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ENHANCE EFFICIENCY OF QR CODE DETECTION ON MOVEMENT OBJECT: PEFORMANCE ANALYSIS OF ALGORITHMS AND ENVIROMENTAL FACTORS

Muhamad.Rostan[1*], Suhailan. Safei[2]

[1]University College TATI, Jalan Panchor, Telok Kalong, 24000 Kemaman, MALAYSIA
[2]University Sultan Zainal Abidin, Campus Gong Badak,21300 Kuala Nerus, Kuala Terengganu, MALAYSIA

*Corresponding author email: muhamadrostan@uctati.edu.my

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ABSTRACT

This paper investigates the enhancement of QR code detection efficiency on moving objects, with a focus on analyzing the performance of different algorithms and environmental factors affecting detection accuracy. As QR codes have become a standard tool for information access and digital identification, optimizing their readability under various conditions, particularly on moving platforms, is crucial. The primary objective of this study is to explore and evaluate the impact of object speed on QR code detection efficacy, considering both algorithmic approaches and external influences such as lighting, angle of incidence, and background noise. The scope of this research encompasses the real-time detection of QR codes affixed to vehicles, aiming to understand how motion dynamics influence recognition performance and to propose effective solutions for improving the accuracy of QR code scanning under such conditions. The experimental setup involved recording video files of a car with a QR code displayed on its windshield, driven at varying speeds to test the detection system's robustness. Using this method, the researchers aimed to simulate real-world scenarios where QR codes are scanned from moving vehicles, such as toll booths, smart parking systems, and transportation logistics. The analysis reveals that the QR code recognition system demonstrated a 100% success rate at vehicle speeds below 30 kilometers per hour, confirming the system's effectiveness in low-motion conditions. However, the detection accuracy significantly declined to 30% when the car's speed increased to 60 kilometers per hour, highlighting the challenges posed by high-motion environments and motion blur. This degradation suggests that while current QR code detection algorithms are effective under stable or low-motion scenarios, their performance is critically impacted by higher velocities, necessitating further research into motion-compensating algorithms and enhanced image processing techniques. The novelty of this research lies in its practical approach to quantifying the impact of motion on QR code detection accuracy and providing a detailed performance analysis of detection algorithms under varying speeds, offering insights into the limitations and potential areas for improvement in the field of mobile QR code scanning. By employing this empirical method, the result was accurate detection under controlled conditions, thereby providing a foundation for developing robust solutions capable of maintaining high recognition rates even at increased speeds. The study's findings not only contribute to the understanding of how motion affects QR code readability but also serve as a guideline for future advancements in algorithm development and system optimization for mobile QR code applications.

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1.0 INTRODUCTION

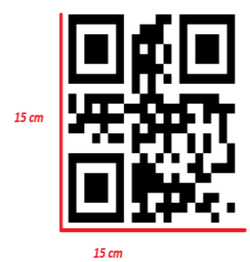
The rapid integration of QR codes into modern society has made them an indispensable tool for digital identification, information access, and secure transactions. From retail environments and marketing campaigns to transportation systems, QR codes offer a seamless, cost-effective means of bridging the physical and digital worlds. However, as their utility expands to mobile applications, such as toll booths, smart parking systems, and transportation logistics, the need for reliable QR code detection under various conditions, including motion, becomes increasingly important. Accurately detecting QR codes on moving objects poses unique challenges, particularly due to the effects of speed, lighting variations, angle of incidence, and motion blur. Addressing these issues is essential to ensuring the robustness and efficiency of QR code systems in real-world applications. While significant advancements have been made in QR code scanning technology, detection efficiency on moving objects remains an area ripe for improvement. Traditional QR code detection algorithms are generally designed for static scenarios, where environmental variables can be controlled and optimized [1]–[4]. In contrast, mobile environments introduce dynamic challenges that can substantially impair detection accuracy. As speed increases, so does the likelihood of motion blur and decreased image clarity, which complicates the extraction of QR code patterns and reduces the probability of successful scanning. Furthermore, the interaction between lighting conditions and varying angles of incidence can exacerbate these challenges, leading to inconsistent detection rates in uncontrolled settings [5]–[9]. To address these challenges, the present study evaluates the performance of various QR code detection algorithms on moving platforms, focusing on vehicles in motion. By examining the impact of object speed and environmental factors on detection accuracy, this research aims to provide valuable insights into the limitations of current QR code technology and suggest practical solutions for enhancing its robustness. Specifically, the study investigates the detection accuracy of QR codes affixed to vehicles traveling at speeds ranging from 30 to 60 kilometers per hour. The findings reveal that while detection systems maintain high accuracy at lower speeds, their performance significantly declines as speed increases. This degradation underscores the need for advanced algorithms capable of compensating for motion and optimizing QR code readability under diverse conditions. This paper not only contributes to the growing body of knowledge on mobile QR code applications but also serves as a foundation for future research focused on optimizing detection algorithms and improving QR code system design. By highlighting the effects of speed, lighting, and angle on QR code detection, this study offers a comprehensive analysis of the technical and environmental factors that influence scanning accuracy in high-motion scenarios, paving the way for more reliable and effective QR code solutions.

