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Vehicle Detection Based on Improved Gaussian Mixture Model for Different Weather Conditions

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ABSTRACT

In the field of vehicle traffic management, the accurate detection of vehicles under varying weather conditions remains a critical challenge. This paper introduces a new method to detect vehicles in different weather conditions, such as regular daytime and nighttime, as well as rainy conditions. Current vehicle detection systems often struggle to work well in bad weather, which can be dangerous. The proposed method is an Improved Gaussian Mixture Model (Improved GMM) designed to adapt to various weather situations. The goal is to ensure accurate and reliable vehicle detection in all conditions, which is important for traffic management. The Improved GMM was tested using real datasets, enabling the simulation of real-world scenarios and the evaluation of its performance. Appropriate measures were selected to assess its effectiveness. Results indicate that the Improved GMM significantly outperforms the traditional GMM in vehicle detection, particularly in challenging weather conditions. Furthermore, the findings reveal that this method is not only effective in diverse weather conditions but also maintains a high level of computational efficiency. In summary, the research suggests that employing the Improved GMM for vehicle detection in different weather conditions can substantially enhance traffic management systems, ensuring reliability regardless of the weather.

Keywords:
Improved Gaussian Mixture Model; vehicle detection; background subtraction

1. Introduction

In recent years, there has been a growing interest in the field of computer vision when it comes to understanding and working with video sequences. This interest has mainly been driven by the increasing importance of applications like video surveillance and multimedia, where accurately detecting vehicles in videos is crucial. One essential aspect of video analysis is recognizing motion in video sequences. This study plays a significant role in tasks like finding specific objects in videos (target detection) [1-3] and understanding how things are moving or behaving in the video (behavior interpretation) [4-5]. To do this, a fundamental step in video analysis is distinguishing between objects that are in the foreground (the main focus) and those that are in the background. This process

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can be done using various methods, depending on the type of data available and how the objects in the video are moving.

Background subtraction is a technique used in video processing to separate objects from the background. However, it can be unstable and easily affected by changes in the environment or interference. To address these issues, researchers have come up with different methods for background subtraction. These methods include basic models [6], background estimation [7], background clustering [8], and mathematical models like subspace learning, kernel density estimation, and GMM. One important application of background subtraction is in vehicle detection for traffic management, which enhances road safety and efficiency [9-11]. This method has led to a growing need for accurate and reliable background subtraction methods in various traffic situations, prompting researchers to work on better techniques.

The GMM is a statistical method commonly used for detecting objects. It works by describing objects as combinations of multiple bell-shaped curves called Gaussian distributions [12]. This approach has been successful in identifying objects in their surroundings and forms the basis for many vehicle detection systems [13, 14]. However, the traditional GMM has limitations when it comes to dealing with different weather conditions, such as normal daytime, normal nighttime, rainy daytime, and rainy nighttime conditions. These different weather conditions can pose significant challenges to standard vehicle detection algorithms. For instance, during rainy days and nights, visibility is often reduced, the appearance of objects changes, and there is the added complication of precipitation like rain. These factors can make it difficult for traditional methods to be consistently and accurately detect vehicles. As a result, the safety and efficiency of traffic systems may be compromised.

Given the challenges with current vehicle detection systems, especially when the weather is bad, there is a big problem: how can we create a better and more reliable way to detect vehicles that work well in all kinds of weather? This research shows that we need a method that is better than the usual vehicle detection systems that use GMM, especially when the weather is not ideal. The problem we are facing is that the usual methods do not work well in all weather conditions, so we need to come up with a new and innovative solution that can handle situations where the old methods fall short.

This research aims to propose and validate a novel approach to vehicle detection by introducing an Improved GMM. Instead of using the traditional GMM, this new method makes it better at handling different weather conditions. The goal is to show that the Improved GMM can be more accurate and dependable, especially when the weather is bad. This research could improve traffic management systems, even in tough conditions.

This paper is structured as follows: In section 2, we discuss the regular GMM and explain the new Improved GMM, including the changes we made and the important parts it has. Section 3 looks closely at the results we got and analyzes them thoroughly. Lastly, in section 4, we wrap up the study and suggest some ideas for future research.

