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Automatic Number Plate Recognition application

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ABSTRACT

Every country now has a serious issue with traffic regulation and vehicle ownership identification. It might be challenging to recognise car owners who drive excessively fast and against the regulations of the road. As a result, it is impossible to apprehend and penalise those individuals since traffic officials may not be able to obtain the vehicle's licence plate from a moving vehicle due to its speed. As one of the answers to this problem, it is necessary to design an automatic number plate recognition (ANPR) system. There are many ANPR systems on the market right now. Although these systems are based on many techniques, it is still a difficult work since various elements, such as a vehicle's rapid speed, non-uniform number plate, language of the number, and changing lighting circumstances, can have a significant impact on the overall identification rate. The majority of the systems function with these restrictions. Using picture size, success rate, and processing time as factors, many ANPR techniques are presented in this study. A suggestion for an extension to ANPR is made toward the end of this paper.

KEYWORDS

Number Plate, Optical Character Recognition, Character Segmentation, Artificial Neural Network (ANN), and Automatic Number Plate Recognition (ANPR)

I. INTRODUCTION

1.1 Automatic Number Plate Recognition (ANPR)

In the recent years, licence plate recognition (LPR), also known as ANPR, has shown to be one of the effective methods for vehicle monitoring.

It can be used in many public locations to accomplish a variety of goals, including traffic safety enforcement, automatic toll text collecting, parking system, and automatic vehicle parking system . In general, ANPR algorithms consist of four steps:

(1) Capturing a vehicle's image
(2) Finding licence plates
(3) Segmenting characters
(4) Recognizing characters

The first stage, which is to take a picture of the car, appears to be relatively simple in Fig. 1, but it is actually a very demanding work since it is quite challenging to take a picture of a moving vehicle in real time such that no part, notably the vehicle number plate, is missing. In many systems nowadays, the processing time for number plate detection and recognition is less than 50 Ms. The effectiveness of the second and third steps in locating the car number plate and separating each character determines the outcome of the fourth step.These systems employ several strategies to identify the car's licence plate and then extract the vehicle number from the resulting image. Optical Character Recognition (OCR), Probabilistic Neural Networks (PNN), Artificial Neural Networks (ANN) , and others make up the majority of ANPR systems (OCR) , Configurable method, MATLAB, feature salient ,Online licence plate matching based on weighted edit distance and colour-discrete characteristics is performed using the sliding concentrating window (SCW), BP neural network , support vector machine (SVM) , inductive learning , region based , colour segmentation , fuzzy based algorithm , scale invariant feature transform (SIFT) , trichromatic imaging, and the Least Square Method (LSM) In , a case study of a licence plate reader (LPR) is thoroughly detailed.By utilising a method known as super resolution, several authors concentrate on increasing the resolution of the low-resolution imageAt times, it is required to evaluate the effectiveness of the ANPR system. A thorough examination of licence plate recognition (LPR) is offered. The terms "number plate" and "licence plate" are used synonymously throughout this text. Section 2 goes into further depth on each ANPR.

