Licence Plate Identification: A Comparative Study Using Image Processing and Frame Grabbing

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Abstract

This paper presents a comparison between two approaches to license plate detection using image processing and frame grabbing. The first approach uses image processing techniques such as segmentation, feature extraction, and pattern matching to detect license plates from digital images. The second approach uses frame grabbing techniques to detect license plates from moving video frames. The results of the two approaches are compared and discussed in terms of accuracy, speed, and ease of implementation. The results show that frame grabbing techniques provide better accuracy and speed in license plate detection, but require more effort in terms of implementation. The paper also provides an overview of existing approaches and presents a discussion on the challenges and opportunities of license plate detection.

Keywords*:* frame grabbing, image capturing, license plate detection, ALPR

.Introduction

License plate detection is a computer vision undertaking that entails the identification and localization of license plates in digital images or video[1]. The objective of license plate detection is to precisely detect and recognize license plates within a given visual context. This technology holds utility across diverse domains, including but not limited to law enforcement and traffic surveillance. The task of detecting license plates has gained significant importance owing to the substantial volume of vehicles present on the roads presently. The difficulty of this task stems from the diverse range of license plate dimensions, configurations, and hues, in addition to the occurrence of obstructions and other impediments, such as inadequate illumination, mist, and precipitation[2].

Intelligent Transportation Systems (ITSs) comprise 16 distinct technology-based systems that can be categorized into two groups: intelligent infrastructure systems as well as intelligent vehicle systems[3]. Intelligent infrastructure systems, including electronic payment systems for toll and parking fees, as well as motorway as well as arterial management systems for traffic monitoring, rely on computer vision and character recognition algorithms to process license plate data[4].

A distinctive identification used to trace the movement of automobiles across the world is the license plate. Computer vision systems employ automated license plate recognition (ALPR) technology to find and recognize automobiles by their license plates[5]. ALPR systems use frame capturing or image processing methods to find and identify license plates. This study compares the effectiveness, accuracy, and resilience of the two ALPR techniques[6].

License plates serve as a crucial visual indicator for the identification of vehicles. Identification markers are commonly produced on metallic or plastic surfaces, exhibiting variations in their dimensions, configurations, and chromaticity. License plates may exhibit variations in their content across different countries[7]. However, they generally comprise the registration number of the vehicle, details pertaining to the owner of the vehicle, and an identifier for the state or province. The license plates in various countries may include supplementary details, such as the type or category of the vehicle.

The task of detecting license plates poses a significant challenge owing to the diverse range of sizes, shapes, and colors that license plates can exhibit, in addition to the potential for occlusions and other obstacles, such as low illumination, fog, and precipitation[8]. Furthermore, license plates have the capability to be produced on diverse materials such as metal, plastic, and paper. The varying reflective properties of different materials pose a challenge in achieving precise license plate detection across all scenarios[9].

Conventional techniques utilized for the detection of license plates comprise of edge detection, template matching, and feature extraction. The process of edge detection involves the identification and highlighting of the boundaries of an object[10]. The utilization of this method is viable for the identification of license plates, given that the edges of the plates exhibit a higher degree of clarity in comparison to the remaining portions of the image. The process of template matching involves the comparison of a template image with a target image, with the aim of detecting and localizing corresponding regions of interest in both images. The aforementioned method has the capability to identify license plates, given that the shape of the plates remains consistent across various images[11]. The process of feature extraction involves the extraction of a set of features from an image. The aforementioned methodology can be employed for the purpose of identifying license plates, given that specific attributes such as the dimensions, configuration, and hue of the plates, tend to remain uniform across various images.

In recent times, the implementation of deep learning and convolutional neural networks (CNNs) has been observed cutting-edge the domain of license plate detection[12]. Convolutional Neural Networks (CNNs) are a category of artificial neural networks that exhibit exceptional proficiency in the domain of image recognition assignments. Convolutional Neural Networks (CNNs) have the potential for employment in the field of license plate detection is being considered in both digital images and videos. The utilization of Convolutional Neural Networks (CNNs) in license plate detection offers the benefit of automated feature extraction from images and videos, resulting in enhanced robustness and accuracy compared to conventional techniques[13].

