizes items using convolutional neural networks (CNN) [7].
SSD - (Single Short Detector) approach uses a single deep neural network to identify objects in photos.
STN – (Spatial Transformer Network)

A neural network can learn how to apply spatial modifications to the input image using STNs, which improve the geometric invariance of the model. Numerous recent research focus on real-time performance for LP detection were motivated by the success of YOLO networks. YOLOv2 networks are a slightly modified variation of the YOLO. Existing models include YOLO, SSD, and Spatial Transformer Networks (STN). Fast multiple item detection and recognition are accomplished by YOLO and STN, however they ignore spatial transformations and produce just rectangular bounding boxes for each detection. STN, on the other hand, can be used to detect non-rectangular regions, but it is limited to applying a single spatial transformation across the entire input and is unable to handle many transformations at once.

IV. PROPOSED MODEL

The three key steps of the suggested method are vehicle detection, LP detection, and OCR. The first module recognizes a car in the scenario from an input image. The proposed Warped Planar Object Detection Network (WPOD-NET) [7] looks for LPs within each detection region and regresses one affine transformation for each detection, allowing rectification of the LP area to a rectangle resembling a frontal view. For final character recognition, an OCR [3] Network receives these positive and corrected detections.

This chapter provides a succinct summary of earlier research on the use of deep learning and machine learning to detect and recognize license plates. The background theory for neural networks and convolutional neural networks is also presented in this chapter [7]. The current generation of license plate readers can be divided into two categories based on their use of deep learning techniques and traditional machine learning techniques [6]. Three distinct processing layers are typically used in license plate recognition [2] algorithms in real-time videos or images:

- Vehicle Detection
- License plate detection
- Optical Character Recognition

These several procedures are quite difficult because of the variety of license plates, various image angles, complex alphanumeric ordering, unpredictable font faces, hazy and noisy photographs, and poor lighting conditions. As a result, the majority of methods are only effective in specific circumstances like fixed lighting, constrained vehicle speed, monochromatic backgrounds, and predetermined font faces. We give a quick overview of the several techniques that have been suggested for detecting and recognizing license plates in this chapter.

A. VEHICLE DETECTION

We chose to use a known model to do car detection rather than creating a detector from scratch because automobiles are one of the fundamental objects featured in several classic detection and recognition datasets like PASCAL-VOC, ImageNet [8], and COCO. On the one hand, a high recall rate is needed because every car with a visible LP that is miss detected will also have an overall LP [2] miss detection.

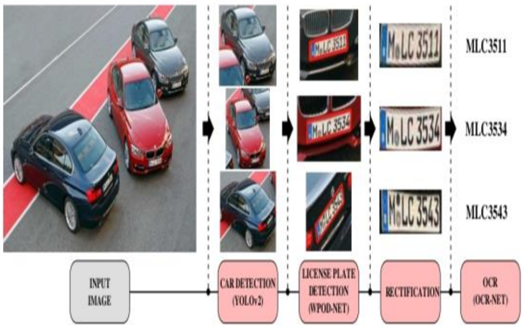

Fig:1 – Illustration of the wpod pipeline

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Low running times are also desired due to the need for WPOD-NET to confirm each incorrectly identified vehicle [7]. Based on our research, from fig:1 we chose to employ the YOLOv2 network because of its quick execution, strong precision-to-recall ratio, and fast execution. We made no changes or refinements to the network; instead, we used it as a "black box," merging the outputs related to cars while disregarding the outputs related to other classes. Before being transmitted to the WPOD-NET, the positive detections are scaled [7].

B. LICENSE PLATE DETECTION

Inherently rectangular and planar, license plates are things that are affixed to vehicles to serve as identification. We suggested a novel CNN dubbed warped Planar Object Detection Network [3] to benefit from its shape. The regress coefficient of an affine transformation "unwraps" the deformed LP into a rectangular shape matching a frontal view after this network learns to detect LPs in a range of various distortions. The division involved in the perspective transformation is greater even though a planar perspective projection may be learned in place of the affine transform.

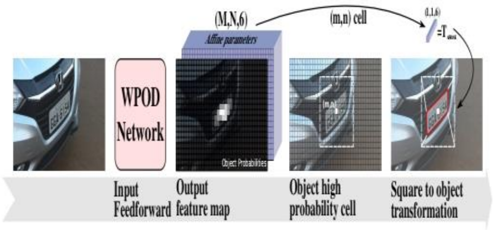

Fig:2 - WPOD license plate detection

The WPOD-NET detection procedure [7] The network is originally fed by the vehicle detecting module's output that has been downsized. The feed forwarding produces an 8channel feature map with affine transformation parameters and object/non-object probabilities encoded. From fig:2, a portion of the regressed parameters are then utilized to create an affine matrix that converts the hypothetical square into an LP zone if the object probability for this cell is greater than a specific detection threshold. This makes it simple for us to unwarp the LP into a vertically and horizontally aligned object.

C. OPTICAL CHARACTER RECOGNITION

Using a modified YOLO network, character segmentation and recognition over the rectified LP is carried out. However, the training dataset in this work was significantly expanded by using synthetic and augmented data to address the LP characteristics of various geographic locations. In order to incorporate Taiwan in the artificial data generation, we also used Taiwanese LPs, but we were unable to locate information about the font by the nation.

