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Parameters Improvement of Gaussian Mixture Model for Vehicle Detection in Different Weather Conditions

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Abstract: Accurate vehicle detection under different weather conditions is crucial to ensure efficient and safe traffic management systems. This paper presents a novel approach for vehicle detection in different weather scenarios, leveraging on Improved Gaussian Mixture Model (Improved GMM). Traditional methods often falter in different weather conditions, posing significant challenges to traffic management. The modified model addresses these challenges by integrating advanced features such as adaptive time-varying learning rates, exponential decay, and outlier processing. This ensures robust performance across different weather conditions, including daytime, nighttime, and rainy weather. Real-world datasets evaluate the model's efficacy, simulating various weather scenarios to assess its adaptability and reliability. Comparative analysis demonstrates the superiority of the Improved GMM over traditional techniques, exhibiting enhanced accuracy and robustness in different weather conditions while maintaining computational efficiency. The findings highlight the potential of the modified model to significantly improve vehicle detection accuracy in different weather conditions, thus contributing to the advancement of reliable traffic management systems irrespective of environmental challenges.

Keywords: Gaussian Mixture Model, Adaptive Time-varying Learning Rate, Exponential Decay, Outlier Processing, Vehicle Detection.

1. Introduction

Accurately detecting vehicles is important for traffic management systems, ensuring smooth traffic flow, safety, and overall road efficiency. In recent years, computer vision techniques have played a pivotal role in vehicle detection and tracking tasks. Researchers have explored various methods for studying vehicle detection, including traditional computer vision, machine learning, deep learning, motion-based approaches, radar-based techniques, and fusion methods. This research concentrates on traditional computer vision techniques, particularly background subtraction, emphasising mathematical contributions. Among these methods, the Gaussian Mixture Model (GMM) proposed by Stauffer and Grimson (1999) has emerged as a popular choice due to its simplicity and effectiveness in background subtraction. However, despite the progress made in the topic, many difficulties remain, making it hard to create robust and adaptable detection systems that can handle the complexities of different environmental conditions, especially those caused by various types of weather.

This study focuses on improving vehicle detection in varying weather conditions—normal day, rainy day, normal night and rainy night. To solve this issue, we propose an Improved Gaussian Mixture Model (Improved GMM) to enhance vehicle detection under these different weather conditions. Traditional GMMs struggle with a constant learning rate that does not adjust to changing data characteristics. This can result in the model either not converging or converging to a suboptimal solution. An Improved GMM addresses this by introducing an adaptive time-varying learning rate, allowing the model to adjust based on current data dynamically, leading to better performance in varying traffic densities.

Traditional GMMs also assume pixels close to the mean belong to the same cluster, which can be a limiting factor. The Improved GMM emphasises these pixels more effectively, improving the identification and separation of objects from the background. Additionally, traditional GMMs treat all observations equally, including outliers, which can distort data distribution estimates. The Improved GMM includes outlier processing to control the influence of new observations on covariance updates.

While previous research have explored various techniques to improve vehicle detection accuracy, there remains a notable gap in the literature regarding comprehensive solutions that address the complexities of different weather conditions. Existing methodologies often fail to provide consistent performance across diverse environmental scenarios, leading to inaccuracies and potential safety hazards. Therefore, this study seeks to bridge this research gap by proposing a novel approach, the Improved Gaussian Mixture Model (Improved GMM), designed explicitly to mitigate the effects of different weather conditions on vehicle detection accuracy. By integrating advanced features such as adaptive time-varying learning rates, exponential decay, and outlier processing, the modified model aims to enhance the adaptability and reliability of vehicle detection systems, thereby

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contributing to the advancement of traffic management systems and overall road safety.

This paper is organised as follows: Section 2 provides a comprehensive review of the relevant literature. Section 3 presents the methodology, beginning with an overview of the traditional GMM, followed by a discussion on the Improved GMM. Section 4 undertakes an in-depth analysis and discussion of the obtained results. Finally, Section 5 concludes the study by summarising key findings.

