Journal of Analysis and Computation (JAC)
(An International Peer Reviewed Journal), www.ijaconline.com, ISSN 0973-2861
Volume XVII, Issue II, July-Dec 2023

REVIEW ON VEHICLE NUMBER PLATE RECOGNITION USING EXISTING SURVEILLANCE CAMERAS

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ABSTRACT

The Video surveillance systems are frequently used for safety and tracking purposes. But spotting moving things in video surveillance is a challenge. Human activity identification and monitoring has increased recently due to the recent decline in price of high-quality video surveillance systems. As a result, automated systems were developed for a number of detecting tasks, but finding vehicles that were parked illegally has mostly been the responsibility of the human operators of surveillance systems. The version uses Wpod-Net to locate the licence plate in the picture or video, and the ANN algorithm was applied to ascertain a person's reputation using the found registration code. The detected licence plate is stored in the database.

Keywords- *Video Survillance, Licence Plate, Detection, Wpod-Net, ANN Algorithm.*

[1] INTRODUCTION

A licence plate to identify automobiles by their registration plates, recognition is a combination of number plate detection, character segmentation, and recognition technologies. This method does not call for the installation of additional hardware on automobiles because it just uses the information from the registration plate for identification. The effectiveness of image technology, such as the camera and lighting, and the quality of registration plate identification software are the two main focuses of registration plate recognition systems. Maximum identification accuracy, increased processing speed, handling a variety of plates, managing a wide range of image quality, and achieving maximum input data distortion tolerance are factors to be taken into account.

To begin the process, a camera snaps a photo of an automobile and its licence plate. Then, using image processing software, the licence plate number is recovered from the picture and improved. In the wake of the licence plate being removed number, the licence plate image is converted into text using a recognition algorithm, which may include methods like optical character recognition (OCR) or pattern recognition. The car is then identified by comparing this text to a database of recognized license plate numbers.

With the application of machine learning algorithms and deep learning models, the technology behind ANPR systems has evolved greatly in recent years, improving the recognition accuracy and capability to operate in difficult situations including dim lighting, obscured plates, and various plate formats.

Traffic management, toll collecting, and security are just a few ofthe uses for ANPR systems. These systems can be used to track vehicles for security and law enforcement purposes, monitortraffic flow, and automatically collect tolls. A number of advantages of ANPR systems include greater automation and efficiency as well as enhanced security due to real-time vehicle tracking. Concerns concerning privacy and the possibility forabuse of the gathered data exist, though.ANPR (Automatic Number Plate Recognition) systems are becoming increasingly important as a technology for a variety of uses, including security, toll collection, and traffic control. Thanks to improvements in image processing and machine learning techniques, ANPR cameras can now read licence plates even in challenging conditions like dim lighting or obscured plates. It's critical to balance these concerns with the benefits that ANPR systems can provide because privacy issues and the potential for data misuse are real concerns. The cost of ANPR systems can vary depending on the complexity of the system and the technology used. Basic systemsmay be less expensive than more advanced systems that use deep learning models and other advanced technologies.

[2] 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 taken into account 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: A screw on a plate could be thought of as a character.

Using the picture segmentation technique, a licence plate can be retrieved. Various literatures contain a variety of image segmentation techniques. The majority of approaches employ image binarization. Some authors transform colour images to grayscale images using Otsu's method for picture binarization. Color segmentation is the foundation of some plate segmentation methods. Discussed in is a study that uses colour segmentation to pinpoint the location of licence plates. The most prevalent methods for extracting licence plates are described in the sections that follow. A full analysis of the picture segmentation methods used in the literature for ANPR or LPR follows this.

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.

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.

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.

Blob detection 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.

CCA or blob extraction is a technique to specifically label subgroups of related components based on a certain heuristic. It scans a binary image and classifies pixels according to their connectedness, such as their north-east, north, northwestern, 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.

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 for the processing of binary images before being expanded to process grayscale functions and images. It includes fundamental operators like erosion, dilation, opening, and shutting.

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.

A method known as sliding concentric window (SCW) is created in order to more quickly locate regions of interest (ROI). It is a two-step process with two concentric windows that move from the image's upper left corner. Statistical data were then calculated for both windows in accordance with the segmentation rule, which specifies 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 specified by the two windows cease sliding after scanning the full image. The threshold value can be established through trial and error. The overall success percentage for connected component analysis is 96%. On a Pentium IV running at 3.0 GHz, the experiment for number plate segmentation took 111ms to complete.

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Fig 1 Number plate with two parameters

Another SCW-based approach for locating Korean licence plates is provided in [8]. After applying SCW to the vehicle image, the authors utilised the HSI colour model to check the colours, and 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.