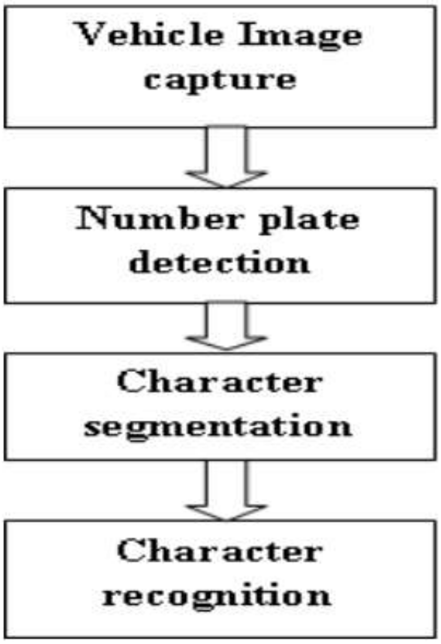

Fig.1. Conventional ANPR system

1.2 Scope of this paper

Since it is impossible to determine which technique is superior, many articles that are based on the steps in Fig. 1 are analysed and grouped according to the methodologies used in each approach. For each method whenever metrics like platform, speed, accuracy, performance, and image size are supplied. The survey of commercial items is outside the purview of this essay because they frequently make accuracy promises that are not always accurate.The remainder of this article is broken out as follows: Section 2 includes an overview of several number plate detection methods. In section 3, character segmentation techniques are discussed, while character recognition techniques are covered in section 4. What is not implemented and the types of ANPR research that are feasible are discussed in the paper's conclusion.

II. NUMBER PLATE DETECTION

Based on various methodologies, the majority of number plate detection algorithms can be divided into more than one category. The following elements should be considered when detecting a vehicle number plate:

(1). Plate size: In a vehicle image, a plate may be of a variable size.

(2). Location of the plate: The plate may be found anywhere in the car.

(3). Background of a plate: Depending on the kind of vehicle, a plate may have a different background colour. For instance, the backdrop of a government vehicle's number plate may differ from that of other public vehicles.

(4) Screw: The presence of a screw on a plate could be regarded as a character.

The picture segmentation method can be used to extract a licence plate. There are several different image segmentation techniques listed in diverse books. Image binarization is employed in the majority of techniques. To turn a colour image into a grayscale image, several authors employ Otsu's image binarization technique.

On colour segmentation, some plate segmentation methods are built. discusses a study on the location of licence plates based on colour segmentation. The most prevalent methods for extracting licence plates are described in the sections that follow. This is followed by a thorough review of the image segmentation techniques used in the literature for ANPR or LPR.

2.1 Image binarization

Black and white image conversion is known as image binarization. In this procedure, specific pixels are classified as black and specific pixels as white using a specific threshold. The key issue, however, is selecting the appropriate threshold value for a given image.The choice of the ideal threshold value might occasionally become very challenging or unattainable. This issue can be solved with adaptive thresholding. Automatic thresholding is the process of selecting a threshold automatically rather than manually via an algorithm.

2.2 Edge detection

The basic technique for feature extraction or feature detection is edge detection. Edge detection algorithms often produce an object boundary with connected curves as their output. Applying this method to complex photos becomes quite challenging since it may produce object boundaries with disconnected curves.Various edge detection algorithms and operators are employed, including Canny, Canny-Deriche, Differential, Sobel, Prewitt, and Roberts Cross.

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2.3 Hough Transform

It is a feature extraction method that was first applied to the detection of lines. It was later expanded to locate positions for arbitrary shapes like circles and ovals. D.H. Ballard generalised the original algorithm.

2.4 Blob recognition

Blob recognise is used to identify areas or spots that stand out from their surrounds in terms of colour or brightness. The major goal of this method is to identify complementary regions that are not picked up by corner or edge detection techniques. Laplacian of Gaussian (LoG), Difference of Gaussians (DoG), Determinant of Hessian (DoH), maximally stable extremal areas, and Principle curvature-based region detector are a few examples of typical blob detectors.

2.5 Connected Component Analysis (CCA)

A method to specifically name subsets of related components based on a particular heuristic is called CCA or blob extraction.

It scans a binary image and classifies pixels according to their connectedness, such as their north-east, north, north-western, and western locations (8-connectivity). 4- Only the north and west neighbours of the current pixel are used for connectedness. The algorithm performs better and is quite beneficial for automated picture analysis. Both plate segmentation and character segmentation can be done using this technique.

2.6 Mathematical morphology

Set theory, lattice theory, topology, and random functions serve as the foundation for mathematical morphology. Although it is frequently utilised with digital images, it can also be applied to other spatial structures. It was initially created to process binary images before being expanded to process grayscale functions and images. It includes fundamental operators like erosion, dilation, opening, and shutting.

