

Survey On Automation Number Plate Recognition

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Abstract: Major global challenges are traffic control and identification of vehicle owners. In many cases, it is not possible to identify the driver violating traffic rules or over-speeding since the traffic personnel fail to capture the license plate numbers of fast-moving vehicles. Thus, ANPR systems have emerged as the most practical solution. While there have been several different approaches to ANPR, with various methods, these still have challenges, such as high vehicle speeds, inconsistent number plate designs, variations in language, and changing lighting conditions, that all reduce the accuracy of recognition. However, most systems do work well under certain conditions. This paper explores the various approaches to ANPR, factoring in such aspects as the size of images, success rate, and processing time. Furthermore, an extension proposal seeks to enhance the performance of ANPR.

Keywords: Automatic Number Plate Recognition (ANPR), Artificial Neural Network (ANN), Character Segmentation, Image Segmentation, Number Plate, Optical Character Recognition.

I. INTRODUCTION

Automatic License Plate Recognition, more popularly known as car plate recognition or vehicle license plate recognition, utilizes image processing technology that automatically extracts and identifies information in a license plate, image, or video frame, making it useful for applications such as electronic toll collection, parking fee systems, road monitoring, and traffic control. However, ALPR systems suffer numerous challenges in real-world scenarios like license plates of different types, fonts, and colors, as well as light, weather, and object obstructions. There exists a variety in terms of colors, languages, and font used in license plates across countries; there may be colored borders or solid-colored backgrounds, which will complicate detection and recognition.

Good accuracy of images is primarily governed by the type of camera, resolution, lighting, and a position of the camera. Classically, ALPR requires cameras and computers of high resolutions as this is an application that uses complex algorithms. Mobile technology development has enabled ALPR implementation on powerful processors and high-resolution cameras on smartphone, similar to expensive digital cameras. This has paved way for portable ALPR systems that are of much advantage to law enforcement officers. It facilitates them to do traffic monitoring any time and any place for identifying stolen vehicles and tracking the violators of traffic rules.

Traditional ALPR systems are often installed, programmed, and maintained at a huge cost. On the other hand, mobile-based ALPR solutions appear more cost-effective. Although there is still very minimal research on mobile ALPR systems, this is an open opportunity for further development in this field. Usually, the four main stages at which the ALPR system usually works include image acquisition, localization of license plate, segmentation, and character recognition—all influenced by environmental conditions, such as illumination and background complexity.

II. BASIC CONCEPTS OF ANPR

1. Image Capture: ANPR systems use high-resolution cameras to capture images of vehicles and their license plates. Cameras can be installed on roadsides, mounted on vehicles (mobile systems), or placed at fixed locations such as parking lots.

2. Image Processing:

-Detection: The algorithm determines the location and orientation of the license plate in the acquired image.

-Segmentation: The plate is separated from the rest of the image; cropping or modifying the image to focus entirely on the plate is common.

3. Optical Character Recognition(OCR)

-Character recognition The OCR engine extracts from the segmented license plate recognized and machine-printed characters, such as letter or numerals, into text format.

-Data extraction The identified characters are extracted and formatted into a textual format, such as "ABC1234."

4. Data Processing:

-Matching: The text is matched against a database in order to identify stolen cars, verify parking permits, or track traffic violations.

- Action: In case of a match, the system could take actions such as logging the car, issuing a fine, or opening a gate.