[3] CHARACTER SEGMENTATION

After finding the number plate, the characters are examined for the following phase. 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 some of the common relevant work in this field. Character segmentation can also be accomplished using several techniques, such as image binarization and CCA, which were already covered in Section 2.
The candidate region is sized down to 78 x 228 pixels using bicubic interpolation before being sent to SCW for segmentation. The authors optimised the results using a threshold value of 0.7. Following character segmentation, each character is enlarged to a 9 by 12 pixel size. Blob colouring and peak-to-valley approaches are deemed unsuitable for Indian number plates by Prathamesh Kulkarni et al. The authors' suggested picture scissoring approach involves scanning a licence plate vertically, cutting it at the row where there are no white pixels, and storing the results in a matrix. Based on the formula provided in this work, a false matrix is eliminated when there are many matrices. The same procedure is carried out again using width as a threshold in the horizontal direction.
The CCA approach is excellent for processing binary images. Prior to character segmentation, horizontal and vertical correction and picture augmentation are carried out. For both horizontal and vertical correction, CCA is utilised. Following these actions, the plate is changed to have white text on a black backdrop and then enlarged to 100 X 200. Then, each character is divided into segments that are each 32 x 32 pixels in size. Methods like connected component labeling and picture binarization are employed.
In, the plate location and binarization, the number of columns in the BW, and the number of rows in the BW are each stored in three matrices. Following the accurate detection of the top and bottom boundaries, vertical projection and Thresholding are used to segment the characters.
For character segmentation, H.Erdinc Kocer employed contrast extension, median filtering, and blob colouring techniques. Image sharpness is achieved by extending the contrast. According to H. ErdincKocer, one common method to enhance the appearance of a poorly contrasted image is histogram equalisation. Unwanted noisy regions are eliminated in median filtering removed. Blob coloring method is applied to binary image to detect closed and

contact less regions. In this method, an L shaped template is used to scan image from left to right and top to bottom.

By acquiring the connections into four directions from zero valued background, this scanning procedure determines the independent regions. To extract the characters from the binary-coded licence plate image, the four-directional blob colouring approach is used. After this process, the numerals are split into 28 x 35-inch squares, and the letters into 30 x 40-inch squares. In [14], another technique based on blob detection is suggested. Character height estimate, character width estimation, and blob extraction make up the character segmentation procedure. The three components that make up character height estimate are colour reverse, vertical edge detection, and horizontal projection histogram. By applying statistical analysis of edges, colour reverse is utilised to make the colour of the characters on licence plates appear black. The finished number plate is found using vertical edge detection. It is carried out using the Sobel mask and picture binarization methods. In order to determine a character's top and bottom boundaries, utilize the horizontal projection histogram. The height of a character is determined by the distance between its upper and bottom bounds. Image binarization and the vertical projection histogram are included in the character width calculation. To convert colour images to black and white, image binarization is utilised. The method of vertical projection is used to identify character gaps. Similar to horizontal projection, the procedure is. Blob extraction is a two-step process that uses algorithms for blob detection and blob testing. The CCA is extended by the blob detection technique. Non-blob characters are taken out of the segmented characters using blob checking.

Characters in the rectangular box are separated using a character clipper in. Each character is then segmented utilising the feature extractor, classifier, post processor, and training phases. An enhanced projection method (IPM) is suggested in. The authors described character segmentation as a three-step process. In, the plate location and binarization, the number of columns in the BW, and the number of rows in the BW are each stored in three matrices. Following the detection of the top and bottom boundaries' exact locations, Corrections are made to horizontal, vertical, and compound tilts in the first stage. Auxiliary lines are then drawn between the first and last character in the second phase to identify related boundaries. After reducing noise, the characters are segmented in the final phase. In order to conduct the experiment, MATLAB 6.5 and VC++ 6.0 were used. According to Thome, Nicolas et al., connected component labeling is accurate but could fail due to a single incorrectly labeled pixel. The authors came to the conclusion that while histogram projection is less precise, it is more reliable. They applied a preliminary set of contours using the linked component labeling method. There are both vertical and horizontal histogram approaches. Character boundaries are established using column sum vectors. The algorithm divides two neighboring characters into two halves.

