ADAPTIVE BACKGROUND SUBTRACTION TECHNIQUE WITH UNIQUE FEATURE REPRESENTATION FOR VEHICLE COUNTING

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DEDICATION

Dedicated to Mom

Thank you so much

To Dad

I hope to be proud

To my Wife

You deserve a lot

To my Sons

I love you so much

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I am very grateful to **ALLAH** Subhanahu Wa Ta'ala who gave me an excellent family to live with and provided me the environment where I could finish my PhD and without whose it will would have been impossible to complete my degree.

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ABSTRACT

Vehicle detection is the first step towards a successful traffic monitoring system. Although there were many studies for vehicle detection, only a few methods dealt with a complex situation especially in traffic jams. In addition, evaluation under different weather conditions (rainy, foggy and snowy) is so important for some countries but unfortunately it is rarely performed. Presently, vehicle detection is mainly performed using background subtraction method, yet it still faces many challenges. In this thesis, an adaptive background model based on the approximate median filter (AMF) is developed. To demonstrate its potential, the proposed method is further combined with two proposed feature representation techniques to be employed in either global or local vehicle detection strategy. In the global approach, an adaptive triangle-based threshold method is applied following the proposed adaptive background method. As a consequence, a better segmented foreground can be differentiated from the background regardless of the different weather conditions (i.e., rain, fog and snowfall). Comparisons with the adaptive local threshold (ALT) and the three frame differencing methods show that the proposed method achieves the average recall value of 85.94% and the average precision value of 79.53% with a negligible processing time difference. In the local approach, some predefined regions, instead of the whole image, will be used for the background subtraction operation. Subsequently, two feature representations, i.e. normalized object-area occupancy and normalized edge pixels are computed and formed into a feature vector, which is then fed into the *k*-means clustering technique. As illustrated in the results, the proposed method has shown an increment of at least 10% better in terms of the precision and 4.5% in terms of F1 score when compared to the existing methods. Once again, even with this significant improvement, the proposed method does not incur noticeable difference in the processing time. In conducting the experiments, different standard datasets have been used to show the performance of the proposed approach. In summary, the proposed method has shown better performances compared to three frame differencing and adaptive local threshold methods.

ABSTRAK

Pengesanan kenderaan merupakan langkah permulaan kepada kejayaan sistem pengawasan trafik. Walaupun terdapat banyak kajian mengenai pengesanan kenderaan, hanya beberapa kaedah sahaja yang memfokuskan kepada situasi yang kompleks terutamanya ketika kesesakan lalu lintas. Tambahan pula, penilaian dalam keadaan cuaca yang berbeza (hujan, kabus dan salji) adalah penting untuk sesetengah negara, namun malangnya amat jarang dilaksanakan. Pada masa ini, pengesanan kenderaan adalah berdasarkan kaedah penolakan latar belakang, namun ianya masih berhadapan dengan pelbagai cabaran. Dalam tesis ini, model latar belakang berdasarkan penapis median anggaran adaptif (AMF) dibangunkan. Bagi mempamerkan potensi model ini, kaedah yang dicadangkan kemudiannya digabungkan dengan dua teknik pewakilan ciri iaitu dengan strategi pengesanan kenderaan secara global atau secara lokal. Di dalam pendekatan secara global, kaedah berdasarkan segitiga ambang adaptif diterapkan diikuti dengan kaedah latar belakang adaptif. Sebagai hasil, segmentasi latar hadapan yang lebih baik dapat dibezakan dengan latar belakang walaupun dalam keadaan cuaca yang berbeza (sebagai contoh: hujan, kabus dan salji). Perbandingan dengan ambang lokal adaptif (ALT) dan kaedah perbezaan tiga-kerangka menunjukkan bahawa strategi yang dicadangkan mencapai nilai purata pulangan sebanyak 85.94% dan nilai purata ketepatan sebanyak 79.53% dengan perbezaan masa pemprosesan yang boleh diabaikan. Bagi pendekatan secara lokal pula, hanya beberapa kawasan tertentu digunakan untuk operasi penolakan latar belakang, bukannya keseluruhan imej. Selanjutnya, dua pewakilan ciri, iaitu penghunian kawasan-objek dinormalisasi dan piksel sisi dinormalisasi, dikira dan dibentuk menjadi vektor ciri, yang kemudiannya dimasukkan ke dalam teknik pengklusteran *k-means*. Seperti mana yang digambarkan di dalam keputusan, kaedah yang dicadangkan telah menunjukkan peningkatan sekurang-kurangnya 10% lebih baik dari segi ketepatan dan 4.5% dari segi skor F1 apabila dibandingkan dengan kaedah-kaedah yang sedia ada. Demikian juga, walaupun dengan peningkatan yang ketara ini, kaedah yang dicadangkan tidak menunjukkan perbezaan yang nyata dalam masa pemprosesan. Dalam menjalankan eksperimen, set data piawaian yang berbeza telah digunakan untuk menunjukkan prestasi kaedah yang dicadangkan. Sebagai kesimpulan, kaedah yang dicadangkan telah menunjukkan prestasi yang lebih baik berbanding dengan kaedah perbezaan tiga-kerangka dan kaedah ambang lokal adaptif.