2.7 Related work in number plate detection

The techniques covered in the earlier sections are typical techniques for plate detection. In addition to these techniques, various works of literature covered plate detecting techniques. It is impossible to conduct a category-by-category analysis of the strategies presented in these literatures because the majority of them combine many approaches. The following discussion covers various number plate segmentation algorithms. In, a method known as sliding concentric window (SCW) is created for quicker region of interest (ROI) detection. It is a two-step process with two concentric windows that move from the image's upper left corner. According to the segmentation rule, which states that the centre pixel of the windows is regarded to belong to a ROI if the ratio of the means or medians in the two windows exceeds a threshold defined by the, statistical measurements were then calculated for both windows. Once the entire image has been scanned, the two windows stop sliding. Trial and error can be used to determine the threshold value. Similarly, the connected component analysis has a 96% success rate overall. The experiment took 111ms to perform for number plate segmentation on a Pentium IV running at 3.0 GHz with 512 MB of RAM.

Another SCW-based approach for locating Korean licence plates is provided in. After applying SCW to the vehicle image, the authors utilised the HSI colour model to check the colours, and then then employed least square fitting with perpendicular offsets to fix the tilt (LSFPO). The gap between the camera and the car is anything between three and seven metres. developed a quick technique for real-time vehicle number plate detection using a cascade structure. This framework segments the licence plate using a small frame detection module. There are three steps in this module: Using gradient characteristics, the first generation of plate area candidates is utilised to eliminate non-plate regions. Extraction of complicated plate areas is the second phase, which entails three steps to distinguish plate regions from non-plate regions. To ensure that no non-plate regions were retrieved in the steps before, plate verification is employed as the third step. On a home computer with a 3-GHz Intel Pentium 4 processor, the experiment was conducted. A programmable technique is suggested in for the detection of multi-style licence plates. A user can modify the algorithm by adjusting a parameter's value in the number plate detection algorithm to detect different styles of number plates. The authors primarily define four parameters:

1.Plate rotation angle: If a plate is skewed, it should be rotated at a specific angle, as shown in fig (a).

2.Character line number: Used in fig. 2(b) to indicate if characters are spread across more than one line or column. The algorithm can handle up to three lines.

3.Models of recognition: can be used to assess whether a licence plate has only alphabets, alphabets and numerals, or alphabets, digits, and symbols.

4. Character formats: To categorise the many types of characters on licence plates. For instance,

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symbols can be represented by the letter S, the alphabet by the letter A, and numbers by the letter D. As a result, the number in Figure 2 can be written as AADAADDDD.

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

Fig. 2. Vehicle number plate with first two parameters as per [17]

Pentium IV 3.0GHz was used to run the algorithm.

A feature-based number plate localisation is suggested to locate Indian licence plates. To transform grey scale photos into binary images, the authors employ Otsu's technique. To remove the number plate off a vehicle photograph without any backdrop image, there are seven steps to follow.

- Usingseveral elements including shape, texture, and colour, a feature several techniques is employed to extract the vehicle number plate.
- Locates licence plates. This technique is used for situations like uneven lighting and is very effective at removing shadows.
- Chinese number plate location in Determine the exact rectangle with the car number by finding the horizontal and vertical difference.
- A unique method that is used to extract characters from a licence plate Based on textural features and wavelets was proposed by Ch. Jaya Lakshmi et al.
- M.S. Sarfraz et al.'s unique approach for CCTV footage, a licence plate detection tool which is used to detect the licence plate.
- The transition locations were discovered using the edge detector operator. According to H. Erdinc Kocer et al., a licence plate often has a black character on a white backdrop.
- A better segmentation technique is developed for detecting licence plates from various countries. An enhanced segmentation approach was given by Ankush Roy et al.