2. Literature review

2.1 Introduction to Vehicle Detection

Vehicle detection is a crucial component of modern transportation systems, with applications ranging from traffic management to autonomous driving. Over the years, significant research efforts have been dedicated to advancing vehicle detection methodologies to improve accuracy, reliability, and efficiency. Researchers in computer vision and intelligent transportation systems have shown substantial interest in traffic identification (Buch, Velastin & Orwell, 2011; Zhang et al., 2011). Various technological initiatives are underway to automate the detection and classification of cars (Saran & Sreelekha, 2015; Wang, Xiao & Gu, 2008). Image processing techniques classify vehicles based on shape, size, texture, colour, and other characteristics (Chen, Ellis & Velastin, 2011; Lai & Yung, 2000). The extracted information is then transmitted to a centralised system for regulation and monitoring (Kim & Kim, 2002; Chen et al., 2023). These advancements aim to improve the efficiency and effectiveness of traffic management systems, ensuring smoother transportation operations in response to the challenges posed by increasing vehicle numbers.

The vehicle detection concept involves identifying a vehicle's precise location on the road in real time within a specific area of interest. However, this task becomes highly complex due to the dynamic nature of the traffic scene and the real-time acquisition of images. The constantly changing traffic scene presents significant challenges in accurately detecting vehicles. Various factors further impact the difficulty of vehicle detection, including changes in lighting, weather conditions, shadows, complex background interference, camera parameters, vehicle movements, occlusions, and so on (Pang, Lam & Yung, 2004; Wang, 2010; Karangwa et al., 2023). GMM is commonly employed to generate a foreground mask to address this issue. However, false positive detections are still likely to occur. To overcome this challenge, ongoing research is exploring enhanced methods of vehicle surveillance that aim to reduce false positive detections (Husain, Maity & Yadav, 2020; Premaratne et al., 2023).

For instance, Zivkovic (2004) developed an adaptive GMM with a configurable number of Gaussian components, producing improved model adaptations to changing conditions. Similarly, Zuo et al. (2019) designed an enhanced method for noise interruption for the traditional GMM. In addition to GMM, deep learning techniques have emerged as promising alternatives for vehicle detection tasks (Braham & Droogenbroeck, 2016; Babaee, Dinh & Rigoll, 2018). For example, Yadav and Xiaogang described an innovative hybrid method that combined GMM, background subtraction, Hue-Saturation-Value (HSV) colour model, feature extraction, and neural networks (Yadav & Xiaogang, 2020). Overall, vehicle detection encompasses a diverse range of methodologies and techniques, each offering unique advantages and addressing specific challenges.

2.2 Different Weather Conditions

Weather conditions such as rain, fog, snow, and varying lighting conditions present substantial challenges for vehicle detection systems. Research by Li et al. (2023) demonstrated that heavy rainfall can reduce the accuracy of vehicle detection systems due to decreased visibility and increased noise in sensor data. Similarly, studies by Zang et al. (2019) highlighted the impact of rain, snow, fog, and hail on vehicle detection, showing a significant decrease in detection rates under the worst conditions. Additionally, low-light conditions pose challenges for detection algorithms, as demonstrated by O'Malley, Glavin, and Jones (2011).

In response to the challenges posed by different weather conditions, researchers have explored various strategies to enhance the adaptability of vehicle detection systems. One approach is the integration of weather-specific features into detection algorithms. For example, Al Machot et al. (2019) proposed a method incorporating raindrop detection to improve vehicle detection accuracy during rainy conditions. Another strategy involves the development of robust detection algorithms capable of dynamically adjusting to changing environmental conditions. Research by Rezaei, Terauchi, and Klette (2015) introduced a dynamic thresholding technique that enables vehicle detection systems to adapt to varying lighting conditions, improving detection accuracy under different weather scenarios.

Generally, vehicle detection in different weather conditions poses significant challenges for existing systems. However, research efforts focused on weather-specific adaptations and robust detection algorithms show promise in improving detection accuracy and reliability under different weather conditions.

3. Methodology

3.1 Gaussian Mixture Model in Vehicle Detection

The GMM is a widely used statistical method in computer vision and machine learning for modelling complex data distributions. It provides a flexible framework for representing data that may arise from multiple underlying probability distributions. At its core, the GMM represents the probability distribution of observed data as a weighted sum of several Gaussian distributions, also known as components or clusters. Each Gaussian component in the mixture model represents a cluster of data points in the feature space, with its mean and covariance matrix. The mixture of these components allows GMM to capture complex data patterns that a single Gaussian distribution cannot adequately model.