Ultimately, license plate detection presents both obstacles and prospects. A significant obstacle pertains to the variability in license plate dimensions, configurations, and hues, which poses a challenge to the precise identification of license plates across all scenarios[14]. Moreover, the presence of obstructing objects within the scene can impede the detection of license plates, thereby posing a challenge. One of the challenges associated with license plate detection is the variability in the materials used for license plate printing, which can result in differential light reflection and pose difficulties in achieving accurate detection across diverse lighting conditions[15].

Nonetheless, license plate detection presents certain prospects. The application of license plate detection can be utilized in diverse domains, including but not limited to law enforcement and traffic monitoring. Furthermore, the utilization of deep learning techniques as well as Convolutional Neural Networks (CNNs) has enhanced the precision of license plate detection, rendering it more resilient and dependable. The utilization of OCR and optical flow techniques has the potential to enhance the precision and efficiency of license plate identification[16].

Image Processing Techniques for License Plate Detection

Image processing is a kind of ALPR that examines photographs of license plates using digital image processing methods. This technique depends on the contrast between the picture backdrop and the text on the license plate[17]. By examining the characters' size, form, and color, it is able to extract the characters from the picture. To identify the vehicle, the retrieved characters are then matched to a database of recognized license plates.

License plate detection has been approached through various techniques, including but not limited to deep learning and convolutional neural networks (CNNs). Optical character recognition (OCR) and optical flow are among the other methods that have been employed for this purpose[18]. Optical Character Recognition (OCR) is a technique utilized to extract textual content from images and videos. The method has the potential to identify license plates by extracting the alphanumeric characters imprinted on them. The optical flow methodology employs the movement of entities within an image or video to monitor their trajectory. The method has the potential to identify license plates by monitoring their movement patterns over a period of time[19].

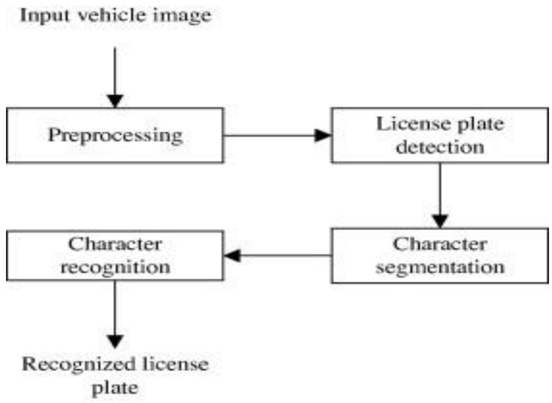

Figure 1 flow chart representing image processing for license plate detection

Another kind of ALPR that uses video cameras to take pictures of license plates is called "frame grabbing." With this technique, the scene is captured in frames and processed in real time. Then it scans the images it has collected for the presence of license plates[20]. After a license plate is found, its characters are retrieved from the frame and used to identify the vehicle by comparing them to a database of recognized license plates. That is explained briefly in below section.

4. Frame Grabbing Techniques for License Plate Detection

The technique of frame grabbing is widely utilized in the detection of license plates, and is considered to be highly prevalent. The aforementioned methodology entails the acquisition of multiple frames of an image or video, followed by the utilization of computer vision algorithms to identify the license plate[21].

The initial stage of frame grabbing involves the extraction of frames from either a video or an image. The extraction of frames at varying resolutions and frame rates can be facilitated through the utilization of software such as OpenCV[22]. After the extraction of frames, diverse computer vision algorithms, including image segmentation and object detection, are employed for their processing. The algorithms have the capability in order to find and identify the license plate present every individual frame[23].

Upon successful identification of the license plate, subsequent analysis may be conducted to extract additional attributes, such as the alphanumeric characters inscribed on the plate. The utilization of OCR (Optical Character Recognition) algorithms is a viable approach for detecting characters on a plate and subsequently converting them into a legible format[24].

The technique of frame grabbing is widely used for detecting license plates due to its simplicity and efficiency. The technology has the capability to identify license plates from both stationary images and moving footage, and has potential applications in diverse fields such as vehicle monitoring and entry management[25].