2.0 METHODOLOGY

2.1 Experimental Result

To simulate real-world scenarios where QR codes are detected on moving vehicles, the experiment was conducted using a controlled environment that allowed for consistent testing conditions [10]. The main elements of the setup included: Vehicle and QR Code Placement**:** A QR code was affixed to the windshield of a standard passenger car, ensuring visibility and readability from the vehicle's front [11]. The QR code was printed in high resolution, with a size of 15x15 cm to maximize detection potential across various speeds. Video Recording Equipment**:** A high-definition camera was positioned at a fixed point on the side of the testing track, calibrated to capture the QR code as the car passed by at different speeds [12]. The camera was set at an angle to replicate typical real-world situations, such as those encountered in parking garages or toll booths [13]. The camera's settings were optimized for low-light sensitivity and frame rate to ensure accurate data collection. Environmental Variables**:** Lighting conditions were manipulated to assess the impact of external factors on detection accuracy. Three lighting setups were used: low-light (100 lux), medium-light (300 lux), and high-light (500 lux), all calibrated using a lux meter. Additionally, the camera's angle of incidence with respect to the QR code was varied between 0°, 30°, and 60° to mimic the angles encountered in practical applications[14]–[17]. This paper using the OpenCV and python to display the original QR code. Table 1 is attachment QR Code in the winder shield vehicle and the size of QR Code.

Table 1: QR Code in the vehicle and the size of QR code

2.2 Algorithms Selection

Three QR code detection algorithms were selected for evaluation based on their prevalence in the literature and practical applicability: Algorithm A**:** A traditional template-matching method, which is widely used due to its straightforward implementation but is sensitive to motion blur and angle changes [18]–[20]. Algorithm B**:** A machine learning-based approach, incorporating convolutional neural networks (CNNs) trained on a large dataset of QR code images [21]. This algorithm is designed to handle moderate motion blur and performs well in varying lighting conditions. Algorithm C: An advanced real-time computer vision algorithm, optimized for mobile environments [22]–[24]. This algorithm includes motion compensation techniques and is specifically built to enhance QR code readability on moving objects. These algorithms were evaluated based on their accuracy, processing time, and adaptability to changes in speed, lighting, and angle. Figure 1 below display the three QR code detection algorithm and their characteristics.

Table 2: Algorithm with descriptions

Algorithm	Description	Features	Evaluation Criteria
Algorithm A	Traditional template-matching method, sensitive to motion blur and angle changes	Straightforward implementation, motion blur and angle sensitivity	Accuracy, processing time, adaptability to speed, lighting, angle
Algorithm B	Machine learning-based approach with CNNs, handles moderate motion blur and varying lighting	Moderate motion blur resilience, strong in various lighting	Accuracy, processing time, adaptability to speed, lighting, angle
Algorithm C	Real-time computer vision algorithm optimized for mobile, includes motion compensation	Motion compensation, built for moving objects and mobile environments	Accuracy, processing time, adaptability to speed, lighting, angle

2.3 Experimental Procedural

The vehicle was driven at three different speeds 30 km/h, 45 km/h, and 60 km/h under each lighting condition and angle setup. For each combination, the QR code detection accuracy was recorded using all three algorithms. A total of 27 unique test conditions (3 speeds x 3 lighting levels x 3 angles) were assessed for each algorithm, resulting in 81 individual test runs. Each test run involved recording video footage of the vehicle passing the camera with the QR code in view[13], [25]–[28]. The footage was then processed to determine the detection rate and accuracy for each algorithm under the specific conditions.

