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A Survey on Automatic License Plate Recognition (ALPR) Systems

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ABSTRACT: Automatic License Plate Recognition (ALPR) is the extraction of vehicle license plate (LP) information from an image or a video. The extracted information can be used in many practical applications, such as automatic toll collection, traffic law enforcement, access control of private spaces and road traffic monitoring, due to which ALPR has been a frequent research subject. In real-world conditions, however, many of the existing solutions are still not reliable as they perform well only under specific constraints. A robust ALPR system should be able to work in unconstrained scenarios accounting for open environments, low quality images, and plate variations. This paper presents a comprehensive review of various techniques that have been developed for ALPR.The initial step for any ALPR system is to locate the LP region in an image and then apply some form of Optical Character Recognition (OCR) method on it to obtain the LP data. Hence, this paper further aims at presenting an explanation of how a typical ALPR system works and a comparative analysis of the different processes used.

KEYWORDS: Automatic License Plate Recognition (ALPR), Automatic Number Plate Recognition (ANPR), License plate identification, License plate segmentation, Optical Character Recognition (OCR).

I. INTRODUCTION

The aim of ALPR is to locate, recognize, and extract LP information in images or sequence of images (videos). ALPR systems are generally composed of the following three processing steps: 1) locating the LP region; 2) segmentation of the plate characters; and 3) recognition of each character. The combination of the last two steps is referredto as OCR, for convenience [6]. Furthermore, high accuracy is desired for the first step, as failing to detect the LP will likely lead to a failure in the next steps. In order to minimize processing time and remove false positives, several methods first look for the vehicle and then its LP [3]. Hence, ALPR is commonly broken into three subtasks that form a sequential pipeline: vehicle detection, LP detection, and OCR (Fig. 1).

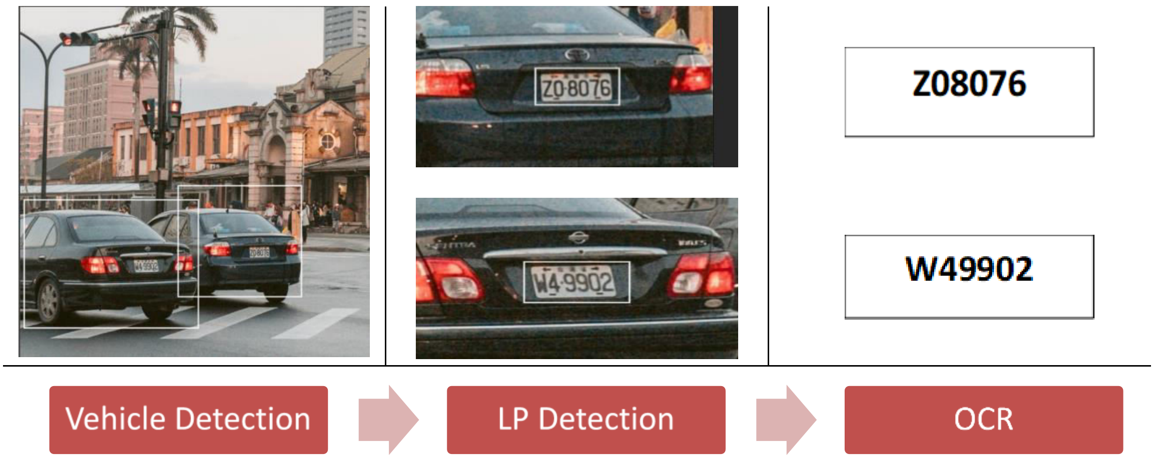


Fig. 1 Sequential pipeline for ALPR

As observed by the authors in [4], ALPR is faced with many challenges consisting of plate and environment variations. A subset of these variations is summarized below and shown in Fig. 2.

1) Plate variations:
    a. Quantity: zero or more LPs may be present in an image
    b. Occlusion: LPs may be hidden (occluded) by another object
    c. Location: LPs can exist in different regions of an image
    d. Distortion: images may be taken by cameras at irregular angles
    e. Font: LPs may be written in different languages and fonts depending on the plates' origin
    f. Other: size, scale, color, intra-class variations (standard vs customized LPs)
2) Environment variations:
    a. Illumination: images can have different types of illumination, due to environmental lighting (day/night), location (indoor/outdoor), and vehicle headlights
    b. Background: region around the LP may contain designs similar to it such as stickers, or advertisement banners, etc.