Enhancing the precision of frame grabbing can be achieved through the utilization of superior resolution frames and advanced computer vision algorithms. Furthermore, this methodology can be employed in tandem with other methodologies, such as neural networks, to enhance the precision of license plate identification.

Systematized License Plate Recognition with Multiple Phases

Currently available ALPR systems may be roughly divided into two groups: multistage approaches and single-stage methods. The majority extant solutions for Automatic License Plate Recognition (ALPR) task have adopted multi-stage approach, comprising three primary stages. The initial phase involves the identification or retrieval of license plate information. Current algorithms employ conventional computer vision methodologies also deep learning techniques featuring object detection to identify license plate's location within image. The conventional methods of computer vision rely heavily on the attributes of the license plate, including but not limited to its shape [4],[26],[27],[28], color symmetry [29], texture [30], [31], [32], [33], [34]. During the second stage, the process of segmenting the license plate and extracting its characters is carried out using various conventional techniques, including mathematical morphology [35], vertical and horizontal projection, relaxation labeling, and related components[36]. The character segmentation phase may not be executed in all multi-stage ALPR systems, as certain segmentation-free algorithms exclude this stage. The ultimate phase involves the identification of the characters through the utilization of pattern matching methodologies such as neural networks along with fuzzy classifiers[37]. Nonetheless, the primary disadvantage associated with the segregation of detection from recognition pertains to its influence scheduled precision & efficacy for comprehensive recognition procedure. The occurrence of this phenomenon can be primarily attributed to the imperfect nature of the detection process, which may be caused by factors for instance inaccuracies in bounding box prediction. If the license plate detection process fails to identify a portion of the plate, it may have a negative impact on the overall precision of the recognition procedure[38]. Therefore, it is crucial to attain satisfactory outcomes in every phase of a multi-stage process. The primary processing stages of a multi-stage plate recognition system are depicted in Figure 2, with a comprehensive discussion of the specifics presented in below section.

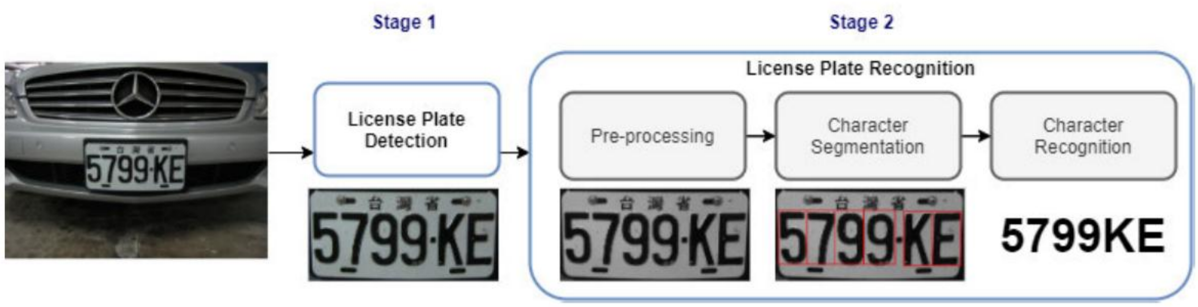

Figure 2 multi-stage plate recognition system

Recognition of license plates in a single phase.