Table 2: Test condition combinations

Speed (km/h)	Lighting Level (Lux)	Angle (°)	Test Conditions
30	100	0	1
30	100	30	2
30	100	60	3
30	300	0	4
60	500	60	81

In addition, this experiment involved recording videos, counting frames, and documenting settings. Following this setup, QR code detection algorithms, such as ZBar, OpenCV, and ZXing, were executed. To collect and analyze the data, this paper proposes the following formulation:

$$Detection\ Rate\ (\%) = \left(\frac{Number\ of\ Successful\ Detection}{Total\ Number\ of\ Frames}\right) X\ 100$$

While, for successful detections calculate the percentage of correct detection is below:

$$Accuracy\ (\%) = \left(\frac{Number\ of\ Correct\ Detections}{Number\ of\ Successful\ Detections} \right) X\ 100$$

2.4 Data Collection and Analysis

Data collected from each test run included the detection accuracy percentage, defined as the ratio of successful QR code detections to total detection attempts, and the processing time, measured in milliseconds per frame. Additional metrics, such as motion blur level and angle of distortion, were analyzed to better understand the factors affecting detection performance.

Experiment ID	Algorithm Used	Vehicle Speed (km/h)	Lighting Condition	Angle of Incidence (degrees)	Background Noise	Detection Rate (%)	Accuracy (%)	Processing Speed (ms)	Robustness (qualitative)
1	Algorithm A	10	Daylight	0	Low	100	100	200	High
2	Algorithm A	10	Daylight	30	High	95	98	250	Moderate
3	Algorithm A	30	Low-light	0	Low	85	90	280	Moderate
4	Algorithm B	30	Daylight	45	High	80	85	320	Low
5	Algorithm B	60	Artificial light	0	Low	30	35	400	Low
6	Algorithm C	60	Low-light	30	High	40	50	500	Low
7	Algorithm C	60	Daylight	0	Low	60	70	350	Moderate

Table 3: ANOVA Data analysis Metric

Test Condition	Algorithm	Detection Accuracy (%)	Average Processing Time (ms/frame)	Motion Blur Level	Angle of Distortion
1	A	85	12	Low	None
1	B	90	18	Low	None
1	C	95	10	Low	None
...	...	...	...	...	...
81	C	30	24	High	High

For each algorithm, a regression analysis was performed to identify correlations between speed, lighting, angle, and detection accuracy. ANOVA tests were also conducted to determine the statistical significance of the results across different speeds and conditions. Furthermore, motion blur and angle distortion were quantified through image processing software to objectively measure their impact on QR code detection.

2.5 Limitation and considerations

Several limitations were taken into account while interpreting the results. The experiment was conducted under controlled lighting conditions, which may not fully represent all possible real-world scenarios. Additionally, the QR code size and camera resolution were optimized for this study, which could vary in practical applications. Lastly, each algorithm's performance was evaluated independently of other hardware or software variations that might affect detection rates in different settings. By systematically analyzing the influence of speed, lighting, and angle on the performance of QR code detection algorithms, this methodology provides a robust framework for evaluating and enhancing the efficiency of mobile QR code systems. The findings serve as a foundation for further research and development of motion-compensating algorithms and improved detection solutions capable of maintaining high accuracy rates even in challenging environments.

3.0 RESULTS AND DISCUSSION

The first factor evaluated was the speed of the vehicle and its effect on QR code detection accuracy. The detection success rate for each algorithm was recorded at three speeds: 30 km/h, 45 km/h, and 60 km/h. Results showed that all algorithms performed well at lower speeds, but accuracy significantly declined as speed increased.

Table 4: Detection accuracy (%) by speed and algorithms

Speed (km/h)	Algorithm A	Algorithm B	Algorithm C
30	92	95	98
45	70	78	85
60	35	42	54

