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ORIGINAL ARTICLE

Evaluating the Best Edge Detection Operator in MATLAB for License Plate Recognition

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ABSTRACT - Edge detection is an image processing method that employs brightness discontinuities to determine the boundaries of objects in an image. This technology is essential for detecting a license plate number, which is necessary for vehicle safety and traffic regulations. Therefore, this study is conducted to identify the best edge detection operator available in MATLAB for license plate number recognition. Sobel, Prewitt, Roberts, Canny, Gaussian's Laplacian, and Zero-Cross are the six operators involved. This simulation included six test conditions for short and long distances during the day, night, and blurry. The performance of the best edge detection operator was identified based on its accuracy in detecting license plates number from close and long distances under the conditions mentioned above. The simulation used 60 image samples to detect numbers ranging from 0 to 9 as well as letters A through Z. According to this study, the Canny operator has a 65.1% accuracy rate, making it the best edge operator for recognizing license plate numbers.

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INTRODUCTION

Over the past few decades, the rapid expansion of urban areas, road networks, and the increasing complexity of traffic scenarios have underscored the need for robust and adaptable traffic monitoring solutions. Vehicle license plate identification and recognition (VLPIR) technology has become a foundation in the efficient management of road traffic and the enhancement of public safety. The ability to recognize and process license plate numbers is crucial for a range of applications including access control to restricted areas, car tracking, theft recovery, and monitoring of erratic or unsafe driving behaviors [1; 2]. The evolution of VLPIR systems has been driven by the necessity for real-time recognition and tracking capabilities, particularly under challenging conditions such as moving vehicles and those momentarily blending into foggy or blurry background [3].

Advances in technology have facilitated the development of systems that are not only effective in various traffic environments but also resilient to sudden changes in lighting conditions. Automatic Number Plate Recognition (ANPR) system is an automated surveillance technology that employs various Digital Image Processing (DIP) techniques and Optical Character Recognition (OCR) to analyze images and accurately read and identify vehicle registration plates [4]. ANPR systems are now instrumental in crime prevention at local, regional, and national levels [5]. They serve in diverse applications including the interception of criminal activities, locating stolen vehicles [6], and managing electronic toll collection [7]. Furthermore, these systems are pivotal in securing access to restricted areas, enforcing traffic laws, and enhancing border security [8].

Despite significant advancements, the performance of license plate recognition systems can still be affected by various factors such as camera quality, motion blur, poor lighting, and image resolution issues

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[9; 10]. Additional challenges include weather conditions, vehicle movement, and the physical condition of the license plate [11]. To address these challenges, image processing techniques, particularly edge detection, play a crucial role in improving the accuracy and reliability of VLPIR systems. Edge detection is a fundamental component of image processing that focuses on identifying the boundaries of objects within an image by detecting discontinuities in brightness [12]. This technique is essential for extracting meaningful features and improving the overall quality of image analysis.

As vehicle usage continues to rise, the demand for accurate and efficient plate recognition systems becomes increasingly critical for traffic management and safety enforcement. This manuscript explores the comparative performance of edge detection techniques to enhance the precision and reliability of VLPIR systems, thereby contributing to improved traffic and safety management on the roads. In this study, MATLAB software is employed to evaluate the effectiveness of various edge detection operators. Namely Sobel, Prewitt, Roberts, Zero-Cross, Canny, and Laplacian of Gaussian. Through a series of tests under different image conditions, this research aims to determine the most effective edge detection operator for license plate recognition.

Although many edge detection techniques have been widely applied in image processing tasks, their effectiveness in license plate recognition might varies depending on environmental conditions and algorithm characteristics. For instance, in a study by Kumar and Karthikamani [13], Canny outperformed Sobel, Roberts and Prewitt in terms of edge clarity and continuity on X-ray images. Another comparative study by Rawahi [14] reported that Prewitt is effective for detecting detailed edges, yet it is relatively slower in terms of processing speed. In contrast, the Sobel operator, due to its built-in smoothing effect, offers a better balance between speed and accuracy, making it more suitable for real-time applications and noisy environments. Despite these findings, few studies have evaluated these operators in various real-world driving scenarios such as at night, in the rain, and in foggy conditions, which this research aims to address using MATLAB simulations across six conditions. This comparison perspective is appropriate for evaluating edge detectors specifically designed for the license plate recognition.