Many researchers have suggested using multimodal probability density functions to handle backgrounds with moving textures (like a car on a highway). For example, Stauffer and Grimson (1999) described a method where each pixel is modelled

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using a mix of K Gaussians. This means that the likelihood of colour appearing at a particular pixel is represented as:

$$f(x_t) = \sum_{k=1}^{K} \Pi_{k,t} \cdot \Phi\left(x_t, \mu_{k,t}, \sigma_{k,t}\right) \tag{1}$$

where x_t is the pixel value; $\Phi(x_t, \mu_k, \sigma_{k,t})$ is the Gaussian component density with mean $\mu_{k,t}$ and covariance matrix $\sigma_{k,t}$; $\Pi_{k,t}$ is the weight associated with the k^{th} Gaussian component. Subsequently, $\Phi(x_t, \mu_{k,t}, \sigma_{k,t})$ is formulated as:

$$\Phi(x_t, \mu_{k,t}, \sigma_{k,t}) = 1/((2\pi)^{\frac{n}{2}}|\sigma_{k,t}|^{\frac{1}{2}})\, e^{-\frac{1}{2}(x_t-\mu_{k,t})^T \Sigma_{k,t}^{-1}(x_t-\mu_{k,t})} \tag{2}$$

$$\mu_{k,t} = (1-\beta)\mu_{k,t-1} + \beta x_t \tag{3}$$

$$\sigma_{k,t}^2 = (1-\beta)\sigma_{k,t-1}^2 + \beta(x_t - \mu_{k,t})(x_t - \mu_{k,t})^T \tag{4}$$

$$\Pi_{k,t} = (1-\alpha)\Pi_{k,t-1} + \alpha\psi_{k,t} \tag{5}$$

where $\beta = \alpha \cdot \Phi(x_t, \mu_{k,t}, \sigma_{k,t})$, $\psi_{k,t}$ is the indicator function, and α is the constant learning rate. The $\mu_{k,t}$ and $\sigma_{k,t}$ parameters of unmatched distributions remain unchanged. At the same time, their weight is decreased according to the formula in (5) to achieve decay. If no component matches x_t, the one with the lowest weight is substituted with a Gaussian distribution having a mean of x_t, a large initial variance σ_0 and a small weight Π_0. After updating each Gaussian, the K weights Π_0 are normalised that their sum equals 1. Next, the K distributions are arranged based on a fitness value calculated as $\Pi_{k,t}$ divided by $\sigma_{k,t}$, and only the B most reliable distributions are selected to be part of the background.

$$B = \operatorname{argmin}\left(\sum_{k=1}^{b} \Pi_k > th\right) \tag{6}$$

where th is the threshold.

3.2 Improved Gaussian Mixture Model

Improved GMM refined the traditional GMM by adjusting the mean, covariance, and weight calculations, following the methodology proposed by Stauffer and Grimson (1999), leading to more accurate vehicle detection across varying weather conditions. These modifications address the limitations of traditional GMM methods by incorporating an adaptive time-varying learning rate, exponential decay, and outlier processing. As a result, these improvements enable Improved GMM to capture variations in weather accurately and enhance detection accuracy. The enhancements implemented in Improved GMM are based on improvements to the mean, covariance, and weight equations proposed by Stauffer and Grimson (1999). These upgrades include:

$$\mu_{k,t} = (1-\beta(t))\mu_{k,t-1} + \beta(t)x_t \cdot e^{-\lambda d_t} \tag{7}$$

$$\sigma_{k,t}^2 = (1-\beta(t))\sigma_{k,t-1}^2 + \beta(t)(1-\gamma)(1 - e^{-2\lambda d_t})(x_t - \mu_{k,t})(x_t - \mu_{k,t})^T \tag{8}$$

$$\Pi_{k,t} = (1-\alpha)\Pi_{k,t-1} + \alpha e^{-\lambda d_t} \tag{9}$$

Incorporating an adaptive time-varying learning rate helps regulate the weights assigned to newly arriving data samples (Fried, Lizarralde & Leite, 2022). This adjustment allows the algorithm to swiftly adjust to changes in traffic flow, leading to more accurate vehicle detection by factoring in the distance between the pixel and the current means. This study replaced the fixed learning rate parameters with an adaptive time-varying learning rate parameter. For this study, the value of $\beta(t)$ is obtained using the Robbins-Monro stochastic approximation method, which requires solving the recursive equation:

$$\beta(t) = c/(c+t) \tag{10}$$

where c is a constant that controls the learning rate. The value of the parameter c is chosen based on prior knowledge of the data, such as possible ranges for model parameters and data distribution. It is important to note that the choice of c significantly impacts the algorithm's performance; selecting an incorrect value can result in slow convergence or instability. The iteration or t value is typically incremented by one with each iteration, representing the number of algorithm iterations or observations analysed both the initial value of t and its growth rate influence convergence speed and algorithm stability. If the initial value of t is too small, the step size may be too large, leading to instability and overestimating the optimal solution. Conversely, if the initial value of t is too high, the step size may be too small, resulting in slow convergence and the risk of getting stuck with a suboptimal solution. The growth rate of t also affects convergence speed and algorithm stability. A rapid increase in t promotes a faster convergence but may lead to instability and overestimation. On the other hand, slower growth in t results in stable behaviour but slower convergence.

The parameter λ adjusts how much each current pixel (mean, covariance, and weight parameters) contributes to the Improved GMM. When this adjustment is made, the precision of vehicle detection is increased by considering the distance between the current pixel and the current mean. Here, $\mu_{k,t-1}$ represents the previous mean, x_t is the current pixel, and d_t is the Euclidean distance between x_t and the previous mean $\mu_{k,t-1}$. Additionally, introducing the exponential decay factor $e^{-\lambda d_t}$ from (7) to (9) ensures that the contribution of each pixel decreases as its distance from the current mean increases (Bishop, 2006). This aligns with the idea that pixels closer to the mean significantly influence parameter changes more than those further away (Ruder, 2016). The additional term $1 - e^{-2\lambda d_t}$ adjusts the contribution of each pixel to the covariance parameter based on

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its distance from the current mean. Moving from (7) to (9), $\Pi_{k,t-1}$ represents the previous weight and $e^{-\lambda d_t}$ modifies the contribution of each data point to the weight parameter relative to its distance from the current mean. This modification ensures that the contribution of each data point to the weight decreases as its distance from the current mean increases (Aboutanios, 2009).

As a pixel moves farther from the current mean, its contribution to the mean parameter decreases. This helps prevent outliers or noisy data points from significantly affecting the estimated mean (Reynolds & Rose, 1995). Pixels that are distant from the current mean may not accurately represent the underlying distribution, and thus, their contribution to the mean should be reduced. In vehicle detection, a pixel corresponding to a vehicle far from the current mean is considered an outlier or an erroneous detection caused by noise in the sensor data. By reducing the contribution of each pixel to the mean, the algorithm becomes more robust to such outliers and reduces the likelihood of false positives or misclassifications. Therefore, adjusting the contribution of each data point to the mean parameter based on its distance from the current mean improves the accuracy and robustness of the GMM algorithm for vehicle detection in real-time traffic flow analysis.

Outlier processing involves introducing a robustness parameter γ to control how much the model reacts to new pixels, making it more resistant to outliers (Stewart, 1999). This adjustment allows for better control over the influence of new observations on covariance matrix updates (Warwick & Jones, 2005). Inclusion of γ in the covariance update equation of the GMM enhances the model's robustness against outliers and noisy data. This updated equation with outlier processing can be spotted in (8). The traditional GMM treats all observations, including outliers, equally. Consequently, the covariance matrix adapts to outliers and incorporates their influence, potentially distorting the underlying data distribution estimates. In contrast, the Improved GMM, introduced with the parameter γ, allows for controlling the influence of new observations on covariance updates. By adjusting the value of γ, the weight assigned to outlier-like observations is reduced, minimising their impact on covariance estimation. When γ approaches 1, the effect of new observations is diminished, enhancing the model's resilience to outliers. Robust estimators effectively mitigate the impact of outliers or deviations from model assumptions, yielding more reliable parameter estimates (Zoubir et al., 2012). Incorporation of γ into the covariance update equation enables control over the model's responsiveness. This mechanism strikes a balance between incorporating new information and safeguarding against outliers. Adjusting γ reduces the weight given to outlier-like observations, enabling the model to prioritise reliable and representative data points (Tadjudin & Landgrebe, 2000).