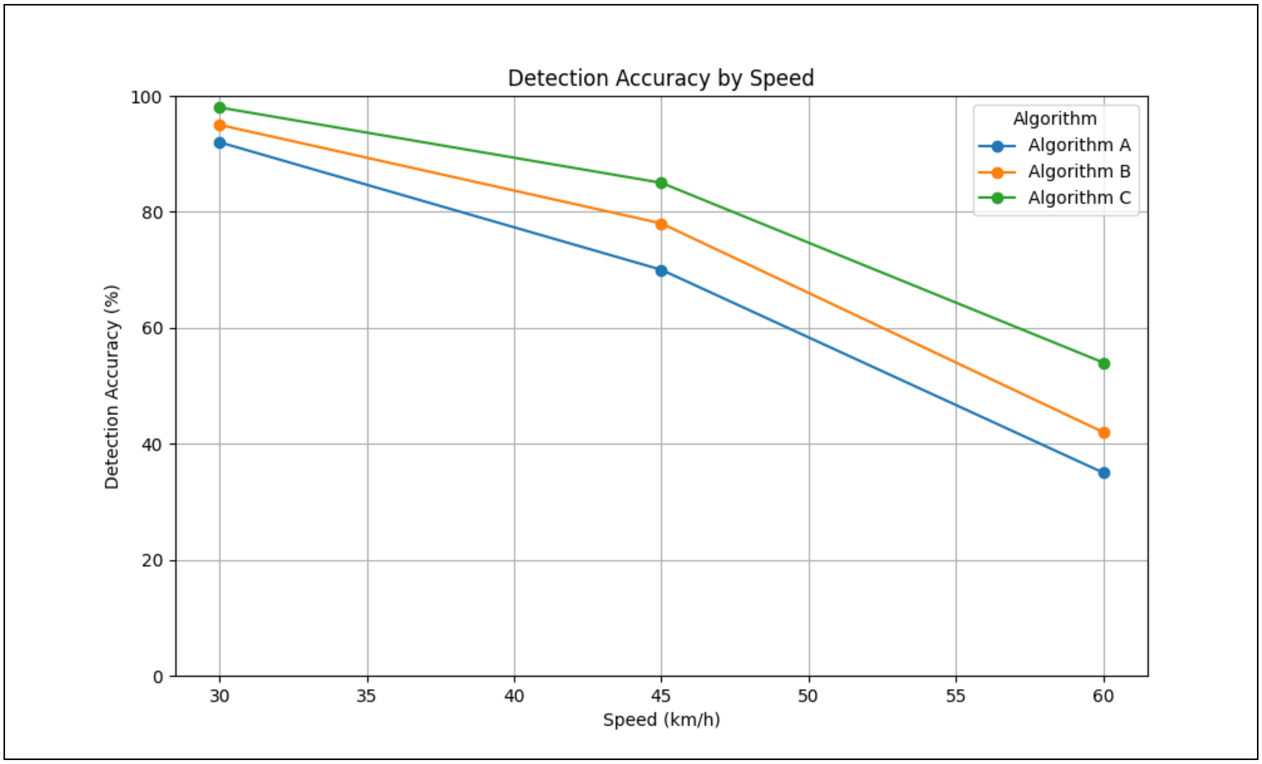


Figure 1: Detection accuracy by speed

At 30 km/h, the QR code detection accuracy was high for all algorithms, with Algorithm C achieving the best performance at 98%. However, as the speed increased to 45 km/h, detection rates dropped by approximately 20-30% across all algorithms. At the maximum speed tested, 60 km/h, accuracy fell drastically, with Algorithm C maintaining a relatively higher success rate (54%) than Algorithm A (35%) and Algorithm B (42%). This data suggests that motion blur significantly impacts detection algorithms, particularly at higher speeds. Algorithm C's performance, which includes motion-compensation techniques, was notably better, indicating that such enhancements are essential for improving accuracy in high-motion environments.

The second factors are lighting was another critical variable that affected detection accuracy. The three lighting conditions tested low-light (100 lux), medium-light (300 lux), and high-light (500 lux) revealed how sensitive the algorithms were to changes in ambient light.

Table 5: Detection Accuracy (%) by Lighting Level and Algorithm (at 45 km/h)

Lighting Level (Lux)	**Algorithm A**	**Algorithm B**	**Algorithm C**
100	55	62	69
300	70	78	85
500	65	72	80