MATERIALS AND METHODOLOGY

The methodology in this study is structured into seven systematic steps to determine the accuracy of the edge detection operators. The following sections detail each step of the methodology:

1) Image Loading

The initial step involves loading a license plate image, which serves as the input for the study. The image is a three-dimensional representation consisting of red, green, and blue (RGB) colours. To demonstrate the process in this study, a sample license plate image as shown in Figure 1 is applied. The RGB image is the starting point for further processing.

Figure 1. Original Image

2) Pre-processing (Grayscale Conversion)

To prepare the image for edge detection, it must be converted from its original RGB format to a two-dimensional grayscale image. This conversion simplifies the image by reducing its color information to shades of gray, which highlights the intensity gradients crucial for edge detection. The grayscale image obtained is depicted in Figure 2. This step is essential for focusing on the structural features of the characters on the plate rather than color variations.

Figure 2. Gray Scale Properties of Input Image

3) Edge Detection

The grayscale image undergoes edge detection to identify the boundaries of the license plate characters. In this sample, the Sobel edge detection operator is used, and the resulting image is displayed in Figure 3. The edges are then processed further in the subsequent steps.

Figure 3. Edge Detection on Gray Scale Image

4) Morphological Processing

Following edge detection, morphological processing is performed to refine the detected edges. This process includes dilation, erosion, and hole filling. The edges are first dilated to improve visibility and connectivity. Noise and small extraneous objects are removed from the dilated edges during erosion. Then, hole filling is the process of filling any gaps (pixels with value '0') within the detected edges with pixels with value '1' to ensure continuity. Objects with a pixel count exceeding 100 are removed to focus on the relevant license plate region. The result of this morphological processing is shown in Figure 4. This step ensures that only the significant portions of the characters are preserved for further analysis.

Figure 4. Morphological Technique on Edges Image

5) Characters Segmentation

The refined edges are extracted, and each significant object is enclosed with a bounding box as illustrated in Figure 5. This bounding box annotation helps in distinguishing individual characters (letters and numbers) on the license plate. This step facilitates the extraction of each character for the subsequent template matching.

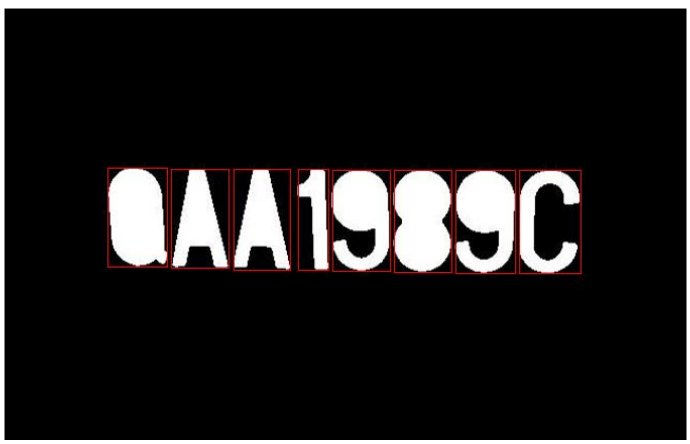

Figure 5. Character Segmentation Process

6) Template Matching and Output Display

In this study, template matching was employed as the recognition algorithm for identifying characters from license plate images. The extracted characters are compared against a stored template database as shown in Figure 6 to identify and classify each character. This matching process is critical for translating the detected objects into readable text. The final recognizable license plate number is displayed in a notepad format. Figure 7 will be displayed when all or some of the characters are recognized. On the other hand, Figure 8 depicts the display when none of the characters can be recognized.