Extensive experiments were conducted on real-world datasets to evaluate the effectiveness of the proposed modification. Performance of the traditional GMM formulation was then compared to the modified version, which incorporates the time-varying learning rate, exponential decay, and outlier processing.

3.3 Evaluation Metrics

A range of performance evaluation metrics were employed to assess the effectiveness of the Improved GMM for vehicle detection. These metrics provide quantitative measures of the model's accuracy, reliability, and robustness in detecting vehicles across various weather conditions. In this assessment, four categories are used to assess the accuracy of segmentation algorithms. Firstly, true positives (TP) denote pixels that the segmentation algorithm correctly identifies as positive and are labelled positive in the ground truth annotation. Conversely, false positives (FP) refer to pixels identified as positive by the algorithm but are negative according to the ground truth. False negatives (FN) represent pixels labelled as negative by the algorithm but are positive in the ground truth annotation. Lastly, true negatives (TN) indicate pixels correctly identified as negative by the segmentation algorithm, aligning with the negative label in the ground truth annotation (Zhang et al., 2015; Lin et al., 2023).

Recall (RCL) assesses how well a model identifies actual positive instances by measuring the ratio of true positives to the sum of true positives and false negatives. Precision (PRC) indicates the accuracy of the model's positive predictions by calculating the ratio of true positives to the sum of true and false positives. The F-measure (FMS), or F1 score, is the harmonic mean of precision and recall, offering a balanced view of the model's performance. It is computed as two times the product of precision and recall divided by their sum. The False Positive Rate (FPR) quantifies the proportion of negative instances incorrectly predicted as positive, calculated as the ratio of false positives to the sum of false positives and true negatives. The False Negative Rate (FNR) measures the proportion of positive instances incorrectly identified as negative, calculated as the ratio of false negatives to the sum of false negatives and true positives. Accuracy (ACY) evaluates the overall correctness of the model's predictions, calculated as the ratio of the sum of true positives and true negatives to the total number of instances. The Wrong Classifications Percentage (WCP) represents the proportion of incorrectly classified instances, calculated as the ratio of false positives and false negatives to the total number of instances. These metrics include RCL in (11), PRC in (12), FMS in (13), FPR in (14), FNR in (15), ACY in (16) and WCP in (17) are defined by Goyette et al. (2012).

$$RCL=TP/(FN+TP) \quad (11)$$

$$PRC=TP/(TP+FP) \quad (12)$$

$$FMS=(2\times RCL\times PRC)/(RCL+PRC) \quad (13)$$

$$FPR=FP/(FP+TN) \quad (14)$$

$$FNR=FN/(FN+TP) \quad (15)$$

$$ACY=(TP+TN)/(TP+FP+FN+TN) \quad (16)$$

$$WCP=(FP+FN)/(TP+FP+FN+TN) \quad (17)$$

These evaluation metrics offer comprehensive insights into the model's performance, enabling a thorough assessment of its capabilities in vehicle detection tasks. By examining these metrics, a more comprehensive insight into the strengths and weaknesses of the Improved GMM is obtained, aiding in informed decision-

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making and identifying areas for potential enhancements in future model iterations.

4. Analysis and discussion

In this section, performance of the Improved GMM was analysed and discussed using a wide range of video sequences for vehicle detection across different weather conditions, including clear and rainy scenarios. The objective is to provide insights into the effectiveness and robustness of the model in addressing the challenges encountered in real-world traffic scenarios. This comprehensive selection enabled us to evaluate how well the proposed methods performed under different weather conditions. The video datasets were sourced from real traffic footage in Kuala Lumpur obtained from Sena Traffic Systems Sdn. Bhd. Our industrial collaborator in Malaysia generously provided these datasets, which also served as valuable case studies. Their contribution closely matched the research problem we aimed to address.

Obtaining ground truth data for the real videos posed challenges, particularly in manually annotating reference images to establish ground truth. Despite these challenges, the model demonstrated promising results, indicating its reliability in accurately detecting vehicles within real traffic flow environments. A significant aspect of the analysis involved the application of a uniform parameter set across all video sequences, chosen based on empirical study. Following Zuo et al. (2019), the parameter values proved effective in various situations, showcasing the model's versatility and robustness in handling different levels of complexity within the traffic flow. The specific parameter values used are listed in Table 1.