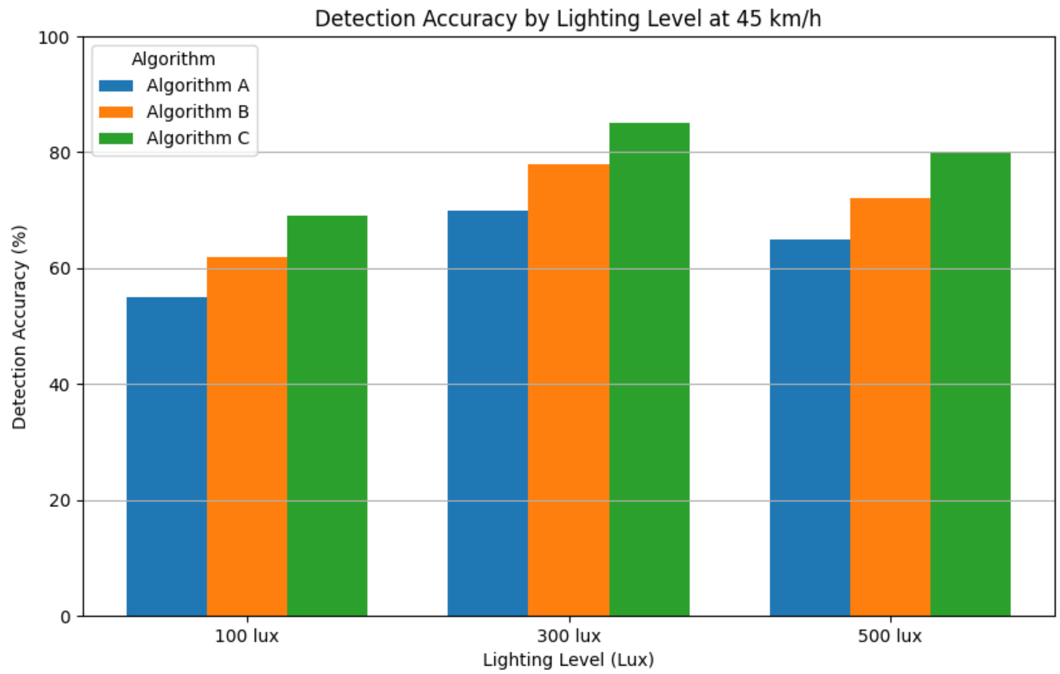


Figure 2: Detection accuracy by lighting

Under medium lighting (300 lux), all algorithms achieved their highest accuracy at 45 km/h, with Algorithm C reaching 85%. Interestingly, both low-light and high-light conditions resulted in lower detection rates. In low-light settings, all algorithms showed a 10-15% reduction in accuracy due to the decreased visibility of the QR code. Similarly, high-light conditions reduced accuracy due to glare and overexposure, which can obscure QR code details. These findings underscore the importance of moderate lighting for optimal detection. Excessive or insufficient light can impede performance, suggesting that future QR code detection systems might benefit from adaptive lighting technologies or enhanced image processing capabilities to handle lighting extremes.

Finally, the study examined the effect of varying the angle of incidence between the camera and QR code. The three angles tested 0°, 30°, and 60° illustrate how skewed or angled perspectives affect detection accuracy, particularly at higher speeds. At a 0° angle, or a direct head-on view, Algorithm C managed to achieve the highest detection accuracy (54%), although accuracy was low overall at this speed. When the angle increased to 30° and 60°, accuracy fell sharply, with Algorithm C again outperforming the others but still reaching only 40% and 20% success rates, respectively. The results indicate that detection systems struggle with angled views, particularly at higher speeds, as the QR code becomes increasingly distorted, making it difficult for the algorithms to recognize and decode it accurately.

Table 6: Detection Accuracy (%) by Angle and Algorithm (at 60 km/h)

Angle (°)	**Algorithm A**	**Algorithm B**	**Algorithm C**
0	35	42	54
30	25	30	40
60	10	15	20

