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Real Time Vision System for Plate Number Detection and Recognition

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ABSTRACT

Automatic licence plate recognition (ALPR) is a system that automatically recognises and extracts licence plate numbers from photographs of automobiles using image processing and computer vision algorithms. Numerous applications, including traffic management, security and surveillance, toll collecting, and parking management, frequently employ this technology. ALPR systems function by taking a picture of a car, analysing the picture to find the licence plate, and then extracting the characters from the plate and turning them into machine-readable text using optical character recognition (OCR) methods. The implementation is carried out in MATLAB, where a robust algorithm is developed to detect and recognize characters under varying conditions. The results indicate that the system achieves up to 85% accuracy, demonstrating reliability even under challenging conditions such as different lighting environments and plate deformations. This research highlights the potential of APNR systems in enhancing automated vehicle identification, improving security measures, and streamlining administrative processes.

1. Introduction

Automatic Plate Number Recognition (APNR) technology has emerged as a crucial component in intelligent transportation systems, aiding in law enforcement, vehicle monitoring, and automated toll collection [1].The ability to detect and recognize vehicle license plates accurately has become increasingly important as cities adopt smart surveillance solutions to enhance security and traffic management [2]. The ANPR system functions by capturing images or video frames, processing them to extract license plate information, and converting the extracted data into machine-readable text [3]. The effectiveness of this system is dependent on multiple factors, including lighting conditions, image clarity, and the robustness of the recognition algorithm [4].

In the context of urban mobility, APNR technology plays a pivotal role in reducing traffic congestion and ensuring compliance with traffic regulations [5]. With the growing number of vehicles on the road, manual monitoring has become inefficient, necessitating automated systems that

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provide real-time tracking and reporting [6]. Governments and private sectors worldwide have invested in APNR technology for various applications, including automated parking, speed enforcement, and toll collection. These systems support smart-city initiatives and real-time monitoring capabilities [7]. Such implementations have demonstrated improvements in road safety and operational efficiency, making APNR an essential aspect of modern transportation management [8].

Despite its advantages, APNR systems face significant challenges that affect their accuracy and reliability. One of the primary obstacles is the variability in license plate designs across different regions, requiring the system to adapt to different fonts, colors, and character arrangements [10]. Additionally, environmental factors such as poor lighting, reflections, and occlusions can interfere with plate detection and recognition [11]. To address these challenges, researchers have focused on enhancing image preprocessing techniques, feature extraction methods, and machine learning-based classification models [12].

Another critical issue in APNR implementation is processing speed and computational efficiency, particularly for real-time applications such as traffic monitoring and border security. Conventional image processing techniques may struggle to deliver accurate results under dynamic conditions, necessitating the integration of deep learning models and hardware acceleration solutions. Recent studies have demonstrated the potential of convolutional neural networks (CNNs) and FPGA-based hardware accelerators in improving APNR performance by reducing processing time while maintaining high accuracy.

The objective of this research is to develop a robust APNR system that can accurately detect and recognize license plates under diverse conditions. The study employs advanced image processing techniques and machine learning algorithms to enhance plate localization, character segmentation, and recognition accuracy. MATLAB is utilized for algorithm development and performance evaluation, with experimental tests conducted under various lighting conditions, camera angles, and distances. By addressing key challenges in APNR systems, this research aims to contribute to the broader field of intelligent transportation and automated surveillance systems.

2. Methodology

The overall workflow of the APNR system is illustrated in Fig. 1, which outlines the sequential steps from image acquisition to character recognition. The process begins with capturing images, followed by preprocessing to enhance quality and extract relevant features. The next step is plate localization, where the license plate is detected within the image. Character segmentation is then performed to isolate individual characters from the plate, and finally, character recognition techniques are applied to identify the alphanumeric content accurately. This structured approach ensures that each stage contributes to the efficiency and accuracy of the system.