Fig. 2 From top-left (clockwise): Illumination variation; Occlusion; Font variation; Multiple LPs in a frame; Distorted LPs

II. PHASES IN ALPR

Phase 1: Vehicle Detection

Vehicle detection is essentially an object detection task, which itself falls in the realm of computer vision and image processing that deals with detecting instances of semantic objects of a certain class.

It is widely accepted that in the past two decades the evolution of object detection has gone through two historical periods: "traditional object detection period (before 2014)" and "deep learning based detection period (after 2014)" [9]. Most of the early object detection approaches were based primarily on handcrafted features. However, due to the availability of large-scale annotated datasets and hardware (GPUs) capable of handling a large amount of information, most modern object detection approaches implement deep learning algorithms and have been ableto achieve a substantial increase in performance. The major techniques used in both the approaches are depicted in Fig. 3.

Due to the success of deep learning algorithms and rise in popularity of object detection as a research subject [8,9], many large-scale visual datasets have been made available in the public domain. Many of these datasets contain numerous objects of different categories while some datasets only focus on vehicles (or auto-mobiles) in particular. Some of the well-known datasets used for vehicle detection are: ImageNet [10], Open Images [11], PASCAL-VOC [12], COCO [13], KITTI Object Detection Benchmark [14], and Stanford's Car dataset [15].

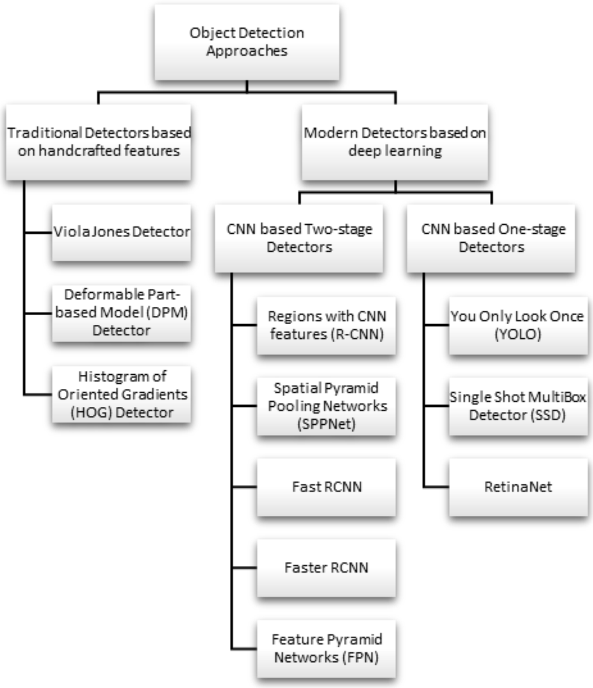
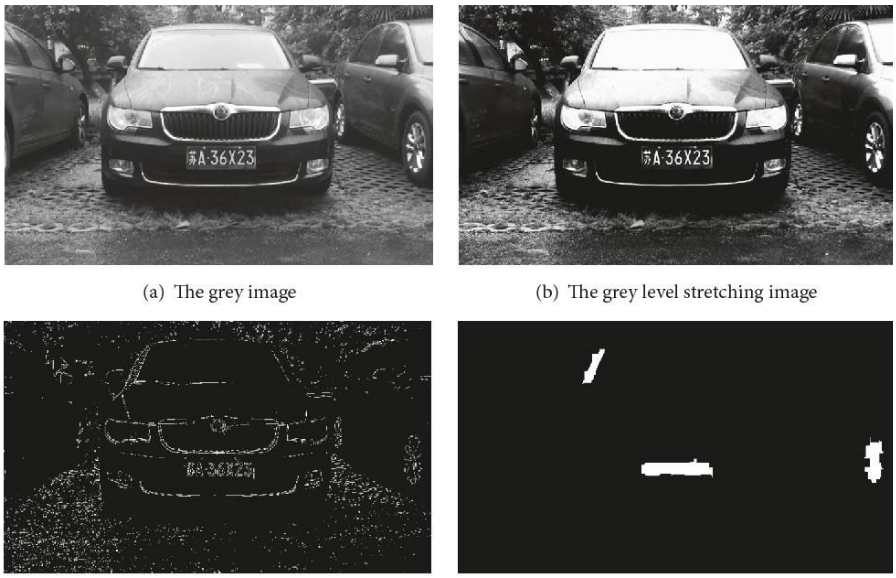