2. Methodology

2.1 Introduction of GMM

The GMM is a commonly used background subtraction algorithm in computer vision and image processing. It is widely used for detecting moving objects or foreground regions within a video sequence by modeling the background as a mixture of Gaussian distributions. GMM is particularly effective when the background is dynamic, non-stationary, or exhibits gradual illumination changes, making it suitable for a wide range of real-world scenarios. To handle different weather conditions in background modeling, researchers have introduced a concept called multimodal probability density functions (PDFs). To illustrate, in the work by Stauffer and Grimson [12], they describe a technique where each pixel in an image is represented using a combination of multiple Gaussian distributions. Therefore, the representation of the likelihood of color occurring at a specific pixel location denoted a x_t is as follows:

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

where $\Phi\left(x_t, \mu_k, \sigma_{k,t}\right)$ represents the k^{th} Gaussian model and $\Pi_{k,t}$ denotes its weight. Subsequently, $\Phi\left(x_t, \mu_k, \sigma_{k,t}\right)$ is formulated as follows:

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

For the sake of computational efficiency and as advised by Stauffer and Grimson [12], an assumption is made that the covariance matrix takes on a diagonal form. The parameters of a matched component, specifically the Gaussian model for which x_t falls within 2.5 standard deviations from its mean, are updated using the following procedure:

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

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

where α represents a learning rate and β is defined as a second learning rate given by $\beta = \alpha \cdot \Phi\left(x_t, \mu_{k,t}, \sigma_{k,t}\right)$, the parameters $\mu_{k,t}$ and $\sigma_{k,t}$ of unmatched distributions remain unchanged while their weight undergoes reduction as follows: $\Pi_{k,t} = (1-\alpha)\Pi_{k,t-1} + \alpha\psi_{k,t}$, causing a decay effect. When there is no matching component for x_t, the one with the lowest weight is replaced by a Gaussian distribution with a mean value of x_t an initial variance of σ_0 and a small weight Π_0. Once all Gaussian components have been updated, the k^{th} weights $\Pi_{k,t}$ are normalized to ensure that they collectively sum up to 1. Next, the k^{th} distributions are arranged in order of fitness value, which is calculated as $\Pi_{k,t}/\sigma$. Only the B most dependable distributions, determined based on this fitness value, are selected to constitute the background model.

$$B = argmin\left(\sum_{k=1}^{b} \Pi_k > th\right) \tag{5}$$

Here, th represents a threshold value. Subsequently, pixels that deviate by more than 2.5 standard deviations from any of the B selected distributions are categorized as “in motion.”

2.2 Improved GMM

Vehicle traffic management needs to work well in different lighting and should effectively remove unwanted noise or unclear pixels. A common method for identifying vehicle detection is background subtraction, which helps create a clear, noise-free image by highlighting the moving parts (foreground) and ignoring the stationary background. The idea is that each pixel's intensity (or brightness) is usually consistent when an object stays still for a while. However, in real life, objects are not a single color but reflect various shades depending on the light around them. Therefore, it is important first to identify and separate (segment) the area of interest and then decide if the pixels in that area are part of the moving object or the background. This method is crucial for accurately identifying vehicle detection. This improvement aims to overcome the traditional limitations of GMM by incorporating features such as a time-varying learning rate. Consequently, these enhancements effectively tackle the challenges associated with weather condition variations and contribute to improved detection accuracy. To ensure a rapid adaptation to alterations in dynamic (moving) regions and a gradual adjustment in static (non-moving) areas, this improvement allows for dynamic adjustments in the weights assigned to incoming data samples [15]. Instead of relying on fixed learning rate parameters, this study introduced a time-dependent learning rate parameter, as detailed in the following theorem.