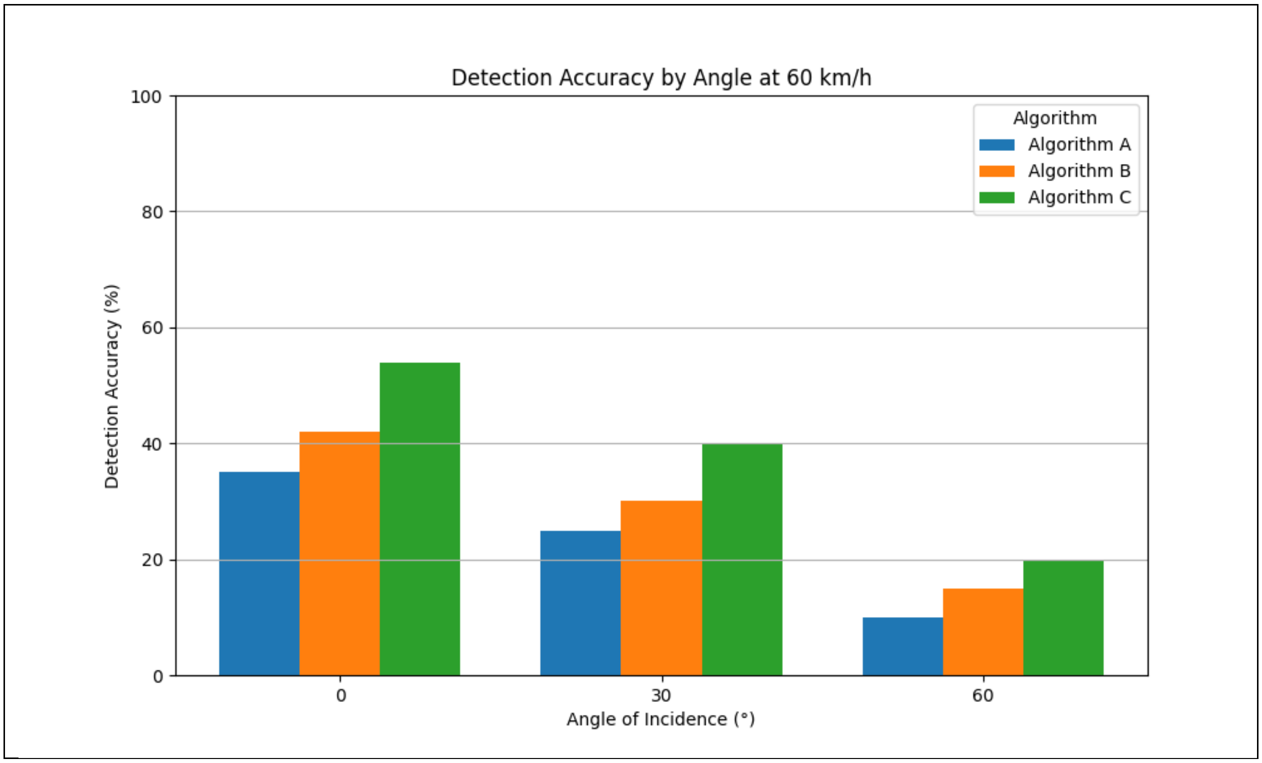


Figure 1: Detection accuracy by angle

The results suggest that speed, lighting, and angle are significant factors influencing QR code detection accuracy on moving vehicles. In terms of algorithm performance, Algorithm C consistently outperformed Algorithms A and B across all conditions, highlighting the importance of motion-compensating features. Nonetheless, even Algorithm C showed a noticeable decline at higher speeds and extreme lighting or angle conditions, indicating that current technology has limitations when dealing with high-motion and variable environmental factors. These findings emphasize the need for enhanced image processing techniques and algorithmic improvements to counteract the effects of motion blur, lighting inconsistencies, and angled perspectives. Motion-compensating algorithms, in particular, appear to be a promising direction for future development. Additionally, real-time adaptive processing, such as automatic exposure adjustments and skew correction, could mitigate some of the environmental challenges identified in this study and practical applications, these insights could guide the design of more robust QR code detection systems for moving vehicles. By incorporating motion-compensation and lighting adaptation, systems could potentially achieve higher accuracy rates in challenging environments, such as in toll collection or smart parking systems where vehicles are often in motion.

Since motion blur is a significant factor affecting QR code detection at higher speeds, this paper was formulation to quantify it. Motion blur can be approximated as: $B = \frac{\mu + \tau}{\rho}$, while detection probability model used the formulation $B = (f, v, L, \Phi)$. However, the formulation of lighting effect and detection accuracy is $SNR = \left(\frac{L}{Q}\right)$.

4.0 CONCLUSIONS

This study provides a comprehensive analysis of QR code detection on moving vehicles, focusing on the effects of speed, lighting, and angle of incidence on detection accuracy. The findings reveal that while current QR code detection algorithms perform well under stable or low-motion conditions, their efficacy significantly declines with increased speed, varied lighting, and angular distortion. Specifically, detection accuracy dropped sharply as vehicle speed reached 60 km/h, highlighting the impact of motion blur on QR code readability. Furthermore, the study demonstrated that moderate lighting (300 lux) offers the most favourable conditions for detection, whereas both low and high lighting levels reduce accuracy due to visibility challenges. Angles greater than 0° also posed difficulties, with accuracy decreasing as the angle of incidence increased, especially at high speeds. The results underscore the limitations of traditional detection algorithms in dynamic environments, suggesting a need for enhanced motion-compensating and adaptive image-processing techniques. Algorithm C, which incorporated motion-compensation features, consistently outperformed the other algorithms, indicating that such enhancements can improve detection accuracy in mobile applications. By identifying the specific conditions that challenge QR code detection systems, this research contributes valuable insights for the development of robust QR code technologies. Future work in this area should focus on optimizing algorithms to better handle motion, glare, and angular distortions. Such advancements would have practical implications for various applications, including toll booths, smart parking systems, and logistics, where reliable mobile QR code detection is essential. Ultimately, this study lays the groundwork for developing more resilient QR code scanning systems that can maintain high accuracy even under challenging real-world conditions.