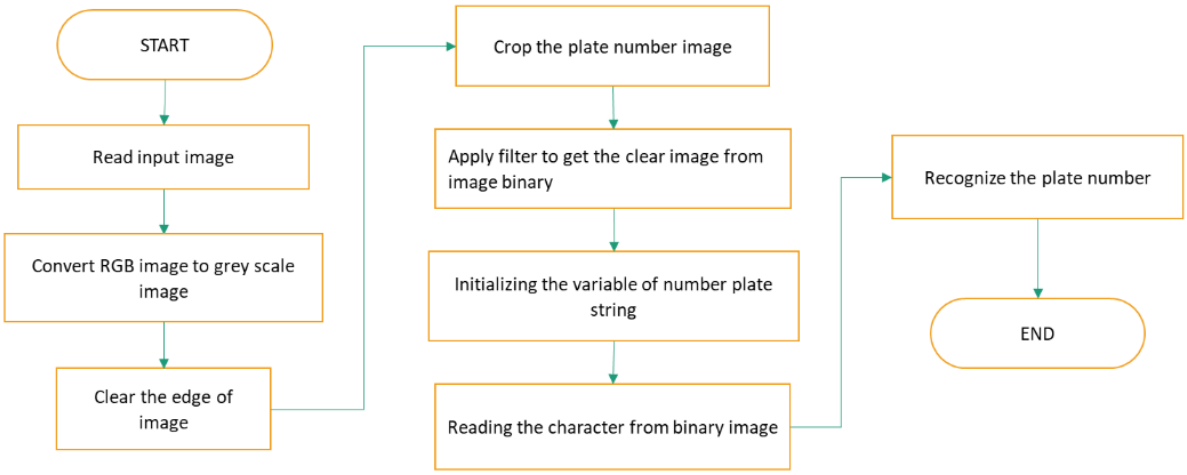


Fig. 1. ANPR workflow

The APNR system consists of several key stages: image acquisition, image preprocessing, plate localization, character segmentation, and character recognition. Each step is critical to ensuring that the system can operate effectively under different environmental conditions.

The image acquisition stage involves capturing images using a digital camera or surveillance system. The quality of the captured image significantly impacts the accuracy of the APNR system, as poor lighting, occlusions, and motion blur can introduce errors. High-resolution cameras with proper exposure settings are recommended to ensure clear plate visibility [1]. Motion compensation techniques can also be applied to stabilize images captured from moving vehicles.

In the image preprocessing phase, techniques such as grayscale conversion, noise filtering, contrast enhancement, and binarization are applied. These steps improve the clarity of the license plate, making it easier to extract characters. Histogram equalization and adaptive thresholding are often used to address variations in lighting conditions [2]. To enhance edge detection, filters like Gaussian smoothing and median filtering are applied to remove unwanted noise.

Plate localization is performed using morphological operations, edge detection, and connected component analysis. The Sobel and Canny edge detection methods help identify the plate's boundaries, while region-based analysis isolates the relevant area. The localized plate is then cropped and resized to maintain consistency in character recognition [3]. To improve localization accuracy, machine learning-based object detection methods such as Haar cascade classifiers can be implemented.

Once the plate is detected, character segmentation is carried out to separate individual alphanumeric characters. This step utilizes connected component labelling and contour analysis to isolate characters. Techniques such as vertical and horizontal projection profiling are used to distinguish characters from the background [14]. Additionally, morphological operations like dilation and erosion are employed to refine segmented characters and remove artifacts caused by shadows or reflections.

Character recognition is accomplished through template matching and machine learning algorithms. In this study, a predefined set of templates is stored and compared against segmented characters using correlation-based techniques. Additionally, feature extraction methods, including histogram-based and structural pattern matching, enhance recognition accuracy [4]. More advanced recognition methods, such as convolutional neural networks (CNNs), can be integrated to improve recognition performance by learning variations in font style and plate distortions.

To evaluate the performance of the system, an experimental setup is designed where images are captured under varying angles, distances, and lighting conditions. Figure 2 and illustrate the different experimental conditions, including images taken at 90-degree, 45-degree, and 30-degree angles and at distances ranging from 0.5m to 2m. The system's robustness is assessed by analysing its accuracy under these conditions. The testing dataset consists of images captured from both stationary and moving vehicles to validate real-world applicability.