- Table 1. Number plate detection rate and image size

Image Size	Success Rate (in %)
40 X 280	Not reported
640 X 480	**Not reported**
Not reported	81,20
640 X 480 768 X 512	97,9
692 X 512	97,14(Four Characters)
480 X 640	61,36(Pixel voting) 90,65 (Global Thresholding) 78,26 (Local Thresholding) 93,78 (Combination of global and local binarization)
1300 X 1030	92,31
640 X 480	98,3
324 X 243	97,6
720 X 576 **768 X 576**	**Not reported**
640 X 480	~75,17
384 X 288	91
600 X 330 768 X 576	94,7
640 X 480	**Not reported**

Bold indicates overall success rate is mentioned but number plate detection rate is not mentioned.

2.8 Discussion

In the majority of the literature, number plate segmentation algorithms only function under specific lighting, number plate form (which is typically a rectangle), size, distance from camera and vehicle, and colour circumstances. It should be emphasised that only a select few algorithmsallow for the real-time video capture of a number plate; otherwise, a static image of the plate is sent to the ANPR for additional processing. Table 1 shows various plate segmentation detection success rates in relation to plate resolution for various ANPR. Table 1 excludes the systems that do not indicate image size or the success percentage of number plate detections. It has been noted that the processing time for plate segmentation ranges from

15 to 1360 milliseconds. While a larger processing time of 1360 was recordedreported a shorter processing time of 15ms. It is clear that the rate at which number plates are detected influences character segmentation and recognition, which in turn influences the overall rate of recognition. Based on the analysis of the literature reviewed in this section, it can be said that the number plate segmentation techniques of image binarization, sliding concentric window (SCW), Sobel operator, Canny-edge operator, connected component analysis (CCA), Hough transform (HT), fuzzy discipline-based approach, probabilistic neural network (PNN), and trichromatic imaging with colour-discrete characteristic approach can yield promising results.
Character segmentation, which is covered in the following section, is a necessary step in order to continue with character recognition.

III. CHARACTER SEGMENTATION

Characters are checked for the next step after locating the number plate. Character segmentation can be done using a variety of approaches, just as plate segmentation. It is impossible to do a category-by-category debate because many approaches fit into more than one area. This section discusses frequent related work in this field before moving on to further discussion. Character segmentation can also be done using some of the techniques, including image binarization and CCA, that were already covered in Section 2.

3.1 Discussion

To execute character recognition with a high level of accuracy, character segmentation is crucial.
Character segmentation mistakes can occasionally prevent characters from being recognised. Character segmentation is not fully covered in some ANPR publications. Character segmentation can be improved with the help of techniques like picture binarization, CCA, vertical and horizontal projection, and others.

IV. CHARACTER RECOGNITION

Character recognition aids in identifying and transforming visual text into editable text, as was covered in Section 2 of this report. Since just one method is used by the majority of number plate recognition algorithms to identify characters. This section explains each technique.

4.1 Artificial Neural Network (ANN)

A linked system of artificial neurons is referred to as an artificial neural network (ANN), sometimes known as a neural network. ANN is the foundation for many algorithms, including. uses a two-layer probabilistic neural network with a 180-180-36 topology. Character recognition took place in 128 milliseconds. Multi-layered perceptron (MLP) ANN model is used in for character classification.consists of an input layer for making decisions, a hidden layer to calculate more complex associations, and an output layer for the final choice. An ANN was trained using the feed-forward back-propagation (BP) algorithm. Systems based on BP neural networks are suggested and have a processing time of 0.06s in. HNN is used in to lessen ambiguity between related characters, such as 8 and B, 2 and Z, etc. The authors assert that their recognition rate is greater than 99%.