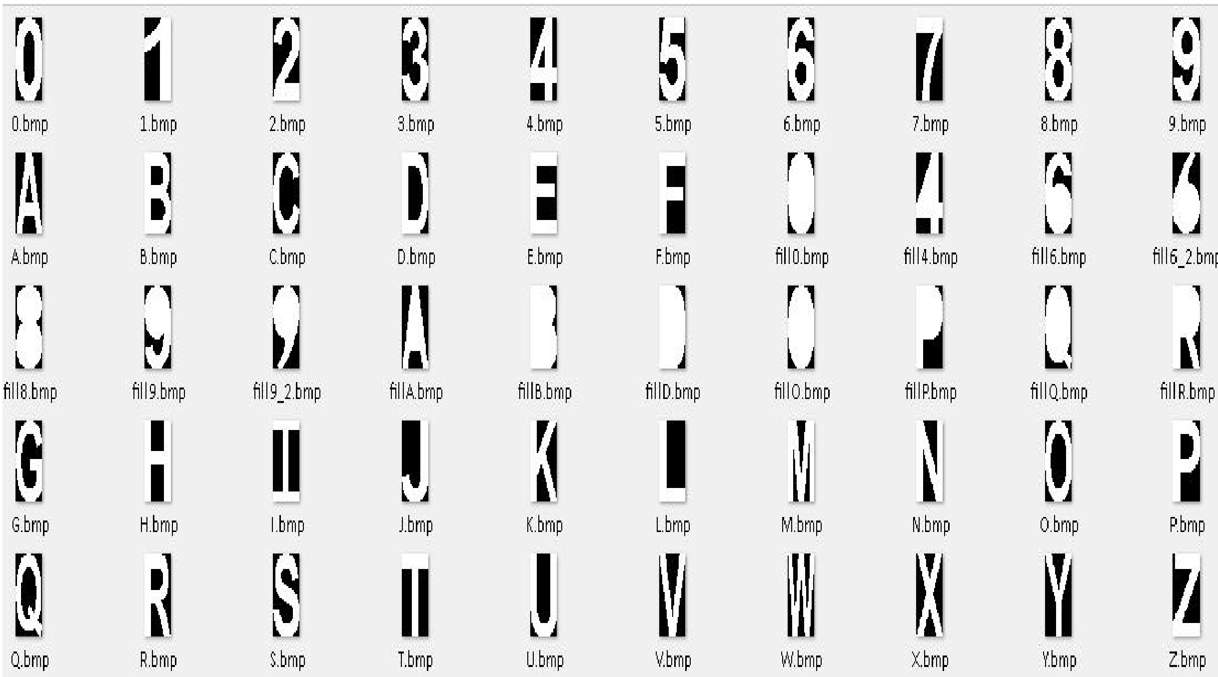

Figure 6. Stored Templates

Figure 7. Display of recognized characters

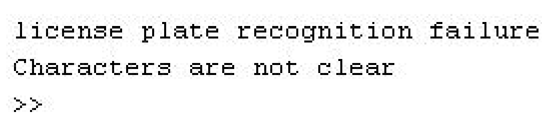

Figure 8. Display when characters unrecognized

7) Accuracy Calculation

To assess the performance of the edge detection operators, the accuracy of the output is calculated using the Equation 1 provided below.

$$Accuracy = \frac{Number\ of\ Correctly\ Identified\ Characters}{Total\ Number\ of\ Characters} \times 100\% \tag{1}$$

DATA ANALYSIS

To analyze the performance of each edge detection operator, steps 1 through 7 were carried out under six distinct conditions. These involved both close (0.5 meters) and far (4 meters) distances, and varied by daylight, nighttime, and blurry conditions. The six conditions are:

Condition 1: Short distance during daylight
Condition 2: Far distance during daylight
Condition 3: Short distance at night
Condition 4: Far distance at night
Condition 5: Short distance in blurry conditions
Condition 6: Far distance in blurry conditions

For each condition, ten license plate images were used to evaluate the performance and accuracy of each edge detection operator. The images were captured with consistent distances and camera angles to maintain uniform testing conditions. Each license image was processed six times with different edge detection operators to ensure a thorough comparison of their effectiveness. This study employed six edge detection operators: Sobel, Prewitt, Roberts, Zero-Cross, Canny, and Laplacian of Gaussian. Actual images of cars taken in daytime rain were used to simulate blurry conditions, as the noise caused by raindrops is similar to that found in blurry images [15]. In total, 60 images representing the various conditions were used for the testing. Table 1 displays one of the sample images for each of the six conditions.