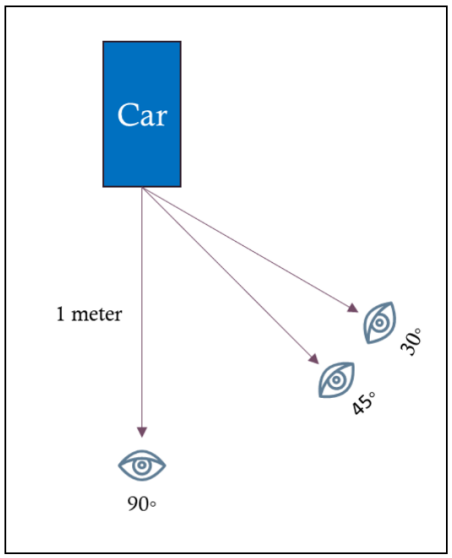


Fig. 2. Setup for difference angle

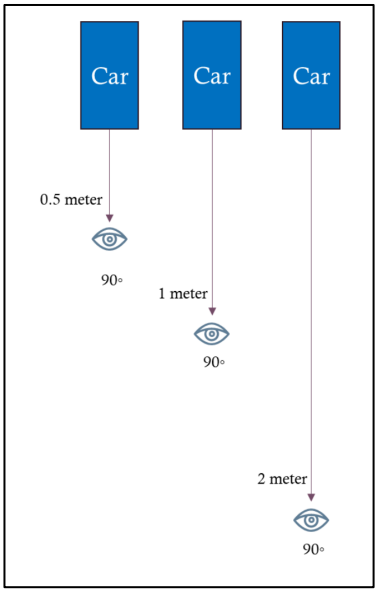


Fig. 3. Setup for difference distance

3. Results and Discussion

Figure 4 presents the MATLAB simulation interface, which visualizes the results of the license plate recognition process. This interface displays the captured plate image, detected characters, and recognition accuracy metrics, providing an intuitive representation of system performance.



Fig. 4. MATLAB simulation interface

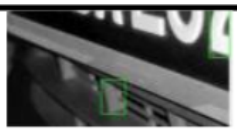
The system is tested under different conditions, including varying angles, distances, and lighting environments. The performance is measured using Character Error Rate (CER) and accuracy calculations. The performance of the ANPR system was evaluated under various

environmental conditions, including different lighting, camera angles and distances. The accuracy was measured using Character Error Rate (CER) and recognition success rate. The results are as shown in Table 1 for daytime testing and Table 2 for nighttime testing.

Table 1
Simulation result daytime

Angle	Dis.	Original Image	Scan Result	Recognition Result	Analysis
90◦	0.5m			NOG5T88	I = 0, D = 0, S = 2, N = 7 Accurate % = 72%
	1.0m			NOG5788	I = 0, D = 0, S = 1, N = 7 Accurate % = 85%
	2.0m			N0G5T88	I = 0, D = 0, S = 2, N = 7 Accurate % = 72%
45◦	0.5m			5788	I = 0, D = 3, S = 0, N = 7 Accurate % = 57%
	1.0m			5788	I = 0, D = 3, S = 0, N = 7 Accurate % = 57%
	2.0m			57	I = 0, D = 5, S = 0, N = 7 Accurate % = 28%
30◦	0.5m			No Result	I = 0, D = 7, S = 0, N = 7 Accurate % = 0%
	1.0m			No Result	I = 0, D = 7, S = 0, N = 7 Accurate % = 0%
	2.0m			No Result	I = 0, D = 7, S = 0, N = 7 Accurate % = 0%