4.2 Template matching

For the purpose of recognising fixed-sized characters, template matching is helpful. Additionally, it can be applied to the general detection of objects in facial recognition and medical image processing. Additional divisions include feature-based matching and template-based matching. When the template image includes prominent features, the feature-based method is useful; otherwise, the template-based approach can be helpful. uses the statistical feature extraction method to get a character recognition rate of 85%.According to training characters, numerous features are retrieved from and salient is computed. For the purpose of adjusting all characters to the same size, a linear normalisation procedure is applied. On a total of 1176 pictures, a recognition rate of 95.7% was attained. For the purpose of feature extraction, Chinese, Kana, and English, numeric characters are combined. For numerals, Kana, and address recognition, the writers' success rates were 99.5%, 98.6%, and 97.8%, respectively. A template-based strategy is suggested. To work with lesser quality images, such as 4 X 8, the authors employed the low-resolution template matching method. To determine how similar two patterns are, the authors employed the similarity function.

4.3 Discussion

Fig.3. Distinguishing parts of ambiguous characters in

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Character recognition systems should be able to handle unclear, noisy, or distorted characters that are obtained from the character segmentation phase because character segmentation is one of the pre-processing phases. With ANN and self-organising (SO) recognition, good results have been recorded. The specifics are presented in Table 2. OCR is a method that is currently in use and popular, hence ANPR engineers are concentrating on improving it. Accuracy of OCR rather than starting from scratch with the ANPR. As was covered in the section above, several developers are improving open-source OCR, like Tesseract, for greater accuracy.

Table 2. Character recognition rate with method and type of category

Method	Success Rate (in %)	Type of Category
Two layer PNN	89,1	Letters
Statistical feature extraction.	85	Not reported
Feature salient	95,7	Not reported
SVM Integration with feature extraction	93,7	English characters, Chinese, Numeral, Kana
Template matching	Not reported	Letters, digits
multi layered perceptron (MLP) ANN	98,17	Letters, digits
multi layered perceptron (MLP) ANN	Not reported	Letters, digits
Open source OCR Tesseract	98,7	Letters, digits
BP neural network	Not reported	Korean Letters, digits
BP neural network	Not reported	Chinese letters, English letters and digits
MRF	Not reported	Letters, digits
character categorization, topological sorting, and self-organizing (SO) recognition	95,6	Letters, digits
Hierarchical Neural Network(HNN)	95,2	Letters, digits
PNN	96,5	Letters, digits
BP neural network	93,5	Letters, digits

V. CONCLUSION

An additional use for ANPR is for vehicle position tracking, vehicle owner identification, vehicle model identification, and traffic control. It may also be used as a multilingual ANPR to automatically determine the language of characters based on training data.It can offer a number of advantages, including the enforcement of traffic laws, security in the event of suspicious vehicle activity, ease of use, fast information availability, and cost-effectiveness for any nation. Some techniques for picture improvement, such as super resolution should be concentrated on low resolution images. The majority of ANPR systems concentrate on processing a single vehicle number plate, although in reality, multiple vehicles may have number plates while the images are being taken.Multiple vehicle number plate photos are considered for ANPR whereas most other systems use offline photographs of vehicles retrieved from internet databases, like as input. As a result, the precise findings may differ from those displayed in Tables 1 and 2. A coarse-to-fine technique may be used to segment multiple vehicle licence plates.

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5.1 Summary

It is obvious that ANPR is a challenging system due to the various number of phases, and currently it is not possible to attain 100% overall accuracy as each phase depends on the phase before it. The effectiveness of ANPR is impacted by various elements such as various lighting conditions, vehicle shadow, non-uniform size of licence plate characters, different font, and backdrop colour.Some systems can only function under these specific circumstances, and they might not produce accurate results under challenging circumstances. Table 3 summarises the systems that were created and are in use in particular countries. Table 3 excludes the systems in which the country is not mentioned. Table 3 makes it clear that just a small percentage of ANPR are produced for India. Therefore, there is a lot of room to construct such a system for a nation like India.The scholars working on these advances can benefit from the thorough analysis of current trends and potential developments in ANPR provided in this paper.

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

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