The basis for the proposed improved GMM draws from the improvements presented by Stauffer and Grimson [12] in the mean, covariance, and weight equations. These enhancements can be summarized as follows:

$$\mu_{k,t} = (1-\beta(t))\mu_{k,t-1} + \beta(t)x_t \tag{6}$$

$$\sigma_{k,t}^2 = (1-\beta(t))\sigma_{k,t-1}^2 + \beta(t)\left(x_t - \mu_{k,t}\right)\left(x_t - \mu_{k,t}\right)^T \tag{7}$$

$$\Pi_{k,t} = (1-\alpha)\Pi_{k,t-1} + \alpha \tag{8}$$

The value of the time-varying learning rate $\beta(t)$ is determined using the Robbins-Monro stochastic approximation method, which involves solving the recursive equation.

$$\beta(t) = \frac{c}{c+t} \tag{9}$$

Here, c is a constant parameter that controls the learning rate. The Robbins-Monro stochastic approximation method is an iterative technique employed to solve non-linear equations like $f(x) = 0$ [16, 17]. This method has its roots in stochastic gradient descent, a widely used optimization algorithm in machine learning and various computer science areas [18]. The update rule presented in Eq. (9) satisfies the Robbins-Monro conditions, ensuring the convergence of the stochastic approximation method. These conditions can be summarized as follows:

i. Condition 1: The sum of the learning rates $\Sigma_t \beta(t)$] should diverge, which can be expressed as:

$$\sum_t \beta(t) = \frac{c}{c+1} + \frac{c}{c+2} + \frac{c}{c+3} + \ldots + \frac{c}{c+t} \tag{10}$$

This sum diverges as t approaches infinity, meeting condition 1.

ii. Condition 2: The sum of the squares of the learning rates $\sum_t \beta^2(t)$ should converge, given by:

$$\sum_t \beta^2(t) = \frac{c^2}{(c+1)^2} + \frac{c^2}{(c+2)^2} + \frac{c^2}{(c+3)^2} + \ldots + \frac{c^2}{(c+t)^2} \tag{11}$$

This sum diverges as t approaches infinity, meeting condition 2.

Meeting both conditions confirms the validity of the updated rule in Eq. (9) within the context of the Robbins-Monro stochastic approximation method [19]. This rule ensures that the learning algorithm converges as the number of iterations t approaches infinity. It assigns more significance to newer data while considering the importance of past data, with the choice of the constant parameter c depending on the specific data characteristics and application requirements [20]. This novel improvement is also a complementary part of Robust GMM, which has been integrated with other enhancements [21].

The selection of the c parameter value relies on a priori knowledge of the data, considering factors like potential value ranges for model parameters and the data distribution. It is important to note that the choice of c significantly impacts the method's performance. Selecting an incorrect c value can result in either slow convergence or instability. The t value, typically incremented by one with each iteration, is also crucial. It represents the number of algorithm iterations or observations analyzed. Both the initial t value and its growth rate influence convergence speed and algorithm stability. If the initial t value is too small, it can lead to an excessively large step size, causing instability and an overestimation of the optimal solution. Conversely, if the initial t value is too high, the step size may become extremely small, resulting in slow convergence and the potential for getting stuck with a suboptimal solution. The growth rate of t also plays a role in convergence speed and algorithm stability. A rapid increase in t can lead to faster convergence but may introduce instability and overestimation. Conversely, slower growth in t results in more stable behavior but leads to slower convergence.

3. Results

The simulations were conducted on a diverse set of video sequences covering different weather conditions encompassing clear and rainy scenarios to assess the performance of the proposed methods. This inclusion allowed us to study how the model performed under different weather situations. These videos were collected from the actual dataset of Kuala Lumpur traffic obtained from Sena Traffic Systems Sdn. Bhd. Our local Malaysian industrial collaborator provided these datasets and served as invaluable case studies, aligning precisely with the research problem we were addressing.