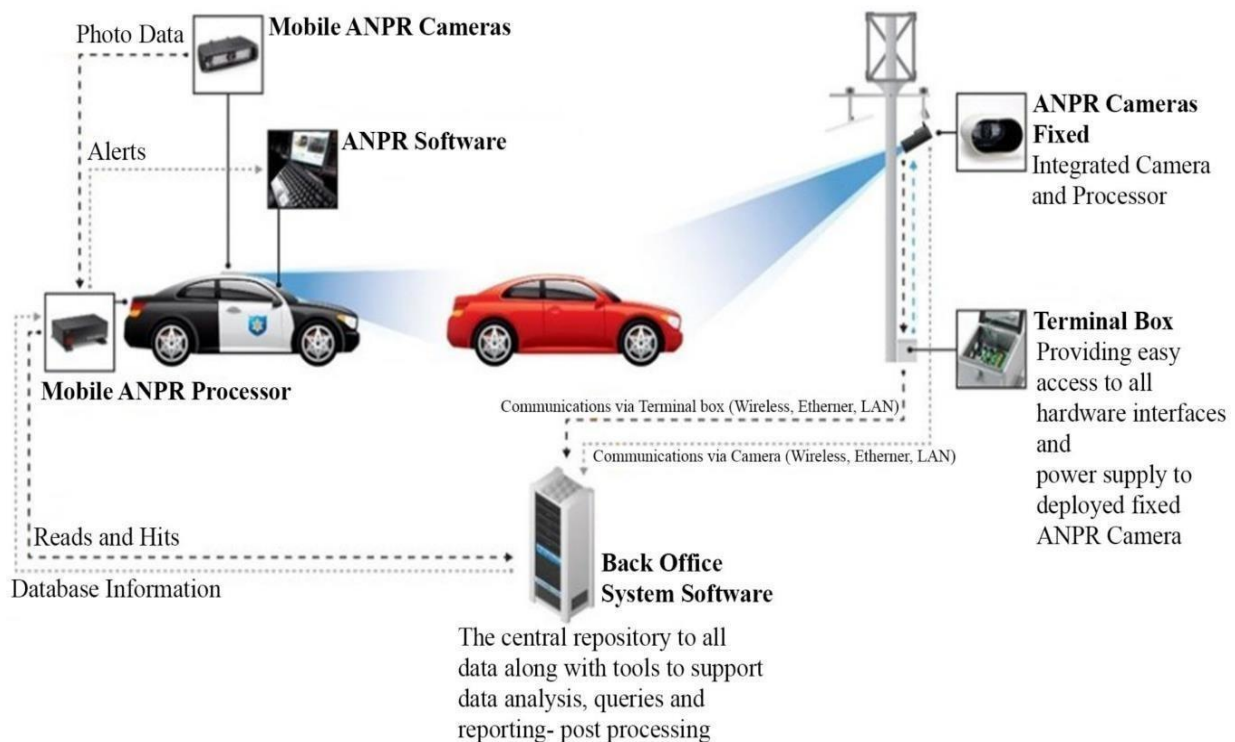


Fig 1.1 Automatic Number Plate Recognition

2.1 GENERAL APPROACH

ANPR systems operate in a multi-step procedure for the correct detection and reading of vehicle license plates. The procedure starts with the acquisition of images or videos from high-resolution cameras capturing vehicles. Images are enhanced by adjusting brightness, contrast, and noise reduction to improve clarity and prepare the images for further processing.

In the next step, image processing algorithms are used to detect and localize the license plate within the captured image. The system separates the plate from the vehicle and background, making it easier to analyze. After detection, the license plate is segmented into individual characters for further processing.

Then, the segmented characters are scanned and converted into a machine-readable format by using OCR technology, so that the complete license plate number is formed. It is then subjected to some post-processing techniques to correct errors so that the data is consistent and accurate, which enhances the overall reliability of the system.

The processed license plate data is cross-checked against various databases for applications such as identifying stolen vehicles, verifying parking permits, and managing toll collections. Based on the verification results, the system can trigger specific actions, such as granting access, logging violations, or issuing alerts, depending on its intended use.

Despite its advantages, the implementation of ANPR systems poses challenges. These include maintaining high accuracy and processing speed, adapting to varying environmental conditions like lighting and weather, and addressing privacy concerns associated with data collection and storage. Nevertheless, ANPR systems play a crucial role in improving traffic monitoring, law enforcement, and automated parking solutions.