Table 1. Parameter Values

K	α	λ	γ	d	c
3	0.9	0.1	0.5	5	100

A comparison of traditional GMM and Improved GMM performance is conducted using these quantitative parameters, as outlined in Table 2. The optimal values are highlighted in bold.

The Improved GMM outperformed the traditional GMM significantly, achieving a recall rate of 0.8915 compared to 0.3983 for the traditional GMM. This indicates that the Improved GMM correctly identified a higher proportion of actual positive instances, showcasing its superior ability to detect vehicles in the given scenarios. PRC measures the accuracy of positive predictions made by the model. The Improved GMM achieved a slightly higher precision rate than the traditional GMM (0.6921 vs. 0.6744). This implies that the Improved GMM exhibited a better ability to minimise false positive predictions while maximising true positive identifications, thus demonstrating its enhanced accuracy in vehicle detection tasks. Meanwhile, FMS, which provides a balanced measure of the model's precision and recall, showed a notable improvement for the Improved GMM (0.7572) compared to the traditional GMM (0.4815). This indicates that the Improved GMM achieved a better balance between precision and recall, leading to more reliable and consistent performance across different evaluation scenarios.

Analysing the FPR and FNR, it is evident that the Improved GMM exhibited superior performance in both metrics, with lower values indicating fewer misclassification instances than the traditional GMM. This suggests that the Improved GMM effectively minimises false positives and negatives, thereby enhancing the overall accuracy of vehicle detection. ACY serves as a measure of the overall correctness of the model's predictions across all classes. Here, the Improved GMM achieved a significantly higher accuracy rate (0.9676) compared to the traditional GMM (0.8661), highlighting its ability to make more precise and reliable predictions across diverse scenarios. Lastly, WCP provides insights into the proportion of instances incorrectly classified by the model. The Improved GMM demonstrated a substantially lower WCP (0.0324) compared to the traditional GMM (0.1339), indicating its effectiveness in reducing misclassifications and improving overall model robustness. Overall, the comparative analysis of performance metrics clearly demonstrates superiority of the Improved GMM over the traditional GMM in vehicle detection tasks, highlighting its potential for enhancing the accuracy and reliability of traffic management systems in various real-world scenarios.

Figure 1 illustrates the F-measure comparison between the traditional GMM and the Improved GMM across different weather conditions. For this measure, the Improved GMM consistently outperformed the traditional GMM across all weather conditions. Specifically, during normal day and night scenarios, the Improved GMM achieved notably higher F-

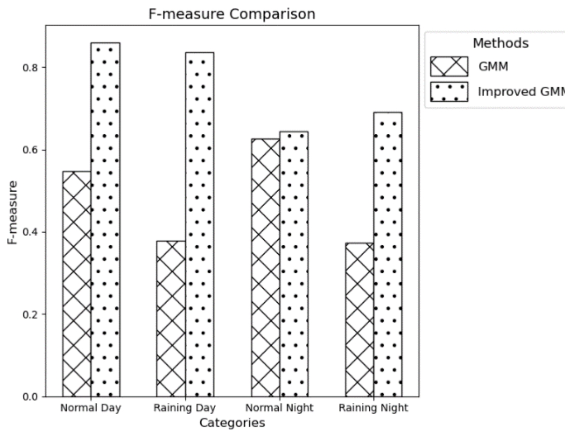

Figure 1. Comparison of F-measure Result of GMM and Improved GMM

Table 2. Summary of Evaluation Metrics of GMM and Improved GMM

Method	RCL	PRC	FMS	FPR	FNR	ACY	WCP
GMM (Stauffer & Grimson, 1999)	0.3983	0.6744	0.4815	0.0303	0.6017	0.8661	0.1339
Improved GMM	**0.8915**	**0.6921**	**0.7572**	**0.0239**	**0.1084**	**0.9676**	**0.0324**

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measure scores compared to the traditional GMM method. This indicates that the Improved GMM model performs better in accurately identifying vehicles under typical lighting and weather conditions. Moreover, even in challenging weather conditions such as rainy days and nights where visibility is significantly reduced, the Improved GMM still demonstrated remarkable performance, with considerably higher F-measure scores compared to the traditional GMM approach. This suggests that the Improved GMM model is more robust and reliable in detecting vehicles for different weather conditions, highlighting its effectiveness in real-world applications. By leveraging robust statistical techniques and adaptive learning mechanisms, the Improved GMM proves to be a promising solution for improving the reliability of vehicle detection systems in real-world applications.