By utilizing this dataset, the aim was to comprehensively examine and validate the proposed model's accuracy in addressing the core challenges of vehicle detection within traffic flow analysis. For the real videos, obtaining ground truth data was more challenging. The ground truth available for the reference images within those real videos was manually annotated. A uniform parameter set was applied across all the videos, and these parameters were chosen based on empirical analysis. The results obtained from the videos, which included different levels of complexity, demonstrated that the default parameter values worked effectively in various situations. The specific parameter values used are listed in Table 1

Table 1
The values of the parameter

K	α	λ	γ	d	c
3	0.9	0.1	0.5	5	100

Background subtraction methods based on GMM have limitations due to their assumption of certain parameters. The performance of these methods varies depending on the challenges encountered. Standard performance metrics are used to assess the performance and robustness of this method against different weather conditions. These metrics include Recall (RCL) in Eq. (12), Precision (PRC) in Eq. (13), F-measure (FMS) in Eq. (14), False Positive Rate (FPR) in Eq. (15), False Negative Rate (FNR) in Eq. (16), Accuracy (ACY) in Eq. (17) and Wrong Classifications Percentage (WCP) in Eq. (18) as defined by Goyette *et al.*, [22].

$$RCL = \frac{TP}{FN+TP} \tag{12}$$

$$PRC = \frac{TP}{TP+FP} \tag{13}$$

$$FMS = \frac{2\times RCL\times PRC}{RCL+PRC} \tag{14}$$

$$FPR = \frac{FP}{FP+TN} \tag{15}$$

$$FNR = \frac{FN}{FN+TP} \tag{16}$$

$$ACY = \frac{TP+TN}{TP+FP+FN+TN} \tag{17}$$

$$\mathrm{WCP} = \frac{\mathrm{FP+FN}}{\mathrm{TP+FP+FN+TN}} \tag{18}$$

Recall, Precision, and F-measure gauge how accurately the method detects pixels as either foreground or background. These metrics are determined by counting the number of true positives (TP), which are correctly classified foreground pixels; false positives (FP), which are background pixels mistakenly classified as foreground; true negatives (TN), which are background pixels correctly classified as background, and false negatives (FN), which are foreground pixels mistakenly classified as background [23-25].

The performance between traditional GMM and Improved GMM is compared based on the analysis using these quantitative parameters, as presented in Table 2. The best values are indicated in bold.

Table 2
The summary of average metrics of GMM and Improved GMM

Method	RCL	PRC	FMS	FPR	FNR	ACY	WCP
GMM [15]	0.3983	**0.6744**	0.4815	**0.0303**	0.6017	0.8661	0.1339
Improved GMM	**0.9310**	0.4837	**0.6110**	0.0418	**0.0690**	**0.9559**	**0.0441**

RCL measures the method's ability to identify all relevant moving objects (cars) correctly. A higher RCL value indicates that the Improved GMM is significantly better at capturing relevant objects compared to the GMM. In other words, the Improved GMM has a lower rate of missing objects in the foreground. PRC determines the method's accuracy in correctly identifying relevant objects among all moving objects classified as positive (true and false positives). Here, the GMM has a higher PRC, meaning it has fewer FP compared to the Improved GMM. The FMS is the harmonic mean of PRC and RCL. The Improved GMM has a higher FMS, indicating a better balance between PRC and RCL. This result indicates that it performs better overall in terms of finding relevant objects while keeping FP in check. FPR evaluates the rate at which the model incorrectly classifies the background as foreground. The GMM has a lower FPR, meaning it is better at avoiding false alarms compared to the Improved GMM. Meanwhile, FNR measures the rate at which the model incorrectly classifies the foreground as background. The Improved GMM has a significantly lower FNR, indicating that it misses fewer foreground objects compared to the GMM. On the other hand, ACY assesses the overall correctness of the model's predictions. The Improved GMM has a higher accuracy, meaning it correctly classifies a larger proportion of the data compared to the GMM. WCP represents the percentage of misclassified instances. The Improved GMM has a significantly lower WCP, indicating a lower rate of misclassifications compared to the GMM. In summary, the Improved GMM outperforms the GMM in terms of RCL, FMS, ACY, and the overall rate of misclassifications (WCP). However, the GMM has a higher PRC and a slightly lower FPR.