Table 1. Sample image for each condition

Condition	Sample	Condition	Sample
Condition 1: Short distance during daylight		Condition 2: Far distance during daylight	
Condition 3: Short distance at night		Condition 4: Far distance at night	
Condition 5: Short distance in blurry conditions		Condition 6: Far distance in blurry conditions	

RESULTS AND DISCUSSIONS

The results summarized in Table 2 reveal the performance of various edge detection operators in terms of their accuracy for detecting license plate numbers. The analysis demonstrates that the Canny edge detector achieved the highest average accuracy of 65.1%. This superior performance can be attributed to its multi-stage approach, which includes Gaussian smoothing to reduce noise, gradient calculation for edge detection, non-maximum suppression to refine the edges, and edge tracking by hysteresis to ensure edge continuity [16; 17]. This comprehensive method allows the Canny operator to detect edges more precisely and handle complex image features effectively. Its ability to maintain edge clarity [18] and reduce false positives [19] contributes to its overall higher accuracy in detecting license plate numbers.

However, this value appears relatively low compared to typical accuracies reported in controlled environments, which can exceed 80% [20; 21]. The discrepancy can be attributed to the challenging real-world conditions under which the images were captured such as varying lighting during day and night time [22] , distances [23] and image noise from rainy conditions [24]. These factors degrade the visual quality of license plate features, directly impacting edge detection accuracy. Additionally, as this study focuses solely on evaluating edge detection algorithms without integrating post-processing, machine learning models, or image enhancement methods, the overall recognition accuracy tends to be low.

With an average accuracy of 28.8%, the Sobel operator follows the Canny detector in performance. The Sobel operator is based on gradient calculation in both horizontal and vertical directions, which helps in detecting edges by highlighting areas of high intensity change [25]. However, its sensitivity to noise leads to less accurate edge detection, particularly in more intricate details or under varying image conditions [26]. The Prewitt operator achieved an average accuracy of 28.1%. Similar to Sobel, the Prewitt operator calculates gradients but uses different coefficients of the mask [27], which can affect the quality of edge detection.

Interestingly, both the Zero-Cross and Laplacian of Gaussian operators showed the same average accuracy of 27.9%. These operators utilize second-order derivative methods to find zero-crossing points in the image, which often occur at the edges [28]. However, the points can also occur where the image intensity gradient changes, even in areas that are not clearly edges. This constraint results in lower accuracy in the edge detection process. With an average accuracy of just 22.1%, the Roberts operator appears to be the least effective method tested for detecting license plate numbers. This operator is a gradient algorithm for detecting edges based on cross difference [29], but it tends to be less effective in scenarios requiring detailed edge detection.

Table 2. Average total percentage of accuracy

Condition	Sobel	Canny	Roberts	Prewitt	Zero-Cross	Laplacian of Gaussian
1	38.6	63.2	0.0	41.4	22.9	22.9
2	41.4	66.3	27.1	32.9	15.7	15.7
3	8.6	75.4	17.1	17.3	43.8	43.8
4	26.4	38.9	28.0	26.4	22.9	22.9
5	45.4	67.1	30.4	38.2	45.3	45.3
6	12.1	79.9	30.0	12.1	17.1	17.1
Average	28.8	65.1	22.1	28.1	27.9	27.9

CONCLUSION

The analysis indicates that the Canny edge detector is the most effective operator for license plate number detection, demonstrating the highest average accuracy across various conditions accounting of 65.1 %. Its advanced algorithm and robust performance in detecting precise edges make it the best choice among the tested operators. The Sobel and Prewitt operators offer moderate performance, while the Zero-Cross, Laplacian of Gaussian, and Roberts operators show less accuracy due to their limitations in handling complex edge features. Future work could explore hybrid approaches to improve edge detection accuracy even further. This may involve integrating aspects of the Canny algorithm with other techniques to address specific challenges encountered in license plate number detection, where clear and precise edge detection is crucial.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest.