Fig. 3 Major object detection approaches used over time

Phase 2: LP Detection

LP detection, similar to vehicle detection, is an object detection task. Therefore, similar approaches [1,2,5,7] have been used to detect LP in the images. Moreover, many algorithms are built to take advantage of the fact that LPs are rectangular in shape. Edge detection methods are commonly used to find these rectangles [6, 16-20] as shown in Fig. 4.



(a) The grey image (b) The grey level stretching image

(c) The edge detection image (d) The morphological operation image

Fig. 4 Using an edge detection method to locate LP region in image

Phase 3: Applying OCR

The final step of the ALPR system is feeding the located LP region to an OCR algorithm. To extract the characters for recognition, the isolated LP is first segmented and then individual characters are recognized, yielding the final LP number (Fig. 5).

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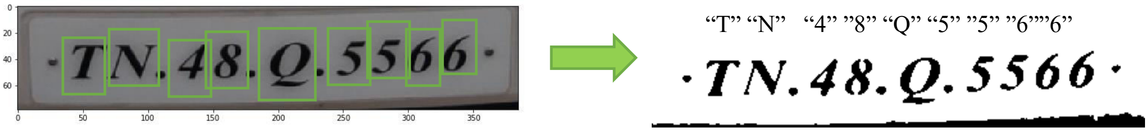

Fig. 5 Character segmentation and recognition of the isolated LP

III. LITERATURE SURVEY

This section gives an overview of a few ALPR systems along with the methods and process pipeline used in them. Finally, Table 1 gives a brief summary of some other ALPR systems, their accuracy and other relevant information.

A. Silva S.M., Jung C.R. (2018) License Plate Detection and Recognition in Unconstrained Scenarios [6]

In this paper, the authors have presented a deep learning ALPR system that focuses on unconstrained scenarios, where the LP might be considerably distorted due to oblique views. They have introduced a novel Convolutional Neural Network (CNN), termed Warped Planar Object Detection Network (WPOD-NET), capable of detecting and unwarping multiple distorted LPs in a single image by generating an affine transformation matrix per detection cell. These rectified images are then fed to an Optical Character Recognition (OCR) method to obtain the final result. Their approach achieved average accuracy of 86.43% when tested on OpenALPR (EU and BR) (available at https://github.com/openalpr/openalpr), SSIG test-set [21], AOLP (RP) [22], and their custom CD-HARD [6] dataset with only read augmented data. The average accuracy increased to 89.33% for the same datasets when they combined real augmented data with artificially generated data for training the OCR network.

B. Li, Hui & Shen, Chunhua. (2016). Reading Car License Plates Using Deep Convolutional Neural Networks and LSTMs [23]

This paper proposes a cascade framework in which a 4 layer 37 class (10 digits, 26 uppercase letters and the negative non-character category) CNN is used in the first phase to detect text in an image. Then another 4 layer CNN classifier is employed to reject false positives and distinguish LPs from general text. Once the LPs have been detected, the second phase utilizes a 9 layer CNN for character recognition, which is robust to distortions, illumination variations, and rotations in the image; and lead to a higher recognition accuracy. Their method is evaluated on two datasets, namely the Caltech Cars (Real) 1999 dataset [24] and the AOLP benchmark dataset [22]. For the Caltech Cars dataset, this method achieved an accuracy of 84.13% and 92.07% for the plate detection and character recognition task respectively. For the AOLP's AC, LE, and RP subsets, it obtained the following accuracy (in percent) for plate detection and character recognition tasks respectively: AC (92.87, 98.38), LE (93.97, 98.19), RP (87.73, 96.56). However, even with the impressive performance in experimental results, the method is not efficient and cannot be used in real-time scenarios due to slow detection speed.