Figure 1 in the paper presents a bar graph that compares the F-measure results of the Improved GMM and the GMM in different weather conditions. Based on the graph, the Improved GMM outperforms the GMM in F-measure in all weather conditions. Specifically, the Improved GMM demonstrates higher F-measure scores during normal days, rainy days, and rainy nights, indicating its robustness in complex weather conditions. On the other hand, the GMM method shows the highest F-measure score during a normal night, suggesting its efficacy in simpler scenarios. The results of this study suggest that the Improved GMM is a more accurate and reliable method for vehicle detection in various weather conditions. The improved GMM's ability to adapt to different weather conditions through its time-varying learning rate and background subtraction techniques allows it to effectively handle variations in weather conditions, leading to improved detection accuracy. These findings have important implications for traffic management and safety, as accurate vehicle detection is crucial for effective traffic flow and accident prevention. The Improved GMM's superior performance in different weather conditions could lead to more reliable and efficient traffic management systems, even in challenging weather conditions.

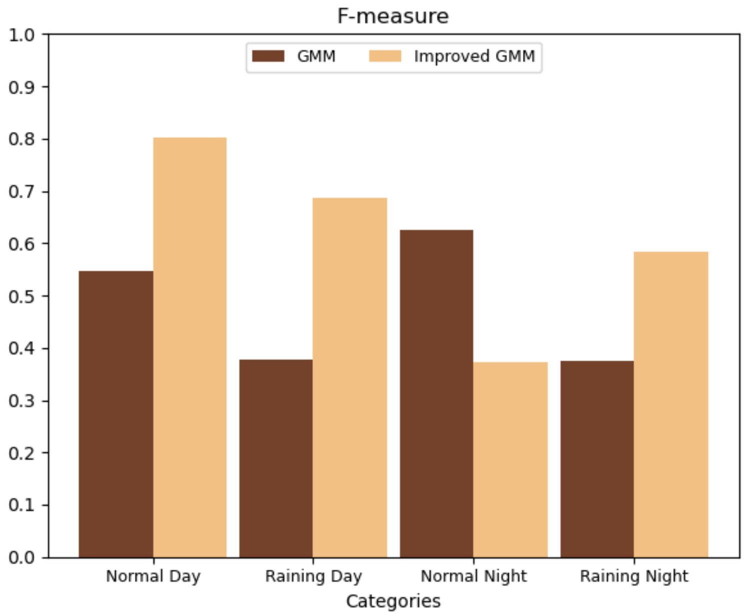


Fig. 1. Comparison of F-measure result of GMM and Improved GMM.

Figure 2 reveals the AC results of two methods for different weather conditions. The data indicates that all methods perform exceptionally well, with accuracies mostly above 0.95. However, there are noticeable differences in their performances. Based on the graph, it is evident that Improved GMM consistently outperforms the standard GMM in all tested conditions. It exhibits higher accuracy levels in both normal and challenging weather conditions. Improved GMM appears more robust to weather conditions, such as rain, as it maintains high accuracy levels on rainy days and nights. Both methods show higher accuracy in normal Night conditions compared to normal days. This result might be attributed to improved visibility and lighting conditions during the night. Improved GMM seems to be the better choice due to its consistently higher accuracy. It can be particularly valuable in scenarios where accurate vehicle detection is critical, such as autonomous driving or surveillance systems. Overall, Improved GMM appears to be a more accurate method for vehicle detection under various conditions, offering better performance than the GMM. This information can be valuable for researchers and practitioners looking to improve vehicle detection systems' accuracy and reliability.

