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Review JoIPPRP

Automatic Number Plate Recognition Based Image Processing

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Abstract

In most countries, traffic control and vehicle owner identification have become important problems. It is almost impossible to identify vehicle owners who break rules of the traffic, especially those driving at high speeds. Another problem inhibits traffic officers from catching the offenders in most cases because solving traffic offenders involves retrieving license plate numbers from fast-moving vehicles. Automatic Number Plate Recognition (ANPR) systems have been developed as an effective solution to address this issue. There are many ANPR systems, but each brings a range of obstacles to recognize, including vehicle speed, non-standardized license plates, different languages on license plates, and varying lighting conditions, which can degrade recognition. Each of these systems functions within these limitations. Image size, success rate and processing time for ANPR are discussed in this study and evaluated with different ANPR approaches. An extension to ANPR is proposed at the end of the study.

Keywords: Character segmentation, image segmentation, number plate, optical character recognition (OCR), artificial neural network (ANN), automatic number plate recognition (ANPR)

INTRODUCTION

Automatic Number Plate Recognition (ANPR)

In recent times, vehicle surveillance with ANPR, License Plate Recognition (LPR), has become popular. The implementation is used in various public spaces for traffic law enforcement, automatic toll collection, parking management, and automated vehicle parking systems. ANPR algorithms generally follow four main steps:

1. Capture vehicle image,
2. Number plate detection,
3. Segment characters, followed by
4. Recognizing characters.

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Figure 1 illustrates that it is not so straightforward to capture the vehicle image [1]. It is particularly hard to capture a clear image of a moving vehicle, which must ensure that there is no miss of the number plate and the most important parts of the vehicle. In most modern systems, the first number plate detection and recognition occurs in less than 50 msec. The dependability of the fourth step (character recognition) is critically reliant on the first two steps (location and character segmentation), which are dependent on efficacy.

For detecting and recognizing license plates ANPR systems use many techniques such as Artificial Neural Networks (ANN), Probabilistic

Neural Networks (PNN), OCR, feature extraction, MATLAB, Sliding Concentric Window (SCW), Back Propagation Neural Networks, Support Vector Machines (SVM), Inductive Learning, Region-based techniques, Color segmentation, Fuzzy algorithm, Scale-Invariant Feature Transform (SIFT), Trichromatic imaging and the Least Square Method (LSM). Online license plate matching with weighted edit distance and color discrete characteristics is used by some systems. License plate recognition (LPR) systems are described in a case study of these approaches.

It even sometimes uses super-resolution techniques to enhance the picture resolution of low-resolution images. Therefore, the quality assessment of an ANPR system is sometimes necessary to assess its effectiveness, and the quality assessment of both visual and ANPR systems is explained in one comprehensive study. In this literature, they use the words 'number plate' and 'license plate' interchangeably. Various ANPR systems have been discussed in more detail later.

Scope of this Study

Because it is hard to pick which approach is best, this study takes a look at and categorizes different methods by the steps in Figure 1. When available, each method is evaluated with respect to speed, accuracy, performance, image size, and platform. However commercial product reviews are excluded because their claimed accuracy may not always be the reality for the reasons of exaggerated promotional bull. The study is structured as follows: It presents a review of some different techniques for number plate detection; then characters segmentation techniques; the characters recognition techniques; and a discussion of what has not yet been implemented in ANPR and some future research directions.

NUMBER PLATE DETECTION

Various techniques are used for most number plate detection algorithms which are more or less categorized. To successfully detect a vehicle's number plate, several factors should be considered:

- *Plate size:* Images of vehicles may contain different-sized number plates.
- *Plate location:* They can be located anywhere on the vehicle.
- *Plate background:* Vehicle type might have a different background (government vehicle might have a different background than private vehicle).
- *Screws:* Sometimes screws on the plate are mistaken for characters.

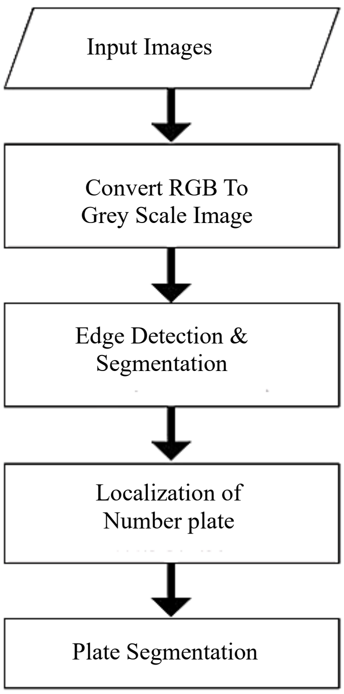

Figure 1. Flow diagram of ANPR system.