Figure 2 compares the AC results obtained from two vehicle detection methods across different weather conditions. The data illustrates remarkably high accuracy levels for both methods, with most accuracy scores surpassing 0.8. However, upon closer examination, notable contrasts in their performances become apparent. The Improved GMM consistently exhibits superior accuracy compared to the traditional GMM across all weather conditions. Notably, it achieves higher accuracy levels in normal weather conditions and challenging scenarios such as rainy days and nights. This indicates the robustness of the Improved GMM model to different weather conditions, emphasizing its reliability in real-world applications where accurate vehicle detection is essential. Interestingly, both methods demonstrate higher accuracy during normal nighttime and daytime conditions. This observation could be attributed to improved visibility and lighting conditions during nighttime, facilitating more accurate vehicle detection outcomes. Overall, the Improved GMM is the preferred choice due to its consistently higher accuracy levels across different weather conditions. Its superior performance highlights its potential value in critical applications such as autonomous driving systems and surveillance platforms. These findings offer valuable insights for researchers seeking to enhance the accuracy and reliability of vehicle detection systems in diverse environmental settings.

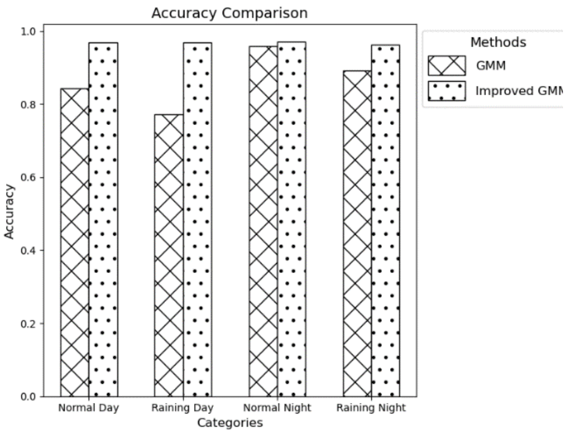
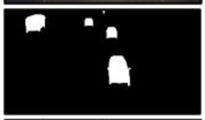
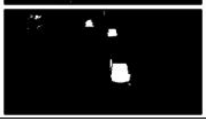
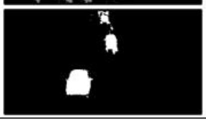


Figure 2. Comparison of Accuracy Result of GMM and Improved GMM

Table 3 compares vehicle detection based on real dataset, offering valuable insights into how well the traditional GMM and the Improved GMM methods detect vehicles across different weather conditions. The table displays original video frames (input) in the first column and manually created GT masks indicating vehicle locations in the second column. The third and fourth columns show the vehicle detection generated by the traditional GMM and Improved GMM methods, respectively. The aim is to evaluate how accurately the detection represents vehicle positions and shapes in the video frames. The results from Table 3 indicate that the Improved GMM produces satisfactory detection outcomes, particularly noticeable in normal daytime conditions. It captures vehicle locations and shapes accurately, showcasing its reliability in typical daytime traffic scenarios. This suggests that the Improved GMM method accurately identifies and outlines vehicles in clear, well-lit conditions, which are common during daytime traffic.

On the other hand, the traditional GMM method demonstrates comparable performance, especially in specific scenarios. While the Improved GMM method excels in normal

Table 3. Comparison of Vehicle Detection for Real Dataset

Weather Condition	Normal Day	Raining Day	Normal Night	Raining Night
Input				
Ground Truth				
GMM				
Improved GMM				

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daytime conditions, the traditional GMM method may perform well in other situations, such as normal nighttime conditions. This suggests that the traditional GMM method may have strengths in more straightforward, well-lit scenarios, highlighting its effectiveness in specific lighting and environmental conditions. However, it is essential to acknowledge that both methods exhibit false positives and negatives to some extent, indicating that neither technique is flawless. The study emphasises the need to develop an algorithm that balances computational efficiency and performance, making it suitable for real-time applications with limited processing time. Furthermore, the increased complexity introduced by the Improved GMM algorithm requires further evaluation to understand its implications completely, particularly in scenarios with different weather conditions.