REFERENCES

[1] Abdullah, M., Al-Nawah, S.M., Osman, H. & Jaffar, J. (2021) License plate recognition techniques: Comparative study. *Malaysian Journal of Computer Science*, pp. 94–105. https://doi.org/10.22452/mjcs.sp2021no1.9
[2] Shi, H. & Zhao, D. (2023) License plate recognition system based on improved YOLOv5 and GRU. *IEEE Access*, 11, pp. 10429–10439. https://doi.org/10.1109/ACCESS.2023.3240439
[3] Mishra, S., Yadav, D.K., Tabassum, F. & Kumar, D. (2021) Detection of Moving Vehicle in Foggy Environment using Google's Firebase Platform. *Turkish Online Journal of Qualitative Inquiry*, 12(6).
[4] Etomi, E.E. & Onyishi, D.U. (2021) Automated number plate recognition system. *Tropical Journal of Science and Technology*, 2(1), pp. 38–48. https://doi.org/10.47524/tjst.21.6
[5] Ahmad, M.B., Ayagi, S.H. & Musa, U.F. (2023) A Review of Automatic Number Plate Recognition. *Global Journal of Research in Engineering: Computer Science and Software Engineering*, 3(5). Available at: https://gjrpublication.com/gjrecs
[6] Blessy, Y., Niranjana, S., Ramya, H., Krishnamoorthy, N. & Mohanavel, V. (2023) A Robust Digital Image Analyzing Methodology to Prevent Vehicle Theft based on Automatic Number Plate Recognition Principle. In: *2023 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES)*. IEEE, pp. 1–7. https://doi.org/10.1109/ICSES60034.2023.10465430
[7] Shahrier, M., Hasnat, A., Al-Mahmud, J., Huq, A.S., Ahmed, S. & Haque, M.K. (2024) Towards intelligent transportation system: A comprehensive review of electronic toll collection systems. *IET Intelligent Transport Systems*, 18(6), pp. 965–983. https://doi.org/10.1049/itr2.12500
[8] Dattani, Y. (2021) Big Brother Is Scanning: The Widespread Implementation of ALPR Technology in America's Police Forces. *Vanderbilt Journal of Entertainment & Technology Law*, 24, p. 749.
[9] Shashirangana, J., Padmasiri, H., Meedeniya, D. & Perera, C. (2020) Automated license plate recognition: a survey on methods and techniques. *IEEE Access*, 9, pp. 11203–11225. https://doi.org/10.1109/ACCESS.2020.3047929
[10] Tang, J., Wan, L., Schooling, J., Zhao, P., Chen, J. & Wei, S. (2022) Automatic number plate recognition (ANPR) in smart cities: A systematic review on technological advancements and application cases. *Cities*, 129, p. 103833. https://doi.org/10.1016/j.cities.2022.103833
[11] Kumawat, K., Jain, A. & Tiwari, N. (2024) Relevance of Automatic Number Plate Recognition Systems in Vehicle Theft Detection. *Engineering Proceedings*, 59(1), p. 185. https://doi.org/10.3390/engproc2023059185

[12] Muntarina, K., Shorif, S.B. & Uddin, M.S. (2022) Notes on edge detection approaches. *Evolving Systems*, 13(1), pp. 169–182. https://doi.org/10.1007/s12530-021-09371-8

[13] Kumar, R.S. & Karthikamani, R. (2020) Performance Analysis of Various Edge Detection Techniques in X-Ray Imaging. In: *IOP Conference Series: Materials Science and Engineering*, 995(1), p. 012024. IOP Publishing. https://doi.org/10.1088/1757-899X/995/1/012024

[14] Al Rawahi, S. (2025) A Comparison of Sobel and Prewitt Edge Detection Operators. *East Journal of Computer Science*, 1(1), pp. 49–58. https://doi.org/10.63496/ejcs.Vol1.Iss1.16