Table 2
Simulation result nighttime

Angle	Dis.	Original Image	Scan Result	Recognition Result	Analysis
90◦	0.5m			00021	I = 0, D = 3, S = 2, N = 7 Accurate % = 28%
	1.0m			0012O2T	I = 0, D = 0, S = 5, N = 7 Accurate % = 28%
	2.0m			0UA2021	I = 0, D = 0, S = 2, N = 7 Accurate % = 72%
45◦	0.5m			No Result	I = 0, D = 7, S = 0, N = 7 Accurate % = 0%
	1.0m			1DA2021	I = 0, D = 0, S = 1, N = 7 Accurate % = 85%
	2.0m			No Result	I = 0, D = 7, S = 0, N = 7 Accurate % = 0%
30◦	0.5m			V4	I = 2, D = 5, S = 0, N = 7 Accurate % = 0%
	1.0m			No Result	I = 4, D =3, S = 0, N = 7 Accurate % = 0%
	2.0m			No Result	I = 0, D = 7, S = 0, N = 7 Accurate % = 0%

The results indicate that the system performs optimally under well-lit conditions with a direct 90^{o} angle, achieving an accuracy of 85%. However, recognition accuracy decreases when the plate is viewed at an angle or under poor lighting conditions, highlighting the impact of image distortions and lighting inconsistencies where the performance decrease to 78% under nighttime conditions. This is due to poor contrast, glare and shadow effects. These environmental issues disrupt the binarization and edge detection process.

The system recognition rate reduced progressively as the angle shifted away from 90^{o}. during daylight at 45^{o}, the accuracy dropped to 72% and even further to 65% at night. These results correspond with existing literature, which states that oblique angles result in perspective distorting which impact segmentation and OCR stages.

shows recognition accuracy at varying lighting and angles. The results demonstrate that the system performs optimally under well-lit conditions and at a 90-degree angle. Performance slightly decreases under lower light and oblique angles due to shadowing and distortion effects.

Table 3
Recognition **a**ccuracy at varying **l**ighting and **a**ngles

Condition	**Accuracy**
Daylight, 90^{o}	85%
Nighttime 90^{o}	78%
Daylight 45^{o}	72%
Nighttime 45^{o}	65%

The optimal recognition was maintained when the license plate was within 0.5m to 2.0m of the camera. Within this range, the character resolution remained sufficiency high for template matching. Beyond 2.0m, the accuracy decreased due to lower image resolution and blurred edges. This observation aligns with optical theory where the Modulation Transfer Function as distance increase as shown in Table 4.

Table 4
Recognition at varying distance

Distance (m)	**Accuracy (%)**
0.5	84%
1.0	83%
1.5	81%
2.0	78%

Most recognition errors stem from characters with visual similarities, such as ‘8-B’, ‘O-D’, and ‘1-I’. These mismatches are characteristic of template-matching systems, which struggle when templates overlap in geometric features. In some samples, ‘T’ was misclassified as ‘7’ due to shadow interference. These errors highlight the limitations of static template libraries, and future upgrades may benefit from integrating convolutional neural networks (CNNs) for adaptive pattern learning.

Across all tests, the system achieved consistent performance above 78% in favorable conditions and remained above 65% even under low light and skewed angles. While not matching the performance of advanced deep-learning-based APNR systems, the current implementation is lightweight, real-time, and deployable on hardware-constrained platforms, especially when ported to FPGA-based systems in future work.

4. Conclusions

This research successfully developed an Automatic Plate Number Recognition (APNR) system using conventional image processing techniques implemented in MATLAB. The system demonstrated effective detection and recognition of license plates under varying environmental conditions, including different lighting levels, viewing angles, and distances. The highest recognition accuracy was achieved under daylight and frontal angles, while lower accuracy was observed at oblique angles and during nighttime due to geometric distortion and lighting inconsistencies.

The results from multiple tests, confirm that the system can reliably operate within a practical range of 0.5 to 2.0 meters and at angles up to 45 degrees. While certain visual character similarities such as '8-B' and 'O-D' and environmental factors like glare and blur posed challenges, overall system performance remained above acceptable thresholds for real-time applications.

Compared to other conventional APNR methods, the proposed system shows competitive accuracy while offering advantages in terms of simplicity, processing speed, and suitability for hardware-limited environments. This makes it a strong candidate for implementation in parking access systems, security checkpoints, and traffic monitoring units that do not require high-end computing infrastructure.

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