C. H. Li, P. Wang and C. Shen, "Toward End-to-End Car License Plate Detection and Recognition With Deep Neural Networks" [25]

In this paper, the authors have presented a single unified deep neural network that performs both the LP detection and character recognition tasks concurrently. By incorporating character recognition directly into the LP detection pipeline, the resulting system becomes more efficient. Moreover, it avoids intermediate error accumulation if the above tasks were performed separately. The results were evaluated on the AOLP's subsets obtaining the following accuracy (in percent): AC (95.29), LE (96.57), and RP (83.63).

D. Selmi, Zied & Ben Halima, Mohamed & Alimi, Adel. (2017). Deep Learning System for Automatic License Plate Detection and Recognition [26]

This paper notes the importance of pre-processing steps that are applied to the input image before passing it to a plate/non-plate CNN classifier. The pre-processing pipeline is as follows: 1) Convert RGB to HSV image, 2) Morphology filtering to contrast maximization, 3) Gaussian blur filter, 4) Adaptive threshold, 5) Finding all contours, 6) Geometric filtering. The resulting image is then passed to the CNN for LP detection. The output from LP detection is passed to another pre-processing pipeline to segment the LP and finally to recognize all the characters using a second CNN with 37 classes. On the Caltech Cars dataset [24], precision of 93.8% and accuracy of 94.8% were achieved for LP detection and OCR tasks respectively. For the AOLP's subsets, the precision (in percent) for LP detection and accuracy (in percent) for OCR is found to be: AC (92.6, 96.2), LE (93.5, 95.4), and RP (92.9, 95.1).

Table 1A summary of some ALPR systems

Author	Title	Methods Used	Dataset	Accuracy (%)
T. D. Duan, D. A. Duc, and T. L. H. Du [27]	Combining Hough transform and contour algorithm for detecting vehicles	Hough transform and contour algorithm. Hidden Markov model (HMM) for OCR	Custom dataset of Vietnamese vehicles	98.76
Sérgio Montazzolli Silva, Cláudio Jung [28]	Real-Time Brazilian License Plate Detection and Recognition Using Deep Convolutional Neural Networks	YOLO for vehicle detection and a novel network, inspired from YOLO architecture, called CR-NET	SSIG	63.18
R. Laroca et al. [3]	A Robust Real-Time Automatic License Plate Recognition Based on the YOLO Detector	You Only Look Once (YOLO) for vehicle detection and CR-NET for OCR	SSIG and UFPR-ALPR	93.53 and 78.33
Lee, Younkwan & Jun, Jiwon & Hong, Yoojin & Jeon, Moongu [29]	Practical License Plate Recognition in Unconstrained Surveillance Systems with Adversarial Super-Resolution	YOLO for LP detection and a novel method based on GAN for OCR	AOLP	96.74
Masood, Zain & Shu, Guang & Dehghan, Afshin & Ortiz, Enrique [30]	License Plate Detection and Recognition Using Deeply Learned Convolutional Neural Networks	CNN for both tasks	OpenALPR {USA, Europe}	LP detection: {86.89, 91.09} LP recognition: {78.36, 84.80}

IV. Proposed Work

Taking note of the various papers surveyed, analysing and comparing the methods used in them, we propose our work to have the following characteristics:

1) Using a deep learning based approach to detect vehicles in the first phase, unlike some of the other approaches that directly detect LPs, in order to reduce false positives.
2) Pre-treatment of extracted LP region using basic image processing techniques to increase performance of OCR.

V. Conclusion

Although significant progress has been made in the last decade, there is still work to be done, as a robust LP detection system should effectively work for a variety of plate conditions/types, environmental illumination, and image acquisition parameters. The task of designing an efficient ALPR system that could accommodate plates from different countries with different character sets and syntax has become challenging due to increased mobility and globalization. This concern has not been discussed sufficiently in the literature so far, as many ALPR systems were country/region specific. In addition, it is apparent that the quality and quantity of testing samples have a direct effect on the overall ALPR performance. However, this factor is often ignored in performance comparison or evaluation, which is the appropriate criterion for an algorithmic assessment.

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