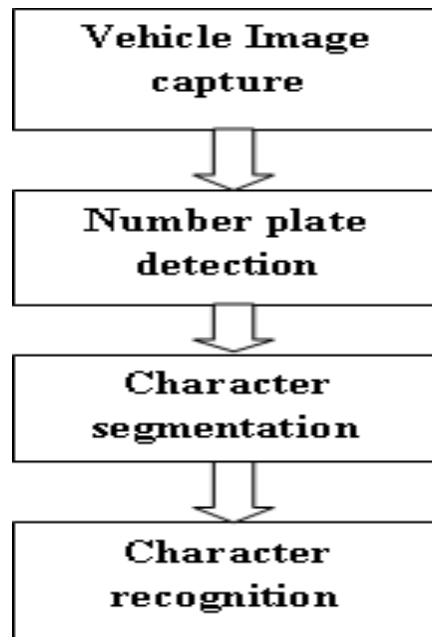


Fig 2.1 Conventional ANPR System

III. CHARACTER SEGMENTATION

Once the license plate is captured by the system, it moves into the extraction of individual characters for more complicated processing. Character segmentation plays the most important role for accuracy in license plate recognition to isolate each character from the other to analyze precisely. So numerous techniques are available to execute character segmentation, overlapping lots of techniques into many groups, making it difficult to class them clearly. Anyway a few widely used methods effectively execute this process. One common technique is called image binarization, whereby an image is transformed into a format of two colors that clearly makes the differentiation of characters from the background easy. It also makes it easier to differentiate between characters and background images since it reduces an image to only two colors, which can be differentiated. Most of the time, it is the first segmentation method in which characters appear clearer from their background.

3.1 RELATED WORK IN CHARACTER SEGMENTATION

1. In [1], the candidate region is cropped to 78×228 pixels using bicubic interpolation and subjected to SCW for segmentation. A threshold value of 0.7 was used for optimization. Post-segmentation, each character is resized to 9×12 pixels.
2. In [2], it has been concluded that blob coloring and peak-to-valley methods are not suitable for Indian number plates. Authors have proposed an image scissoring algorithm, where number plate is vertically scanned and split at rows with no white pixels. This information is stored in a matrix, and false matrices are discarded using a specific formula. The same process is repeated horizontally, using width as the threshold.

3. In [3], CCA is noted as an efficient method of processing binary images. Image enhancement, horizontal and vertical corrections are done as pre-processings. The plate image is converted to black text on white background and re-sized to 100 x 200 pixels. Further, characters are separated using two methods, namely image binarization and connected component labeling, in 32 x 32 pixels size.

4. In [4], three matrices are used to store plate location, binarization details, and the number of rows and columns in the binary image. The top and bottom boundaries are detected, followed by vertical projection and thresholding to segment characters.

H. Erdinc Kocer used contrast extension, median filtering, and blob coloring for segmentation. Contrast extension sharpens the image, and histogram equalization improves poorly contrasted images. Median filtering eliminates noise, and blob coloring is used to detect closed, contactless regions in the binary image by scanning in four directions using an L-shaped template.

A four-directional blob coloring algorithm separates the numbers into 28×35 pixels and the letters into 30×40 pixels. Other blob detection algorithms are height estimation of characters, width estimation, and blob extraction. The estimation of height involves color reversal, vertical edge detection, and horizontal projection histograms. The width estimation includes binarization and vertical projection histograms for gap detection between characters. Blob extraction consists of blob detection, an extension of CCA, and blob checking to filter out non-character blobs. 5. In [5], a character clipper separates characters into rectangular boxes. Each character is processed using feature extraction, classification, post-processing, and training.

6. In [6], an improved projection method (IPM) is presented. Step one corrects horizontal, vertical, and compound tilts. Step two uses auxiliary lines between the first and last characters to detect boundaries. Step three segments characters after noise removal. Experiments were performed using MATLAB 6.5 and VC++ 6.0.

7. Thome, Nicolas et al. [7] concludes that the algorithm is correct but can fail for a single labeling error of mislabeling. Histogram projection is robust but not precise. The authors applied the preliminary contour detection with the CCL algorithm and utilized vertical and horizontal histograms employing column sum vectors for determining character boundaries that are efficient for separation of adjacent characters.