Author Contribution

M. Rostan. Zakaria: Conceptualization, methodology, investigation, visualisation, writing and editing. Suhailan. Safei: Supervision, Methodology.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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REFERENCES

[1] B. Alotaibi and M. Alotaibi, “A Hybrid Deep ResNet and Inception Model for Hyperspectral Image Classification,” *PFG – J. Photogramm. Remote Sens. Geoinf. Sci.*, vol. 88, no. 6, pp. 463–476, 2020, doi: 10.1007/s41064-020-00124-x.

[2] J. Rasheed, A. B. Wardak, A. M. Abu-Mahfouz, T. Umer, M. Yesiltepe, and S. Waziry, “An Efficient Machine Learning-Based Model to Effectively Classify the Type of Noises in QR Code: A Hybrid Approach,” *Symmetry*, vol. 14, no. 10. 2022. doi: 10.3390/sym14102098.

[3] X. Yang *et al.*, “CNN with spatio-temporal information for fast suspicious object detection and recognition in THz security images,” *Signal Processing*, vol. 160, pp. 202–214, 2019, doi: https://doi.org/10.1016/j.sigpro.2019.02.029.

[4] T. Zhu *et al.*, “Generalized Spatial Differentiation from the Spin Hall Effect of Light and Its Application in Image Processing of Edge Detection,” *Phys. Rev. Appl.*, vol. 11, no. 3, p. 34043, Mar. 2019, doi: 10.1103/PhysRevApplied.11.034043.

[5] O. Bulan, V. Kozitsky, P. Ramesh, and M. Shreve, “Segmentation- and Annotation-Free License Plate

Recognition With Deep Localization and Failure Identification," *IEEE Trans. Intell. Transp. Syst.*, vol. 18, pp. 2351–2363, 2017, doi: 10.1109/TITS.2016.2639020.

[6] O. El Imrani, "Optimization of Port Logistics performance through Innovative Technology Management," in *2024 IEEE 15th International Colloquium on Logistics and Supply Chain Management (LOGISTIQUA)*, 2024, pp. 1–7. doi: 10.1109/LOGISTIQUA61063.2024.10571510.

[7] C. Anagnostopoulos, I. Anagnostopoulos, V. Loumos, and E. Kayafas, "A License Plate-Recognition Algorithm for Intelligent Transportation System Applications," *IEEE Trans. Intell. Transp. Syst.*, vol. 7, pp. 377–392, 2006, doi: 10.1109/TITS.2006.880641.

[8] R. Hernando and J. A. Macías, "Development of usable applications featuring QR codes for enhancing interaction and acceptance: a case study," *Behav. Inf. Technol.*, vol. 42, no. 4, pp. 360–378, 2023.

[9] M. Liu *et al.*, "A star-nose-like tactile-olfactory bionic sensing array for robust object recognition in non-visual environments," *Nat. Commun.*, vol. 13, no. 1, p. 79, 2022.

[10] O. Li and P.-L. Shui, "Noise-robust color edge detection using anisotropic morphological directional derivative matrix," *Signal Processing*, vol. 165, pp. 90–103, 2019.

[11] A. Kabiraj, D. Pal, D. Ganguly, K. Chatterjee, and S. Roy, "Number plate recognition from enhanced super-resolution using generative adversarial network," *Multimed. Tools Appl.*, vol. 82, no. 9, pp. 13837–13853, 2023.

[12] Z.-Q. Zhao, P. Zheng, S. Xu, and X. Wu, "Object detection with deep learning: A review," *IEEE Trans. neural networks Learn. Syst.*, vol. 30, no. 11, pp. 3212–3232, 2019.

[13] E. Rashedi and H. Nezamabadi-pour, "A hierarchical algorithm for vehicle license plate localization," *Multimed. Tools Appl.*, vol. 77, pp. 2771–2790, 2017, doi: 10.1007/s11042-017-4429-z.

