IJITCE

ISSN 2347- 3657

International Journal of
Information Technology & Computer Engineering

Email : ijitce.editor@gmail.com or editor@ijitce.com

International Journal of Information Technology & Computer Engineering
ISSN 2347–3657
Volume 12, Issue 1, 2024

AUTOMATIC VEHICLE NUMBER PLATE RECOGNITION USING MACHINE LEARNING

Mr. G. Rajkumar, Assistant Professor, Department Of ECE, SICET, Hyderabad
Siramdas Shivanjali, Varikupala Shirisha, Ramini Ashwin, Thandra Sathwik Reddy
Department Of ECE, SICET, Hyderabad

ABSTRACT

Vehicle control and identification of vehicle owner has become a major problem faced by many countries. Sometimes it is difficult to detect car owners who break driving rules and drive too fast. Therefore, it is not possible to catch and punish such people, as drivers will not be able to obtain the license plate of the movi ng vehicle due to the speed of the vehicle. Therefore, automatic license plate recognition (ANPR) systems should be developed as a way to solve this problem. There are now many ANPR systems. These systems ar e based on many methods, but it is still a very difficult task because factors such as the high speed of the ve hicle, not having the same driver's license, driver's license and different lighting conditions can generally h ave a positive effect. recognition. . Most machines operate within these limits. This article describes variou s ANPR methods that use image size, completion rate, and processing time as metrics. At the end of the for m, an extension of the ANPR is requested.

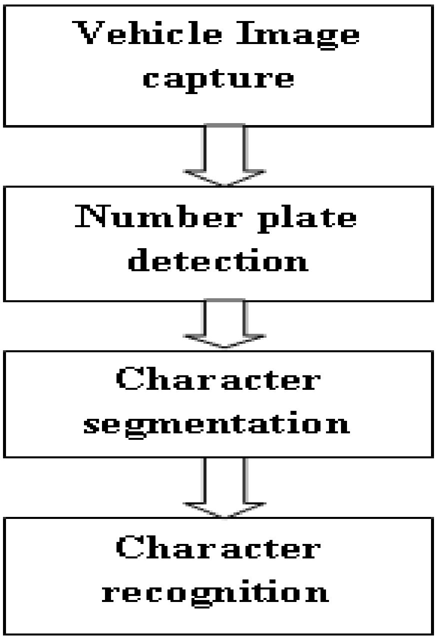

Fig.1. Conventional ANPR system.

Photography uses a technique called superresolution [30], [31]. Sometimes it is necessary to evaluate the quality of the ANPR system. A good analysis of vision and ANPR is well desc ribed in [9]. [4] provide good guidelines for driver license recognition (LPR) research. In thi s case, license license and licensing license are used interchangeably. Details of each ANPR are discussed in Section 2.

1.2 Scope of this paper

Since it is not possible to say which method is better, different documents were searched ac cording to the steps indicated in Figure 1 and all aspects were classified according to the me

ISSN 2347–3657
Volume 12, Issue 1, 2024

thod. For each method, there are only parameters such as speed, accuracy, performance, ima ge size and advertised platform. Analysis of the products is beyond the scope of this article because these products are sometimes claimed to be more authentic than advertised. The re mainder of this article is divided into the following sections: Section 2 contains an analysis of the different methods used to check the license. Chapter 3 examines the behavior segmen tation process, and Chapter 4 includes a discussion of behavior recognition. The article conc ludes by discussing what is not used in ANPR and what types of research can be done

2. License Plate Detection

Most license plate detection algorithms are divided into different categories based on differe nt technologies. When checking a driver's license the following should be taken into accoun t:(1). License plate size: The license plate in the vehicle image may have many different siz es. (2). License plate location: The license plate can be located anywhere on the vehicle. (3). Front License Plate: Depending on the vehicle type, the license plate may be in different co lors. For example, a government vehicle license may have a different history than other publ ic vehicles. (4). Screw: There may be a screw on the plate that can be considered a character .

Licenses can be extracted using image segmentation. There are many image segmentation m ethods in many documents. Most methods use image binarization. Some authors use Otsu's i mage binarization method to convert color images into gray images. Some license segmenta tion algorithms rely on color segmentation. [22] discussed local license plate research based on color segmentation. The most common license plates are shown below and then the ima ge segmentation techniques used in various ANPR or LPR files are discussed in detail.

2.1 Image Binarization

Image binarization converts images to black and white. In this model, a threshold is chosen to divide some black pixels and some white pixels. But the real problem is how to choose th e right threshold for a particular image. Sometimes it becomes very difficult or impossible t o choose the best. Adaptive thresholds can be used to solve this problem. The initializer can be selected manually by the user or by an algorithm called the initializer.

2.2 Edge Detection

Edge detection is a simple detection or feature extraction method. In general, the result of us ing edge detection algorithms is a boundary object with an associated curve. It becomes ver y difficult to apply this method to complex images because it can create borders of objects with curved lines. Different edge detection algorithms/operators such as Canny, Canny-Deriche, Differential, Sobel, Prewitt and Roberts Cross are used for edge detection

.

2.3 Hough Transform

It is a feature extraction technique originally used for straight lines. He then started finding t he surface of random shapes like circles or ovals. The first algorithm was D.H. Ballard [32].

2.4 Blob Detection

Blob detection is used to detect points or areas that differ in brightness or color compared to the surrounding environment. The main purpose of using this method is to find additional r egions that cannot be found by edge detection or edge detection algorithms. Some detectors include Laplace of Gaussian (LoG), Difference of Gaussian (DoG), Determinant of Hessian (DoH), maximum stable region, and central curvature-based region detectors.