The predominant research on license plate recognition has centered around multi-stage procedures, however, a number of prosperous endeavors have recently emerged in the realm of single-stage processes. To the best of our knowledge, all of these endeavors utilize a solitary deep neural network that is trained to detect, localize, and recognize license plates in a single forward pass, achieving end-to-end functionality. License plate recognition can be regarded as a distinct instance within the realm of object detection. Like single-stage object detectors, these models can leverage the high correlation between license plate detection and recognition, as noted in reference [10]. This enables the sharing of parameters among models and results in a reduced parameter count compared to that of a conventional two-stage model. Consequently, they exhibit superior speed and efficiency in comparison to analogous two-stage technique[39]. The initial endeavor of which we are aware was carried out by Li et al. [39]. The methodology employed by the authors involved utilizing VGG16, a model of convolutional neural network [32], as a means of extracting features. The VGG16 architecture has been adapted by reducing the number of pooling layers from five to two, as the license plate typically occupies a smaller region within the image. Subsequently, the feature extractors' output is inputted into a Region Proposal Network (RPN) [33]. The modifications implemented involve the utilization of dual rectangular convolution filters in lieu of the conventional 3 × 3 filters. The utilization of license plates' greater aspect ratio and the superior performance of rectangular filters as compared to square filters is being optimized. The filters were utilized to extract local features, which were subsequently concatenated to preserve both local and contextual information. This process was employed to facilitate the license plate classification stage. Subsequently, the concatenated feature maps are inputted into distinct sets of convolutional layers to perform license plate classification and box regression. Subsequently, the Reverse Polish Notation (RPN) underwent end-to-end training[40]. Out of a considerable quantity of proposals, solely the 256 anchors generated by the RPN were randomly selected and subjected to loss calculations. During the testing phase, the proposals underwent a process of non-maximum suppression in order to exclusively retain 100 proposals that exhibited greater confidence levels[41]. The proposal posits that regions exhibit heterogeneity in terms of their size and are subject to the pooling of Return on Investment (RoI). This is supported by reference [34]. Subsequent to RoI pooling, the resulting output is directed towards two distinct sub-networks, namely the license plate detection network and the other license plate recognition network. The License Plate Detection Network is a neural network that is fully connected and has two output nodes. One pertains to the likelihood of the Region of Interest (RoI) being a license plate, while the other pertains to the coordinates of the bounding box. The license plate recognition network is tasked with the responsibility of identifying and recognizing the characters present on a license plate. To prevent the division of characters, the approach taken involves the utilization of Bidirectional RNNs to frame the task as a sequence labelling problem.

Xu et al. [42] proposed a comparable methodology. Rather than employing a pre-existing network like VGG16 [32] for feature extraction, the researchers utilized a streamlined Convolutional Neural Network (CNN) comprising of 10 layers. The CNN sub-network has undergone training to make direct predictions of bounding boxes. Subsequently, the feature extractor's first, third-, and fifth-layers’ results were utilized as input to several classifiers through RoI pooling[43]. Multiple layers have been utilized in order to incorporate outputs, as each layer possesses distinct receptive field sizes[44]. This capability has facilitated the detection of license plates at varying distances from the camera. In contrast to the approach taken in reference [44], wherein a singular Bidirectional Recurrent Neural Network (BRNN) was employed for license plate recognition, the authors of this study utilized more straightforward classifiers for each individual character within the license plate. This approach was based on the inherent characteristic of license plates having a predetermined number of characters. The utilization of distinct classifiers and uncomplicated feature extractions has enabled the creation of a model that is comparatively less complex, resulting in expedited processing in contrast to alternative single and multi-stage methodologies. To the best of our knowledge, the approach employed by the authors is currently the most accurate model for license plate detection, despite its relative simplicity.

Comparison of Image Processing and Frame Grabbing Techniques

This section will examine the methodology, findings, and limitations of both approaches.

Author	Method Used	Findings	Limitations/future work
[45]	The study proposed a framework for multi-directional car license plate detection utilizing a CNN-based MD-YOLO approach.	99.5% of accuracy	paradigm for end-to-end multidirectional detection and identification, need to be investigated.
[46]	The proposed approach is a hierarchical Convolutional Neural Network (CNN) based method for Automatic License Plate Recognition (ALPR) that operates in an end-to-end manner.	93.5% of accuracy rate is absorved.	In future research, it is intended to incorporate car manufacturer and model recognition into the Automatic License Plate Recognition (ALPR) pipeline. This would enable the resolution of ambiguous license plates by matching them to the corresponding make and model in a real-world scenario.
[47]	Pixel connectivity	92.7 % accuracy rate is absorved	Not suitable to apply joined or broken characters

Author	Method used	Results	Limitations/ Future works

[48]	state-of-the-art YOLO object detector	93.45% of accuracy rate is observed.	The study aims to enhance the speed of vehicle and license plate detection stages by restricting the use of CNN architectures. Additionally, the study intends to rectify the alignment of inclined license plates and characters to enhance character segmentation and recognition.
[49]	end-to-end DL-ALPR	97.3% of accuracy rate is obtained.	study objective is to enhance the performance of our ALPR system through the implementation of a more robust approach for character recognition. An effective letter recognition system can greatly enhance the overall precision.
[50]	Deep neural networks	80.43 % of accuracy rate is absorved	The quantity of letters on the license plate should be understood to be specific to the places where they were designed to work, since they should be sensitive to noise and font variations.