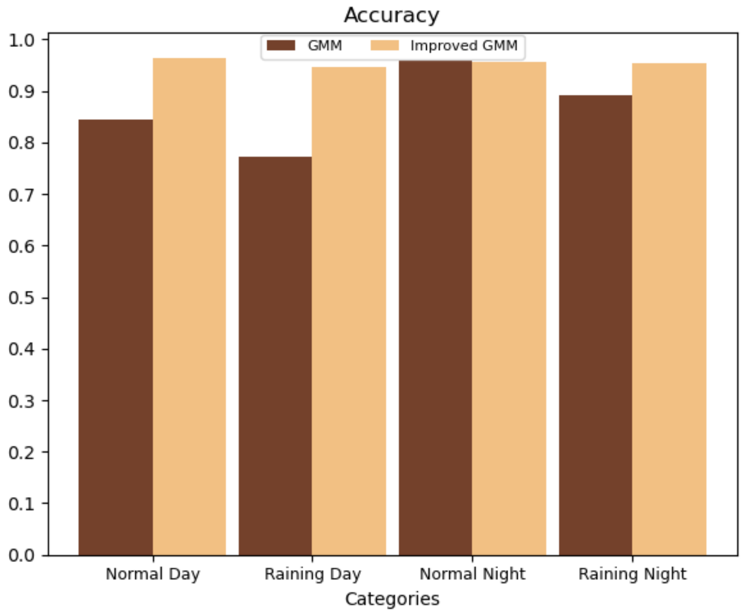


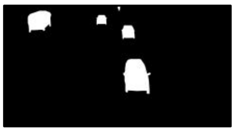
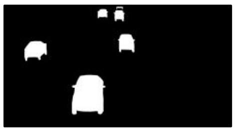
Fig. 2. Comparison of accuracy result of GMM and Improved GMM.

Table 3 presents the comparison of segmentation masks for the real dataset reveals interesting insights into the performance of the methods, GMM and Improved GMM, in detecting vehicles under different weather conditions. This table displays the original video frames (input) captured by the camera in the first column. The second column showcases the ground truth (GT), a manually created mask indicating the vehicle locations in these frames. The third and fourth columns exhibit the segmentation masks GMM and Improved GMM generated, respectively. The goal is to assess how well these masks accurately represent the vehicles' positions and shapes in the video frames.

According to the findings in Table 3, the segmentation masks obtained using the Improved GMM method demonstrate satisfactory detection results, particularly evident in scenarios during normal day conditions. The Improved GMM method effectively captures the location and shape of the vehicles with a fair degree of accuracy, indicating its robustness in typical daytime traffic scenarios. This result suggests that the Improved GMM method accurately identifies and delineates vehicles in clear, well-lit conditions, which are common during normal daytime traffic. Conversely, the GMM method exhibits competitive performance, particularly in specific scenarios. While the Improved GMM method shows strength in normal day conditions, the GMM method may demonstrate its efficacy in other scenarios, such as normal night conditions. This result implies that the GMM method may have specific strengths in simpler, well-lit scenarios, showcasing its effectiveness in certain lighting and environmental conditions.

However, it is important to note that both methods exhibit false positives and negatives to some extent, indicating that neither method is without limitations. The study emphasizes the development of an algorithm that aims to balance computational efficiency and performance, intending to make it feasible for real-time applications where processing time is limited. Additionally, the increased complexity introduced by the Improved GMM algorithm warrants further evaluation to fully understand its implications, particularly in scenarios with varying weather conditions and lighting.

Table 3
The comparison of segmentation masks for the real dataset

Weather Condition	Normal Day	Raining Day	Normal Night	Raining Night
Input				
Ground Truth				
GMM [15]				
Improved GMM				

4. Conclusions

This research has introduced and validated an innovative approach to vehicle detection using the Improved GMM. The study addressed the critical challenge of accurately detecting vehicles under varying weather conditions, including normal daytime, nighttime, and rainy conditions. Current vehicle detection systems often struggle in adverse weather conditions, seriously affecting traffic management and safety. The study's results demonstrate that the Improved GMM significantly outperforms the traditional GMM in vehicle detection, especially in challenging weather conditions. Key performance metrics also consistently favored the Improved GMM. This result indicates that the Improved GMM excels in capturing relevant objects in the foreground, maintaining a balance between precision and recall, achieving higher accuracy, and reducing misclassifications. It also adapts effectively to different weather conditions, making it a robust solution for accurate vehicle detection. Adopting the Improved GMM for vehicle detection in diverse weather conditions can significantly improve the accuracy, reliability, and effectiveness of traffic management systems. This advancement has important implications for various applications, including autonomous driving, surveillance systems, and road safety. As traffic management continues to evolve, the Improved GMM offers a promising solution to address the challenges of adverse weather conditions, ultimately contributing to safer and more efficient transportation networks. Future research may further refine the Improved GMM algorithm and explore its application in real-world traffic management scenarios.