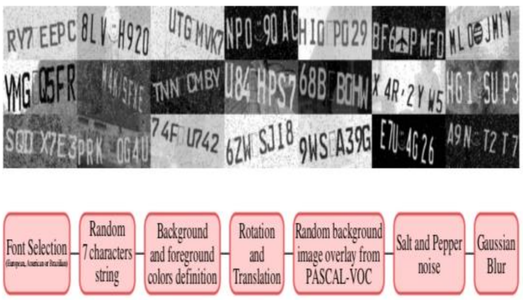

Fig:3 – Segmentation of license plates

The synthetic data is produced by pasting a string of seven characters onto a textured background and applying random transformations including rotation, translation, noise, and blur. The use of synthetic data dramatically improved network generalization, from fig:3 allowing the exact same network to function well for LPs of different parts of the world. Some generated samples and a brief summary of the methodology for synthetic data synthesis.

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D. EVALUTION DATASETS

The AOLP Road Patrol (RP) subset, which seeks to imitate the situation where a camera is installed in a patrolling vehicle or is handled by a person, is the most difficult dataset currently being used in terms of LP distortion. The SSIG dataset seems to be the most difficult in terms of the separation between the camera and the vehicles. It is made up of photos of excellent resolution. To the best of my knowledge, there isn't a more general-purpose dataset containing the difficult photos in the literature, even if all these datasets together cover a variety of situations.

V. RESULT

Test Case 1: Import all the predefined libraries that are required. After loading all of the previously trained models, we must develop a function named nameplate-example that can read images. We will now picture our car's license plate. These data come from a variety of nations, including Germany, Thailand, Vietnam, India, and Turkey. If there is no plate foundation, something is wrong.

WPOD-net can recognize number plates, however if the image is too unclear or if there are obstructions in the way, the plate model may not be successful.

Fig:4 – Extracting Number Plate

Test Case 2: The image processing which we shall implement on our image is:
1.Convert to grayscale
2.Blur image
3.Image thresholding
4.Dilation

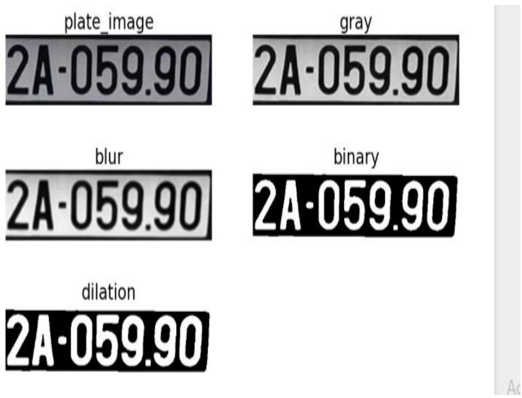

Fig:5 – Applying Image processing technique

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To locate the license character's coordinate, we shall use OpenCV contours. Additionally, it puts them in the proper order.

Fig:6 – Detecting contour of License Plate and Visualizing segmented characters

Test Case 3: To predict characters from photos, train a CNN model. Rebuild our model architecture first with the weight we conserved during the training phase and from the original label classes. In crop-characters, a loop is created over each character picture, storing all model predictions in the end result and plotting each image with the appropriate predictions.

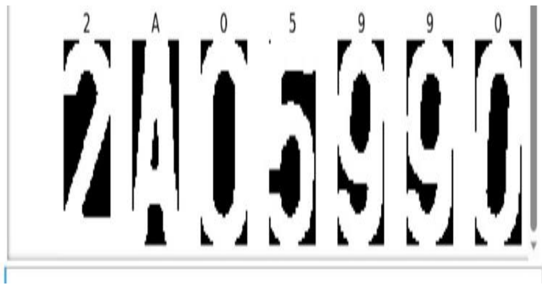

Fig:7 – Plotting character image with corresponding predictions

The stable designates these two versions as "Ours" and "Ours (no art.)", respectively. However, there was a significant accuracy loss in datasets with difficult oblique NPs (AOLP-RP and the suggested CD-HARD), contrary to expectations, the results were primarily frontal datasets, (being even somewhat better for ANPR-EU). While the first YOLOv2 vehicle detection and OCR-NET were constructed and carried out using the Dark Net framework, the proposed WPOD-NET was implemented using the TensorFlow framework. The two frameworks were combined using a Python wrapper. Our trials were conducted using an Intel Xenon processor, 12GB of RAM, and an NVIDIA Titan X GPU. With such setup, we are able to operate the whole ANPR systems at an average frame rate of 5FPS. The input image has a significant impact on this time. As a result, raising the vehicle detection threshold will increase FPS while lowering recall rates.

VI. CONCLUSION

We demonstrated a comprehensive deep learning ANPR system for unrestricted settings in this paper. Our findings show that the suggested methodology works significantly better than existing methods on difficult datasets with NPs collected at severely oblique viewpoints while maintaining good results on more controlled datasets.

The fundamental contribution of this study is the development of a unique network that produces an affine transformation matrix for each detection cell to enable the detection and unwarping of distorted NPs. The OCR network now has less work to do because there will be less distortion. Additionally, we provided a new difficult dataset for testing ANPR systems in captures with the most oblique NPs as an added contribution. We intend to expand our method in order to find motorcycle NPs in further work. This presents new difficulties because of the disparities in aspect ratio and layout. Additionally, we want to investigate the affine transformations that we have got for the automatic camera calibration issue in traffic surveillance scenarios.

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