[15] Xue, P. & He, H. (2021) Research of Single Image Rain Removal Algorithm Based on LBP-CGAN Rain Generation Method. *Mathematical Problems in Engineering*, 2021(1), p. 8865843. https://doi.org/10.1155/2021/8865843

[16] Rorden, C. et al. (2024) Improving 3D edge detection for visual inspection of MRI coregistration and alignment. *Journal of Neuroscience Methods*, 406, p. 110112. https://doi.org/10.1016/j.jneumeth.2024.110112

[17] Hwa, S., Bade, A. & Hijazi, M.A. (2020) Enhanced Canny edge detection for Covid-19 and pneumonia X-Ray images. In: *IOP Conference Series: Materials Science and Engineering*, 979(1), p. 012016. IOP Publishing. https://doi.org/10.1088/1757-899X/979/1/012016

[18] Dhillon, D. & Chouhan, R. (2022) Enhanced edge detection using SR-guided threshold maneuvering and window mapping: Handling broken edges and noisy structures in canny edges. *IEEE Access*, 10, pp. 11191–11205. https://doi.org/10.1109/ACCESS.2022.3145428

[19] Luo, C., Sun, X., Sun, X. & Song, J. (2021) Improved Harris corner detection algorithm based on canny edge detection and Gray difference preprocessing. In: *Journal of Physics: Conference Series*, 1971(1), p. 012088. IOP Publishing. https://doi.org/10.1088/1742-6596/1971/1/012088

[20] Kalyan, M., Reddy, D.R.K., Reddy, P.Y., Gautam, P.T.S. & Mohammed, I.B. (2020) Design and development of automated lane detection using improved canny edge detection method. *Psychology and Education*, 57(9), pp. 1350–1358.

[21] Medvedeva, E., Trubin, I. & Kasper, P. (2020) Vehicle license plate recognition based on edge detection. In: *2020 26th Conference of Open Innovations Association (FRUCT)*. IEEE, pp. 291–296. https://doi.org/10.23919/FRUCT48808.2020.9087537

[22] Plavac, N., Amirshahi, S.A., Pedersen, M. & Triantaphillidou, S. (2024) Performance of Automatic License Plate Recognition Systems on Distorted Images. *Journal of Imaging Science & Technology*, 68(6). https://doi.org/10.2352/J.ImagingSci.Technol.2024.68.6.060401

[23] Ariff, F.N.M., Nasir, A.S.A., Jaafar, H. & Zulkifli, A.N. (2019) Comparability of edge detection techniques for automatic vehicle license plate detection and recognition. In: *National Technical Seminar on Unmanned System Technology*. Springer, pp. 891–910. https://doi.org/10.1007/978-981-15-5281-6_64

[24] Weihong, W. & Jiaoyang, T. (2020) Research on license plate recognition algorithms based on deep learning in complex environment. *IEEE Access*, 8, pp. 91661–91675. https://doi.org/10.1109/ACCESS.2020.2994287

[25] Eftekhar, P. (2019) Comparative Study of Edge Detection Algorithms. *California State University, Northridge*.

[26] Tian, R., Sun, G., Liu, X. & Zheng, B. (2021) Sobel edge detection based on weighted nuclear norm minimization image denoising. *Electronics*, 10(6), p. 655. https://doi.org/10.3390/electronics10060655

[27] Baareh, A.K.M., Al-Jarrah, A., Smadi, A.M. & Shakah, G.H. (2018) Performance evaluation of edge detection using Sobel, Homogeneity and Prewitt algorithms. *Journal of Software Engineering and Applications*, 11(11), p. 537. https://doi.org/10.4236/jsea.2018.1111032

[28] Goswami, B. & Misra, S.K. (2016) Analysis of various Edge detection methods for X-ray images. In: *2016 International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT)*. IEEE, pp. 2694–2699. https://doi.org/10.1109/ICEEOT.2016.7755185

[29] Wei, Y. & Xu, M. (2021) Detection of lane line based on Robert operator. https://doi.org/10.21595/jme.2021.22023