Previous research in vehicle detection has provided valuable insights into the challenges and advancements in this area. Our study builds upon and contributes to this existing body of knowledge by introducing Improved GMM as a novel approach to address the limitations of traditional vehicle detection methods, particularly in different weather conditions. While previous studies have explored various methodologies for vehicle detection, our approach differs significantly in its focus on robustness and adaptability across different weather conditions. Unlike previous methods that may specialise in specific weather scenarios or rely solely on image processing techniques, the Improved GMM integrates advanced features such as adaptive time-varying learning rates, exponential decay and outlier processing to enhance performance in challenging environments.

Methodological differences between our study and previous research may influence the interpretation of results. For example, while some studies may have utilised synthetic datasets or controlled environments for evaluation, our study employed real-world traffic footage obtained from Kuala Lumpur, providing a more realistic assessment of model performance in practical scenarios. Additionally, variations in parameter settings, dataset characteristics, and evaluation metrics may contribute to differences in reported outcomes across studies. Our findings may diverge from those of previous studies in certain aspects. For instance, while some studies may have reported higher accuracy rates under specific weather conditions using alternative methodologies, our results demonstrate the superior performance of the Improved GMM across a range of environmental scenarios. These discrepancies may stem from differences in model complexity, dataset composition, or evaluation criteria, highlighting the importance of context-specific interpretations.

While our study benefits from real-world data and a comprehensive evaluation framework, it may be limited by dataset availability, annotation accuracy, and computational resources. Conversely, our approach offers advantages in adaptability and robustness, addressing critical gaps identified in previous methodologies. Future research in vehicle detection could further explore the implications of our findings and address the remaining challenges. Areas for future investigation may include refining the Improved GMM algorithm, validating its performance in diverse geographical locations, and assessing its applicability in emerging technologies such as autonomous vehicles and intelligent transportation systems. Additionally, comparative studies with alternative approaches could provide valuable insights into different detection methods' relative strengths and weaknesses. The practical implications of our study extend to various domains, including transportation management, urban planning, and public safety. By improving the accuracy and reliability of vehicle detection systems, particularly in adverse weather conditions, our approach can enhance the efficiency of traffic management operations, reduce congestion, and mitigate risks associated with adverse weather events. Policymakers and practitioners may benefit from integrating robust detection technologies into existing infrastructure and decision-making processes to improve transportation resilience and sustainability.

5. Conclusion

In addition to the comprehensive analysis and evaluation of vehicle detection methods under different weather conditions, this study introduces a novel approach, Improved GMM, to address the inherent challenges in traditional methodologies. Unlike previous approaches that may focus on specific weather scenarios or rely solely on image processing techniques, the Improved GMM leverages advanced features such as adaptive time-varying learning rates and outlier processing to enhance adaptability and reliability across diverse environmental settings. Through extensive experimentation and evaluation using real-world datasets, our findings demonstrate the superiority of the Improved GMM over traditional methods, particularly in accurately detecting vehicles under challenging weather conditions. The Improved GMM exhibits remarkable adaptability and robustness, showcasing its potential to significantly improve the accuracy and reliability of traffic management systems in real-world scenarios. Furthermore, this study provides valuable insights into the performance of both traditional and novel methods, highlighting the importance of balancing computational efficiency and performance in real-time applications. While the traditional GMM method may excel in specific scenarios, the Improved GMM emerges as the preferred choice for its consistent and superior performance across various environmental settings.

In conclusion, this study contributes to the advancement of vehicle detection systems by introducing a novel approach that addresses the limitations of traditional methodologies. The findings offer valuable implications for researchers aiming to improve the accuracy and reliability of traffic management systems in real-world scenarios. Future research directions may involve further exploration of the Improved GMM algorithm's implications, particularly in scenarios with varying weather conditions and lighting, to enhance its effectiveness and applicability in critical applications such as autonomous driving systems and surveillance platforms.

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