Number plates can be extracted using image segmentation methods and such methods have been discussed in several research papers. In normal cases, we use the image binarization. There are some authors like us who used Otsu's method for binarization of the color images and converted them to grayscale. In addition, some of the algorithms are based on color segmentation. For example, in the study by Tang *et al*., the authors discuss a study on license plate detection with color segmentation [2]. Common number plate extraction methods have been discussed below and image segmentation techniques used in ANPR/LPR research are elaborated upon in detail below:

Image Binarization

The binarization of an image can be converted to black and white. This method is characterized by a selection of a threshold for classifying pixels as either black or white. Selecting the right threshold however is complicated, since often it is difficult to choose the right value for some specific image. Manual setting of the threshold by the user and automatic thresholding performed by some algorithm (also called adaptive thresholding) can help solve this problem.

Edge Detection

Edge detection is an important means of getting features. Even in general, edge detection boundaries are connected curves. While applied to complex images, the boundaries may not even form complete, connected curves. Commonly used here are different edge detection algorithms/operators such as Canny, Canny-Deriche, Differential, Sobel, Prewitt and Roberts Cross (Figure 2).

Hough Transform

Initially, feature extraction technique was used to detect lines (Hough transform). Later, detection of arbitrary shapes, including circles or ovals, was extended [3].

Plate Detection

The techniques mentioned here are prevalent plate detection methods. However, most algorithms rely on more than one mechanism and thus are hard to categorize.

A configurable method for detecting number plates of various styles has been proposed. With this method, users can fine-tune algorithm parameters to detect different styles of number plates. Four main parameters are defined:

- *Plate rotation angle:* If the number plate is skewed (Figure 3(a)), it adjusts the angle of the number plate.
- *Character line number:* Determines whether the characters take up more than one line or column (Figure 3(b)). It can also take up to three lines.
- *Recognition models:* It checks whether these digits in a number plate contain alphabets or only a mixture of alphabets of digits or a combination of alphabets and digits and symbols.
- *Character formats:* It classifies the characters by type. It (like the other forms) represents symbols as 'S', letters as 'A', and digits as 'D'. Hence, the number in Figure 3 could be written as "AADAADDDD".

+1	+2	+1
0	0	0
-1	-2	-1

Gx

+1	+2	+1
0	0	0
-1	-2	-1

Gy

Figure 2. Edge detection using Sobel Mask.

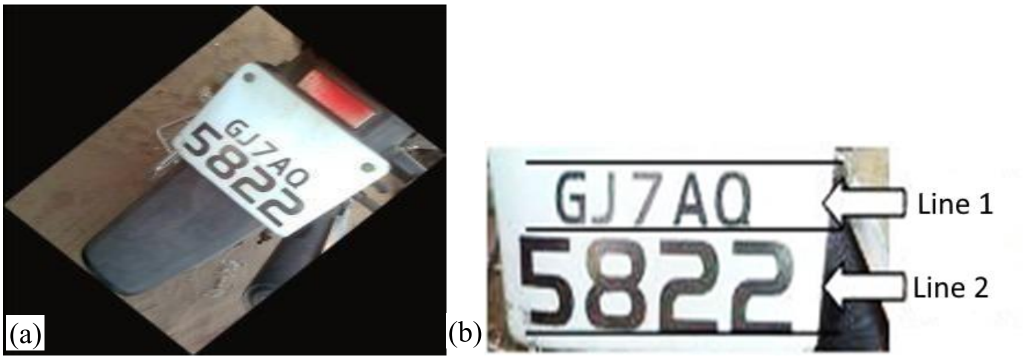

Figure 3. Vehicle number plate with first two Parameters: (a) A skewed image, (b) A number plate with multiple lines.

All these license plate detection mechanisms can be developed once you start analyzing color, edges, and other distinguishing features. An edge-based, color-aided method for license plate detection is proposed in the study by Arora *et al*. [4]. The authors then suggest the use of intensity variance and edge density techniques for image enhancement. Then, the license plate detection process starts. The vertical edge density estimation is a key step to prevent missing plate edges in case of poor lighting conditions. Then, we apply the Gaussian mixture model to highlight the uniformity of a number of pixels with the same intensity value in the horizontal direction in the plate region. An 80% threshold is employed to identify a candidate region, followed by morphological processing and color analysis to segment the license plate. The average processing time taken by this system, developed in MATLAB, on a Pentium 3.0 GHz processor, was approximately 1.36 sec.

They also propose another MATLAB-based system in which their work is converted to binary image forms during a preprocessing stage. Further refinement of license plate extraction is applied to vehicle images in the manner of adaptive median filtering, gray stretch, and gradient sharpening.