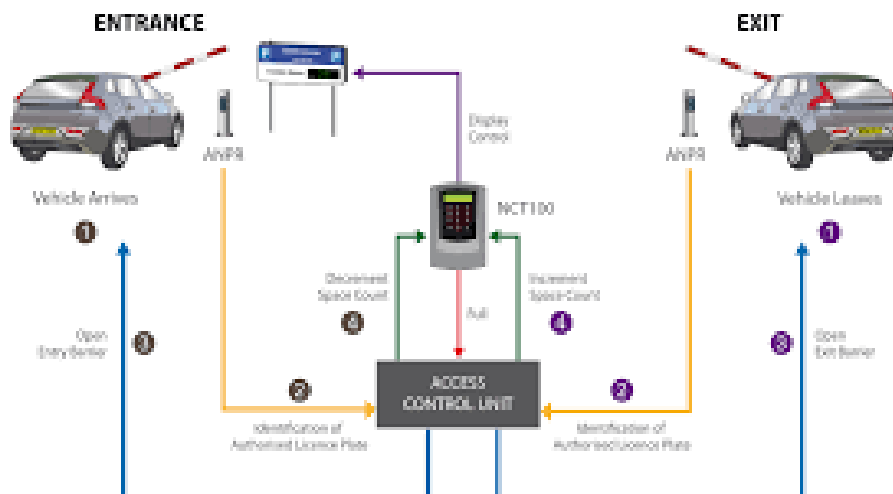


Fig 3.1 ANPR Car Park Management

Table 1,1.RELATED WORK OF ANPR

Reference NO	Authors/Organization	Year	Methodology	Key Findings	Applications	Challenges
1	You-Shyang chen and Ching-Hsue Cheng	2010	Delphi-based rough sets fusion model	Extracting payment rules of vehicle license tax	Government sector	Complexity in rule extraction
2	Anton Satria Prabuwo and Ariff Idris	2008	Optical Character Recognition (OCR)	Effective car park Control System	Car park management	OCR accuracy in varied lighting conditions
3	A Albiol, L Sanchis, and J.M Mossi	2011	Spatiotemporal maps	Detection of parked vehicles	Parking enforcement	Handling occlusions and varying perspectives
4	Christos Nikolaos E. Anagnostopoulos et al	2006	License plate recognition algorithm	Improved accuracy for ITS applications	Intelligent transportation systems	Computation complexity and real-time processing
5	H. Erdinc Kocer and K.Kursat Cevik	2011	Artificial neural networks	High accuracy in vehicle license plate recognition	Various ITS applications	Training data requirement and network complexity
6	Christos Nikolaos E. Anagnostopoulos et al	2008	Survey of various methods	Comprehensive overview of LPR techniques	License Plate Recognition	Variations in plate Design and environment AI Conditions
7	A Roy and D.P Ghoshal	2011	Improved segmentation	Number plate recognition across different countries	International ANPR systems	Handling diverse plate formats and characters
8	Md. Shamsul Arifin and Md. Saiful Islam	2014	Morphological processing and edge detection	Enhanced character segmentation accuracy	License plate detection	Challenges with blurred or low-quality images
9	K.S. Sandeep and S. Vijayanandh	2017	Fuzzy logic-based ANPR	Improved recognition accuracy in complex backgrounds	Toll collection systems	Handling motion blur and varying plate orientations

IV. CONCLUSION OF ANPR

An ANPR system is an advanced innovation in traffic management and security. Using sophisticated imaging technology and strong algorithms, ANPR systems are capable of capturing and interpreting vehicle registration numbers in real-time. These systems bring along numerous advantages, such as better law enforcement, efficient traffic management, and efficiency in toll collection and parking operations. ANPR also contributes to public safety by making it easier and faster to identify stolen cars, monitor criminal activities, and ensure road regulations.

Still, although these benefits are realized upon deploying ANPR, there's a significant concern about how data privacy and security come into play. It means that the data collected be used responsibly and stored so it does not lose public and legal standards. ANPR can also be used maximally for vehicle owner identification models; traffic control, speed enforcement, and location tracking, for examples of utilizing vehicle activity.

It includes the challenges of dealing with low-resolution images and capturing multiple number plates in real-time scenarios.

Techniques such as image super-resolution and coarse-to-fine segmentation strategies may improve performance. While traditional ANPR systems often process offline images from databases, real-time applications must accommodate multiple vehicle plates within a single frame for accuracy.

To recap, ANPR systems stand at the forefront of modernizing transportation infrastructure, providing large-scale benefits in security and efficiencies as well as data-informed decision-making. Given that ANPR can benefit from integration with existing structures and addressing privacy concerns, cities and law enforcement alike can unlock its full capacity

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