Discussion

The extant LPD solutions can be generally categorized into two groups: multi-stage license plate recognition and single-stage license plate recognition. The license plate recognition process is commonly divided into three stages in multi-stage systems. These stages include license plate detection, character segmentation, and character recognition. Over the course of the last twenty years, a significant majority of research endeavors in the field of LPD have adhered to multi-stage license plate recognition methodologies. During the license plate detection phase, conventional computer vision methods are employed to extract the plate by taking into account various features such as shape, color, texture, and the presence of characters. Moreover, a number of research studies employed statistical classifiers that utilized Haar-like features to enhance their performance.

The license plate detection process has incorporated object detection techniques in light of the recent advancements in the deep learning paradigm. In contrast to traditional techniques, deep learning based methods exhibited exceptional and resilient performance in constrained scenarios. The primary emphasis of previous research endeavors encompassed an evaluation of various approaches, with a particular emphasis on conventional computer vision methodologies. Approximately half of the studies conducted have employed edge-based techniques for the purpose of detecting license plates. In recent years, a majority of studies, exceeding 80%, have incorporated deep learning techniques for the purpose of detecting license plates.

Various pre-processing techniques, including binarization, are utilized on images prior to character segmentation to enhance recognition accuracy.

Pre-processing techniques are commonly employed to address issues such as rotations, noise removal, and contrast level enhancement. Character segmentation techniques take into account various factors, including the color contrast between the background of the license plate and the foreground of the characters. During the recognition phase, the characters that have been segmented are subjected to classification techniques such as pattern matching, statistical classifiers, and deep learning methods. In addition, traditional pattern matching methodologies have been substituted by advanced deep learning approaches, such as object detectors, in order to address limitations related to memory and performance. The development of a universal and efficient solution for Automatic License Plate Recognition (ALPR) is a complex task, as it is subject to various environmental and license plate-related constraints. These constraints include but are not limited to rotations, occlusions, illumination changes, interfering objects, and shadows. As per the available literature, a limited number of Automated License Plate Recognition (ALPR) systems have demonstrated effective performance in demanding scenarios.

This survey has taken into account over 50 relevant studies that have been published in reputable academic journals and conferences. Approximately 30 studies were published in academic journals, while approximately 20 articles were presented at conferences and subsequently published between the years 2015 and 2020. The indexing and ranking information for the journals in question can be found in the appendix section. Despite the limited number of surveys conducted in this particular area, our study presents the most recent research findings utilizing cutting-edge solutions. This assertion is based on our analysis of existing literature. Our study offers a rigorous evaluation and insightful commentary on the extant literature pertaining to ALPR, highlighting certain constraints and obstacles that warrant attention. Furthermore, we offer a comparative analysis of current Automatic License Plate Recognition (ALPR) techniques, highlighting their primary benefits and drawbacks in real-world applications. In addition, our study offers suggestions for enhancing the ALPR algorithms with regards to latency, performance, and cost-effectiveness. These recommendations are expected to be advantageous for upcoming researchers and developers.

Conclusion

The comparative analysis conducted on License Plate Detection utilizing Image Processing and Frame Grabbing has revealed that the efficacy of the outcomes is contingent upon the technology employed, despite the fact that both approaches can be employed for license plate detection. In the realm of license plate identification, Image Processing has been found to exhibit greater precision than Frame Grabbing. However, it necessitates a greater allocation of resources and is associated with a higher cost. The process of Frame Grabbing is comparatively more efficient and cost-effective, however, it lacks precision when compared to Image Processing. Ultimately, selecting the appropriate approach is crucial, contingent upon the particular use case and the available technological resources.

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