Discussed for possible application in license plate detection are several image segmentation techniques including color texture-based, coarse to fine strategies, wrapper-based, content-based image retrieval, and dynamic region merging. Among these other methods are Dual Multiscale Morphologic Reconstructions, background recognition and perceptual organization, niching particle swarm optimization, and constraint satisfaction of neural networks. It also considers two-stage self-organizing networks, adaptive local thresholds, and vectorial scale-based fuzzy connected image segmentation. License plate detection can be served by many of these unsupervised methods. For example, the technique in the study by Laroca *et al*. is particularly useful for multiple object detection in the images, when used for segmenting multiple vehicle number plates in the traffic images (Table 1) [5].

CHARACTER SEGMENTATION

The characters are further examined, and further processed after we identified the number plate. Several methods are available for character segmentation as it is similar to the plate segmentation issue. These methods overlap a lot between categories, so it is difficult to talk about them by category. In this section, a general discussion and a highlight of notable related work in this area are presented. Image binarization and Connected Component Analysis (CCA), can also be applied to character segmentation.

Related Work in Character Segmentation

According to the study by Laroca *et al.*, the candidate region is down-sampled to 78×228 pixels using bicubic interpolation and segmented using the sliding concentric window (SCW) method [5]. The results were optimized at a threshold value of 0.7. Then each character was down-sampled to 9×12 pixels after segmentation.

Table 1. Number plate detection rate and image size.

Sr. No.	**Image size**	**Success Rate (%)**	**Image Size**	**Success Rate (%)**
1	1024×768	96,5	40×280	Not reported
2	640×480	Not reported	**640×480**	**Not reported**
3	720×576 1920×1280	90,1	Not reported	81,20
4	Not reported	87	640×480 768×512	97,9
5	640×480	97,3	692×512	97,14 (Four Characters)
6	**236×48**	**Not reported**	480×640	61,36 (Pixel voting) 90,65 (Global Thresholding) 78,26 (Local Thresholding) 93,78 (Combination of global and local binarization)
7	640×480	97,16	1300×1030	92,31
8	360×288 to 1024×768	94	640×480	98,3
9	220×50	98,82	324×243	97,6
11	640×480	89	640×480	~75,17
12	**640×480**	**Not reported**	384×288	91
13	768×256	87,6	600×330 768×576	94,7

Based on the Indian number plates, Kulkarni *et al*. observed that the blob coloring and peak-to-valley methods are not appropriate [6]. Up next, they proposed an image scissoring algorithm where the number plate is scanned vertically and cuts at the row with no white pixels. By doing this the result is stored in a matrix and if more than one matrix is found they are discarded using a formula.

In the study by Salau *et al.*, three matrices were used to store plate location and binarization data [7]: There are one for the number of columns in BW and one for the number of rows in BW. Projections along the vertical axis have then been used to segment the characters appropriately after the detection of the precise top and bottom boundaries.

In the study by Silva and Jung a "character clipper" was used to clip each character in a box [8]. The segregation process included feature extraction, classification, training, and post-processing process.

An improved projection method (IPM) was proposed in the study by Gloger et *al*. [9]. The principle of this method is based on a three-step procedure of character segmentation. Corrected first are horizontal, vertical, and compound tilts. Then, both the first and last character's lines are drawn and used to detect connected boundaries. Secondly, the characters are segmented, and noise removed at the same time. The experiment is simulated using MATLAB 6.5 and VC++ 6.0.

As Thome *et al*. noted, connected component labeling tends to be accurate, but segmentation crashes can ensue from a single mislabeled pixel [10]. However, the authors also found that histogram projection is more robust but less accurate. However, a set of preliminary contours was processed using connected component labeling.

Vertical and horizontal histogram methods are used for character boundary determination. Adjacent characters were separated by using column sum vectors.

DISCUSSION

Character segmentation is key to execute character recognition with high degree of accuracy. However, occasional character segmentation errors can make it impossible to identify characters. Some

ANPR publications do not cover character segmentation in detail. Techniques, including picture binarization, CCA, vertical and horizontal projection, can improve character segmentation.

CHARACTER RECOGNITION

Character recognition is done for the purpose of converting text from images into editable formats. Today, most number plate recognition systems use a single method for this task. Several methods of character recognition are described in this section.

Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs) are artificial neurons connected together to form a mathematical framework, sometimes called just neural networks. ANN is used for character recognition in many algorithms. For example, a two-layer probabilistic neural network with a topology completed the recognition of a character in 128 msec. A multilayer perceptron (MLP) ANN model is further used for character classification.

The model that proposing here has an input layer, a hidden layer to process the complex association, and then an output layer to conclude the decision. Training of ANNs is often done using the feed-forward back propagation (BP) algorithm. Some researchers reported BP neural network systems had processing times of 0.06 sec [8, 10]. In addition, a hybrid neural network (HNN) was used to reduce confusion between similar characters like '8' and 'B' or '2' and 'Z'), the authors say with a recognition rate of over 99%.