ISSN 2347–3657
Volume 12, Issue 1, 2024

2.5 Coherence Analysis (CCA)

CCA or drop extraction is a method that specifically describes connections between components as a specific heuristic. It examines binary images and labels pixels based on the coordinates of the current pixel (8-link link), such as northeast, north, west, and west. 4-Link only to the north and west neighbors of the current pixel. This algorithm provides more efficient and effective automatic image analysis. This method can be used for license segmentation and character segmentation.

2.6 Mathematical Morphology

Mathematical morphology is based on demand, lattice theory, topology and random functions. It is mainly used for digital images but can also be used for other spatial models. It was initially designed to process binary images and later went on to process grayscale motion and images. It has basic functions such as corrosion, expansion, opening-closing.

2.7 Work on driver's license check

The process discussed earlier is a way to check a driver's license. In addition to this process, many documents discuss the license plate inspection process. Since more than one method was used in most of the interviews in this literature, a categorical interview was not possible

(a) Skewed image (b) Number plate with lines

FIG. 2. VEHICLE NUMBER PLATE WITH FIRST TWO PARAMETERSAS PER [17]

RELATED WORK:

TABLE 1. NUMBER PLATE DETECTION RATE AND IMAGE SIZE

Ref	Image size	Success Rate (in %)	Ref	Image Size	Success Rate (in %)
[5]	1024 X 768	96,5	[43]	40 X 280	Not reported
[33]	640 X 480	Not reported	[44]	640 X 480	Not reported
[17]	720 X 576 1920 X 1280	90,1	[45]	Not reported	81,20
[34]	Not reporte d	87	[49]	640 X 480 768 X 512	97,9
[15]	640 X 480	97,3	[47]	692 X 512	97,14(Four Characters)

[13]	236 X 48	Not reported	[50]	480 X 640	61,36(Pixel voting) 90,65 (Global Thresholding) 78,26 (Local Thresholding) 93,78 (Combination of global and localbinarization)
[19]	640 X 480	97,16	[51]	1300 X 1030	92,31
[39]	360 X 288 to 1024 X 768	94	[52]	640 X 480	98,3
[6]	220x50	98,82	[21]	324 X 243	97,6
[14]	648 × 486	96,4	[23]	720 X 576 768 X 576	Not reported
[8]	640 X 480	89	[53]	640 X 480	~75,17
[41]	640 X 480	Not reported	[11]	384 X 288	91
[42]	768 X 256	87,6	[28]	600 X 330 768 X 576	94,7
			[38]	640 X 480	Not reported
Bold indicates overall success rate is mentioned but number plate detection rate is not mentioned					

The content of the license plate segmentation algorithm was proposed in [46], [72] without explanation and clarity, and [73] well explained the comparative study of image segmentati on ideas and matching products using segmentation.

2.8 Discussion

In most cases, license plate segmentation algorithms work based on constraints such as illu mination, plate (usually rectangular), size, distance between the camera and the car, and col or. It should be noted that only a few algorithms are suitable for real-time video images of the license plate [33], [30], [39], [51], [61], otherwise static images of the license will be fed. will be forwarded. To ANPR for further action. Table 1 describes the relationship between plate resolution and plate segmentation detection success for different ANPRs. The system where the image size and license plate detection success rate are not sp ecified is not included in Table 1. It has been determined that the plate segmentation process ing time is between approximately 15ms and 1360ms. A lower processing time of 15 ms wa s reported in [52], while a higher processing time of 1360 ms was reported in [53]. Obviousl y, license plate identification value affects behavioral segmentation and identification, whic h in turn affects the overall experience. Based on the research of many documents in this sec tion, the following conclusions can be drawn: image binarization, sliding concentric windo w (SCW), Sobel operator, Canny edge operator, coupling with analysis (CCA), Hough trans form (HT), fuzzy rule-based Method, probabilistic neural network (PNN). and three-color image with color discrete feature method can provide good results as it allows paper s egmentation.

ISSN 2347–3657
Volume 12, Issue 1, 2024

5. Conclusion

5.1 Future Work

ANPR can also be used for vehicle owner identification, vehicle identification models, vehi cle speed control and vehicle location tracking. It can be extended to multilingual ANPR, w hich recognizes the language of characters based on training data. It can bring many benefits to vehicle owners, such as safety management, safety in unpredictable conditions of the veh icle, ease of use, availability of updated information, compared to the manual guide for regis tration informationAffordable price for all countries at low price For higresolution images, we should focus on some enhancement algorithms such as superresolution images [30], [31]. Most ANPRs focus on processing a single license number, but when capturing images in r eal time there may be multiple license numbers. In [5], ANPR considers multiple bus image s, while in most other systems, offline images of vehicles obtained from online data (e.g., [7 8]) are used to input ANPR, so actual results may differ from the results shown. . inside. Ta ble 1 and Table 2. To classify multiple drivers, the coarsetofine concept [56] will be helpful.

Table 3. Different ANPR systems with country supported

Ref	Country(In which ANPR is applied)
[5]	European
[17]	USA, China, Singapore, Australia, South Africa
[34]	India
[15],[35],[18],[23], [22],[40]	China
[7]	Nigeria, Cyprus, Denmark, Germany, Estonia, Finland, France, India, Norway, Slovakia, Portugal, U.S.A, Bulgaria, Czech Republic
[44]	Dutch
[45]	Israel, Bulgaria
[47],[26],[51]	Korea
[52]	Multi-country
[20]	Turkey
[21]	Australia
[53],[24]	Iran
[27]	USA
[28]	China and 104 Countries