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References

[1] Liu, Tong, Xiaochun Cao, and Jianmin Jiang. "Visual object tracking with partition loss schemes." *IEEE Transactions on Intelligent Transportation Systems* 18, no. 3 (2016): 633-642. https://doi.org/10.1109/TITS.2016.2585663

[2] Waykole, Tushar S., and Yogendra Kumar Jain. "Detecting and tracking of moving objects from video." *International Journal of Computer Applications* 81, no. 18 (2013): 0975-8887. https://doi.org/10.5120/14224-2410

[3] Dai, Yimian, Yiquan Wu, Fei Zhou, and Kobus Barnard. "Attentional local contrast networks for infrared small target detection." *IEEE transactions on geoscience and remote sensing* 59, no. 11 (2021): 9813-9824. https://doi.org/10.1109/TGRS.2020.3044958

[4] Devanne, Maxime, Stefano Berretti, Pietro Pala, Hazem Wannous, Mohamed Daoudi, and Alberto Del Bimbo. "Motion segment decomposition of RGB-D sequences for human behavior understanding." *Pattern Recognition* 61 (2017): 222-233. https://doi.org/10.1016/j.patcog.2016.07.041

[5] Zhang, Xiao-Yu, Haichao Shi, Changsheng Li, Kai Zheng, Xiaobin Zhu, and Lixin Duan. "Learning transferable self-attentive representations for action recognition in untrimmed videos with weak supervision." In *Proceedings of the AAAI conference on artificial intelligence* 33, no. 01, (2019): 9227-9234. https://doi.org/10.1609/aaai.v33i01.33019227

[6] Bouwmans, Thierry. "Recent advanced statistical background modeling for foreground detection-a systematic survey." *Recent Patents on Computer Science* 4, no. 3 (2011): 147-176. https://doi.org/10.2174/1874479611104030147

[7] Yu, Xiaqiong, Xiangning Chen, and Heng Zhang. "Accurate motion detection in dynamic scenes based on ego-motion estimation and optical flow segmentation combined method." In *2011 Symposium on Photonics and Optoelectronics (SOPO)*, pp. 1-4. IEEE, 2011. https://doi.org/10.1109/SOPO.2011.5780637

[8] Shah, Munir, Jeremiah D. Deng, and Brendon J. Woodford. "Video background modeling: recent approaches, issues and our proposed techniques." *Machine vision and applications* 25 (2014): 1105-1119. https://doi.org/10.1007/s00138-013-0552-7

[9] Ge, Dong-yuan, Xi-fan Yao, Wen-jiang Xiang, and Yue-ping Chen. "Vehicle detection and tracking based on video image processing in intelligent transportation system." *Neural Computing and Applications* 35, no. 3 (2023): 2197-2209. https://doi.org/10.1007/s00521-022-06979-y

[10] Zhong, Kaiyang, Zhaoyangm Zhang, and Zhengyu Zhao. "Vehicle detection and tracking based on GMM and enhanced camshift algorithm." *Journal of Electrical and Electronic Engineering* 6, no. 2 (2018): 40-45. https://doi.org/10.11648/j.jeee.20180602.11

[11] Mittal, Usha, and Priyanka Chawla. "Vehicle detection and traffic density estimation using ensemble of deep learning models." *Multimedia Tools and Applications* 82, no. 7 (2023): 10397-10419. https://doi.org/10.1007/s11042-022-13659-5

[12] Stauffer, Chris, and W. Eric L. Grimson. "Adaptive background mixture models for real-time tracking." In *Proceedings. 1999 IEEE computer society conference on computer vision and pattern recognition (Cat. No PR00149)*, vol. 2, pp. 246-252. IEEE, 1999. https://doi.org/10.1109/CVPR.1999.784637