Template Matching

They are also used in object detection (for example, in facial recognition and medical imaging) and in facial recognition where the size of the character is known, or even in medical imaging (as it is not certain, but expected that the characters have the same size and location in each case). This method is categorized into two approaches: template-based matching and feature-based matching. If the template image has strong features, the feature-based method is good, otherwise, the template-based method is better. An 85% character recognition rate was achieved using a statistical feature extraction method.

From the training characters, features including multiple features were extracted and salient ones (computed) gave a recognition rate of 95.7% for 1,176 images. An SVM-based method for feature extraction was applied to Chinese, Kana, and English numerics, to achieve 99.5, 98.6, and 97.8% success for numerics, Kana, and address learning, respectively. Study also discusses an additional template based approach where a lower resolution template matching method has been used on images of 4×8 pixels. A similarity function was used to compare patterns (Figure 4).

ANN and self-organizing (SO) recognition techniques showed positive results in the character segmentation phase of the system. The results of the study are presented in Table 2. Since ANPR is widely adopted, developers of Automatic Number Plate Recognition (ANPR) system are more and more engaged on how to make OCR more accurate than reconstruct the whole ANPR system. Some developers, as previously noted, are modifying open source. To improve precision, we use OCR tools such as Tesseract as shown in Tables 1 and 2.

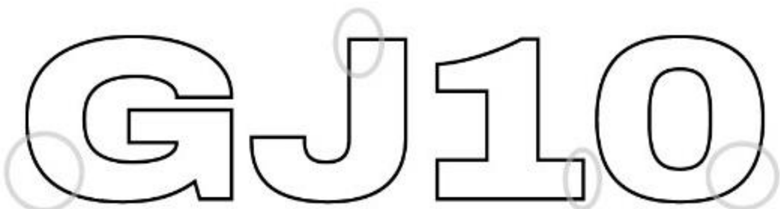

Figure 4. Distinguishing some aspects of characters that are unknown.

Table 2. Character recognition rate per category and method.

Sr. No.	Method	Success Rate (%)	Type of Category
1	Two-layer PNN	89,1	Letters
2	Statistical feature extraction.	85	Not reported
3	Feature salient	95,7	Not reported
4	SVM Integration with feature extraction	93,7	English characters, Chinese, Numeral, Kana
5	Template matching	Not yet reported	Letters, digits
6	Multi-layered perceptron ANN (MLP)	98,17	Letters, digits
7	Multi-layered perceptron ANN (MLP)	Not yet reported	Letters, digits
8	Open-source OCR Tesseract	98,7	Letters, digits
9	BP neural network	Not yet reported	Korean Letters, digits
10	BP neural network	Not yet reported	Chinese letters, English letters and digits
11	MRF	Not yet reported	Letters, digits
12	character categorization, topological sorting, and self-organizing (SO) recognition	95,6	Letters, digits
13	Hierarchical Neural Network (HNN)	95,2	Letters, digits
14	PNN	96,5	Letters, digits
15	BP neural network	93,5	Letters, digits

Table 3. Nations that have effectively adopted the ANPR system.

Sr. No.	Country (In which ANPR is applied)
1	European
2	USA, China, Singapore, Australia, South Africa
3	India
4	China
5	Nigeria, Cyprus, Denmark, Germany, Estonia, Finland, France, India, Norway, Slovakia, Portugal, USA, Bulgaria, Czech Republic
6	Dutch
7	Israel, Bulgaria
8	Korea
9	Multi-country
10	Turkey
11	Australia
12	Iran
13	USA
14	China and 104 Countries

CONCLUSION

Future Work

Other applications of ANPR include vehicle owner identification, vehicle model identification, traffic management, speed regulation and position monitoring. It can be done by any nation and at a cost it can afford. We do this by focusing on some super resolution strategies (photos super resolving for example) on low resolution images. While the images are taken, several vehicle number plates may be present in real-time, but most ANPRs process one at a time.

Unlike most other systems, most of which ingest offline vehicle photos taken from internet databases on ANPR, ANPR opens-up to many vehicle number plate images. The results may therefore be somewhat different. This could be useful in the coarse-to-fine strategy for the segmentation of multiple vehicle number plates.

Summary

The current numbers of phases make ANPR a difficult system since it is impossible to have 100% overall accuracy and each phase depends on the one before it. A variety of variables, such as changing lighting conditions, vehicle shadows, license plate characters of varying size and irregularity, font, and backdrop color, all affect ANPR performance. Under these limited conditions, some systems may only work and provide false results in unfavorable situations. Some of the systems created and used for nations are summarized in Table 3. Table 3 leaves off the systems in which the nation is not mentioned. It is no secret that the ANPR, India is the target of ANPR; Table 3 makes that clear. So, much room is there to create such a system for a country like India.

This study does a thorough analysis of current and coming trends with ANPR, for the benefit of the researchers working on these advancements.

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