[4] CHARACTER RECOGNITION

A linked system of artificial neurons is referred to as an artificial neural network (ANN), sometimes known as a neural network. On ANN, a number of algorithms are based. 180-180-36 topology in a two-layer probabilistic neural network. Character recognition took place in 128 milliseconds. Multi-layered perceptron (MLP) ANN model is used in [6] for character classification. It has an input layer used to make decisions, a hidden layer used to calculate more complex associations, and an output layer used to display the final choice. An ANN was trained using the feed-forward back-propagation (BP) algorithm. With a processing time of 0.06s, BP neural network-based systems are suggested. HNN is used to lessen ambiguity between similar characters, such as 8 and B, 2 and Z, etc. The authors assert that their recognition rate is greater than 99%. 4.2 T

For the purpose of recognizing 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. Feature-based matching and template-based matching make up the remaining two divisions. When the template image includes prominent features, the feature-based method is useful; otherwise, the template-based approach can be helpful. To achieve a character recognition rate of 85%, statistical feature extraction is used. On the basis of training characters, a number of features are retrieved, and salient is computed. To make sure that all characters are the same size, a linear normalisation procedure is utilized. An overall identification rate of 95.7% on 1176 images was achieved. 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. In, 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.

Optical character recognition (OCR) software is sometimes used in algorithms to do character recognition. There is a wide variety of OCR processing software available. Tesseract, a Google-maintained open source OCR programme that supports multiple languages, is one of these tools. For character recognition, it is employed. To get a character recognition rate of 98.7%, the author changed it. In the authors' Markov Random Fields (MRF) character extraction approach, randomization is used to describe the uncertainty in pixel assignment. To maximize a posteriori probability, character extraction is carried out as an optimization problem based on prior knowledge. The cost of computation is then decreased by using a greedy mutation operator. Character classification, topological sorting, and self-organizing (SO) recognition make up the three steps of the strategy suggested in. Character classification is used to group characters into alphabetic and numeric categories. The second phase involves computing the input character's topological properties and comparing them to character templates that have already been saved. The character template that most closely resembles the input character will be chosen from a test group of compatible templates. The SO character recognition method does the template test. To handle noisy, damaged, or incomplete characters, self-organized neural networks are based on Kohonen's self-organized feature maps. The authors established an ambiguity set with the characters 0, 8, B, and D in order to distinguish comparable characters from character pairings like (8, B) and (O, D). The non-ambiguous components of each character in the set are provided as illustrated in fig. 3. A small comparison between the unknown character and the classed character is conducted once the unknown character has been identified as one of the characters in the ambiguity set. Then, only clear-cut aspects of characters are highlighted during the comparison process. The writers were able to identify 95.6% of the photos of upright licence plates. In a survey, the use of automatic character recognition is covered. The fundamental difficulty in character recognition, according to Anju K. Sadasivan and T. Senthil kumar, is dealing with unidentified text arrangement, various font sizes, various lighting conditions, reflections, shadowing, and aliasing.

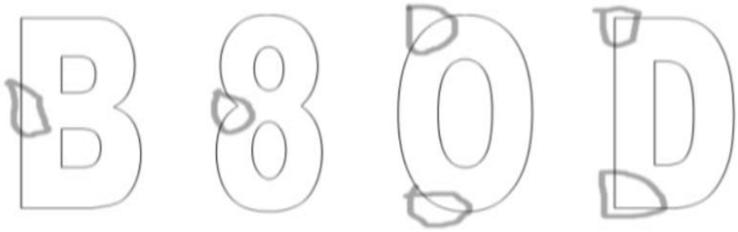

Fig.2 Distinguishing parts of ambiguous characters

The recognizer system should be able to handle unclear, noisy, or distorted characters received from the character segmentation phase because character segmentation is one of the pre-processing processes in character recognition. With ANN and self organizing (SO) recognition, good results have been recorded. Information is summarized in Table 2. OCR is a method that is now extensively used and popular, hence ANPR engineers are concentrating on increasing OCR's accuracy rather than completely redesigning the ANPR. As was covered in the section above, several developers are improving open source OCR, like Tesseract, for greater accuracy.

[5] CONCLUSIONS

An additional use for ANPR is for vehicle position tracking, vehicle owner identification, vehicle model identification, and traffic control.
It is inferred from the comparative study in Table 1 that ANPR can be further extended as multilingual to automatically identify 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 improvement strategies, such as super resolution of photos, 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 taken into account by ANPR, although in the majority of other systems, offline photographs of vehicles collected from online databases, such those in Tables 1 and 2, are provided as input. As a result, the precise findings may differ from those presented in Tables 1 and 2. A coarse-to-fine technique may be used to segment several automobile licence plates.
It is obvious that A]NPR is a challenging system due to the various number of steps, and that 100% overall accuracy is currently not attainable due to the dependency between each phase. 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 some of the systems that have been created and are in operation in particular nations. Table 3 excludes the systems in which the country is not mentioned. It is clear from table 3 that relatively few ANPR have been established for India. Therefore, there is a lot of room to construct such a system for a nation like India. The complete examination of present trends and possible developments in ANPR provided in this study can be useful to the academics working on these advancements.

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