[13] Swathi, Patakamudi, Miriyala SaiShree, Dara Sai Tejaswi, Venubabu Rachapudi, Mohammad AmanullaKhan, and Dinesh Kumar Anguraj. "A novel survey on ml based vehicle detection for dynamic traffic control." In *2023 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS)*, pp. 219-225. IEEE, 2023. https://doi.org/10.1109/ICSCDS56580.2023.10104771

[14] Indu, T., Y. Shivani, Akhila Reddy, and S. Pradeep. "Real-time classification and counting of vehicles from cctv videos for traffic surveillance applications." *Turkish Journal of Computer and Mathematics Education (TURCOMAT)* 14, no. 2 (2023): 684-695. https://doi.org/10.17762/turcomat.v14i2.13700

[15] Fried, Jonathan, Fernando Lizarralde, and Antonio C. Leite. "Adaptive image-based visual servoing with time-varying learning rates for uncertain robot manipulators." In *2022 American Control Conference (ACC)*, pp. 3838-3843. IEEE, 2022. https://doi.org/10.23919/ACC53348.2022.9867387

[16] Toulis, Panos, Thibaut Horel, and Edoardo M. Airoldi. "The proximal Robbins–Monro method." *Journal of the Royal Statistical Society Series B: Statistical Methodology* 83, no. 1 (2021): 188-212. https://doi.org/10.1111/rssb.12405

[17] Robbins, Herbert, and Sutton Monro. "A stochastic approximation method." *The annals of mathematical statistics* (1951): 400-407. https://doi.org/10.1214/aoms/1177729586

[18] Watanabe, Masafumi. " On Robbins-Monro stochastic approximation method with time varing observations." (1975): 73-91. https://doi.org/10.5109/13096

[19] Liu, Chen-Wei, Björn Andersson, and Anders Skrondal. "A constrained metropolis–hastings Robbins–Monro algorithm for Q matrix estimation in DINA models." *Psychometrika* 85, no. 2 (2020): 322-357. https://doi.org/10.1007/s11336-020-09707-4

[20] Amini Tehrani, Hamed, Ali Bakhshi, and Tony TY Yang. "Online jointly estimation of hysteretic structures using the combination of central difference Kalman filter and Robbins–Monro technique." *Journal of Vibration and Control* 27, no. 1-2 (2021): 234-247. https://doi.org/10.1177/1077546320925604

[21] Mohd Aris, Nor Afiqah, and Siti Suhana Jamaian. "Background subtraction challenges in motion detection using Gaussian mixture model: a survey." *Background subtraction challenges in motion detection using* 12, no. 3 (2023): 1007-1018. https://doi.org/10.11591/ijai.v12.i3.pp1007-1018

[22] Goyette, Nil, Pierre-Marc Jodoin, Fatih Porikli, Janusz Konrad, and Prakash Ishwar. "Changedetection. net: A new change detection benchmark dataset." In *2012 IEEE computer society conference on computer vision and pattern recognition workshops*, pp. 1-8. IEEE, 2012. https://doi.org/10.1109/CVPRW.2012.6238919

[23] Roslan, Rudee, Sokchoo Ng, and Lee Chin Yee. "Machine learning techniques for sustainable smart cities traffic management." *Journal of Advanced Research in Applied Sciences and Engineering Technology* 33, no. 1 (2023): 246-255. https://doi.org/10.37934/araset.33.1.246255

[24] Ankireddy, Priyanka, and V. Lokeswara Reddy. "Automated recognition and tracking of stationary and moving cars in images and videos: YOLOv5 and SSD analysis." *Journal of Advanced Research in Applied Sciences and Engineering Technology* 40, no. 2 (2024): 221-241. https://doi.org/10.37934/araset.40.2.221241

[25] Zaman, Fadhlan Hafizhelmi Kamaru, Nooritawati Md Tahir, Yusnani Mohd Yusoff, Norashikin M. Thamrin, and Ahmad Hafizam Hasmi. "Human detection from drone using you only look once (YOLOv5) for search and rescue operation." *Journal of Advanced Research in Applied Sciences and Engineering Technology* 30, no. 3 (2023): 222-235. https://doi.org/10.37934/araset.30.3.222235