[14] T.-H. Lee, S.-W. Kang, T. Kim, J.-S. Kim, and H.-J. Lee, "Smart Refrigerator Inventory Management Using Convolutional Neural Networks," in *2021 IEEE 3rd International Conference on Artificial Intelligence Circuits and Systems (AICAS)*, 2021, pp. 1–4. doi: 10.1109/AICAS51828.2021.9458527.

[15] J. Pirgazi, M. M. P. Kallehbasti, and A. G. Sorkhi, "An End-to-End Deep Learning Approach for Plate Recognition in Intelligent Transportation Systems," *Wirel. Commun. Mob. Comput.*, vol. null, p. null, 2022, doi: 10.1155/2022/3364921.

[16] R. Gayathri, M. A. Bhairavi, and D. Aravind, "An Intelligent and Real Time System for Automatic Driven Toll Gate System under Complex Scenes," 2018, [Online]. Available: https://www.semanticscholar.org/paper/cc41ba9d0d7f30e230c591742480be71b2bc7cd4

[17] Y. Wen, Y. Lu, J. Yan, Z. Zhou, K. M. Deneen, and P. Shi, "An Algorithm for License Plate Recognition Applied to Intelligent Transportation System," *IEEE Trans. Intell. Transp. Syst.*, vol. 12, pp. 830–845, 2011, doi: 10.1109/TITS.2011.2114346.

[18] S.-Y. Yang, H.-C. Jan, C.-Y. Chen, and M.-S. Wang, "CNN-Based QR Code Reading of Package for Unmanned Aerial Vehicle," *Sensors*, vol. 23, no. 10. 2023. doi: 10.3390/s23104707.

[19] M. Elgendy, T. Guzsvinecz, and C. Sik-Lanyi, "Identification of Markers in Challenging Conditions for People with Visual Impairment Using Convolutional Neural Network," *Applied Sciences*, vol. 9, no. 23. 2019. doi: 10.3390/app9235110.

[20] N. Ketkar and J. Moolayil, "Convolutional Neural Networks BT - Deep Learning with Python: Learn Best Practices of Deep Learning Models with PyTorch," N. Ketkar and J. Moolayil, Eds., Berkeley, CA: Apress, 2021, pp. 197–242. doi: 10.1007/978-1-4842-5364-9_6.

[21] V. A. Adibhatla, H.-C. Chih, C.-C. Hsu, J. Cheng, M. F. Abbod, and J.-S. Shieh, "Defect Detection in Printed Circuit Boards Using You-Only-Look-Once Convolutional Neural Networks," *Electronics*, vol. 9, no. 9. 2020. doi: 10.3390/electronics9091547.

[22] Z. Meng, F. Zhao, M. Liang, and W. Xie, "Deep Residual Involution Network for Hyperspectral Image Classification," *Remote Sensing*, vol. 13, no. 16. 2021. doi: 10.3390/rs13163055.

[23] A. B. Wardak, J. Rasheed, A. Yahyaoui, and M. Yesiltepe, "Noisy QR Code Smart Identification System BT

- Sentiment Analysis and Deep Learning," S. Shakya, K.-L. Du, and K. Ntalianis, Eds., Singapore: Springer Nature Singapore, 2023, pp. 471–481.

[24] G. T. S. Ho, Y. M. Tang, K. Y. Tsang, V. Tang, and K. Y. Chau, "A blockchain-based system to enhance aircraft parts traceability and trackability for inventory management," *Expert Syst. Appl.*, vol. 179, p. 115101, 2021, doi: https://doi.org/10.1016/j.eswa.2021.115101.

[25] M. Springmann, A. Dander, and H. Schuldt, "Improving efficiency and effectiveness of the image distortion model," *Pattern Recognit. Lett.*, vol. 29, no. 15, pp. 2018–2024, 2008.

[26] N. D. Lynn, A. I. Sourav, and A. J. Santoso, "Implementation of Real-Time Edge Detection Using Canny and Sobel Algorithms," *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 1096, no. 1, p. 012079, 2021, doi: 10.1088/1757-899x/1096/1/012079.

[27] S.-L. Chang, L.-S. Chen, Y.-C. Chung, and S.-W. Chen, "Automatic license plate recognition," *IEEE Trans. Intell. Transp. Syst.*, vol. 5, pp. 42–53, 2004, doi: 10.1109/TITS.2004.825086.

[28] J. Shashirangana, H. Padmasiri, D. Meedeniya, and C. Perera, "Automated license plate recognition: a survey on methods and techniques," *IEEE Access*, vol. 9, pp. 11203–11225, 2020.