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LIST OF ABBREVIATIONS

ITS	-	Intelligent Transportation System
BS	-	Background Subtraction
SVM	-	Support Vector Machine
SIFT	-	Scale-Invariant Feature Transform
HOG	-	Histogram of Oriented Gradient
GMM	-	Gaussian Mixture Model
ALT	-	Adaptive Local Threshold
AMF	-	Approximate Median Filter
MI	-	Motion Index
TTD	-	Three Temporal Differencing
EM	-	Expectation Maximization
TP	-	True Positive
FP	-	False Positive
FN	-	False Negative
SD	-	Sigma Delta
MDPS	-	Motion Detection With Pyramid Structure
FCDH	-	Fuzzy Color Difference Histogram
CDH	-	Color Difference Histogram
MCC	-	Mathew's Correlation Coefficient
PCC	-	Percentage OF Correct Classification
ACTC	-	Average Computational Time Per Pixel Per Clock
ROI	-	Region of Interest
PTRF	-	Preset Threshold Based Region Filling Method
GDVM	-	Grey Level Differential Value Method
HE	-	Histogram Estimation
MRF	-	Markov Random Filed
CRF	-	Conditional Random Filed
JRF	-	Joint Random Filed
NR	-	Actual Number of Vehicles
ND	-	Number of Detected Vehicles
NOAO	-	Normalized object area occupancy
NAEP	-	Normalized aggregate edge pixel

LIST OF SYMBOLS

t	-	Frame number
b_g	-	Final background model
vg	-	Brightness value
N_{ref}	-	Number of pixels inside reference region
N	-	Number of pixels inside detection region
C	-	Current Frame
α	-	Learning rate for minimum value
β	-	Learning rate for maximum value
L'	-	Compensated image
Fl	-	Floor value
Ce	-	Ceiling value
L_{max}	-	Maximum intensity value
L_{min}	-	Minimum intensity value
c	-	Hypotenuse of the right angle
d	-	Maximum distance
$h(b_{max})$	-	Maximum histogram brightness value
$h(b_{min})$	-	Minimum histogram brightness value
R_i	-	Detection region number i
z_i^k	-	Local maximum point
E	-	Total edge pixels
J	-	Objective function
C_j	-	The center of cluster j
w_{opt}	-	Optimum frame number
f	-	Time needed to model background
gt	-	Ground truth
y	-	The output of multiplying the processing time with the difference between the background model output and the ground truth
P	-	Precision
R	-	Recall
F	-	F-measure

th	-	Threshold value
D_c	-	Binary motion detection mask
H	-	Height
W	-	Width

CHAPTER 1

INTRODUCTION

1.1 Overview

Intelligent Transportation Systems (ITS) can be defined as an application of new information and communication technologies of vehicles and roads for monitoring and managing traffic flow, decreasing congestion, improving security and optimizing the use of roads and transportation. In addition, it is useful in informing the drivers with the best route and the travel time for their destination in real-time [1]. Consequently, the development of ITS that extracts information from the traffic surveillance systems plays an important role in traffic management. It can ensuring better safety, directing smoother traffic flow, improving better traffic control in a congested urban area, and maintaining law and order of traffic and traffic signals [1,2].

One of the primary keys to ITS is the video-based surveillance system. It can be used for extracting some useful information such as vehicle counting, detection, tracking and recognition [3]. Traditionally, such information can be extracted by utilizing induction loops, passive magnetic sensors or pneumatic tubes under the road. These methods, in general, have limitations such as unable to detect stationary vehicles in addition to being highly complex in the hardware design, which translates to high cost [4]. Moreover, it can only extract local information from a specific location, causing limitation of the effectiveness of traffic management [5]. Therefore, the vision-based traffic monitoring system has attracted many researchers due to its two-fold advantages: less costly and easier to deploy [6]. Moreover, the advancement in the development of computational technologies has made vision-based vehicle counting an extremely attractive option for ITS. Nevertheless, such a system does face some challenges, such as changing lighting conditions, occlusion, and unfavorable weather conditions. Such problems have opened up a new horizon of research opportunities. Therefore, vehicle detection based on video camera becomes an active research field.

Figure 1.1 Main components in traffic management based on CCTV system [7].

Figure 1.1 shows the main components for a traffic management system based on a CCTV system. Two types of cameras can be used; analog or digital. A digital camera has an advantage over the analog as it has high storage capacity and high resolution. The captured video can be reviewed in real-time or recorded to manage the traffic flow. A central controller is responsible for some pre-processing steps such as shadow removal, noise removal, and other processing steps such as feature extraction and background subtraction processes. In addition, post-processing steps such as morphological operations can be included for better vehicle detection performance.

Monocular cameras are usually deployed for the human operator; however, stereo cameras can provide more depth information about the scene [8]. In monocular vision-based monitoring systems, a stationary camera is mounted at a high position, such as on the traffic lights or bridges to capture the passing vehicles. As a consequence, detecting vehicles can be affected by many challenges such as occlusion, changing lane and illumination conditions [9].

Conversely, stereo cameras and 3D modeling are deployed mainly to overcome the occlusion problem by improving the scene analysis obtained from the extracted depth information. These models, however, are computationally intensive, which, in return, affect the real-time speed and require prior tracking information [9]. For a typical surveillance system, a traffic camera network is used to analyze and extract parameters from the captured scene and then transmit them in real-time [10].

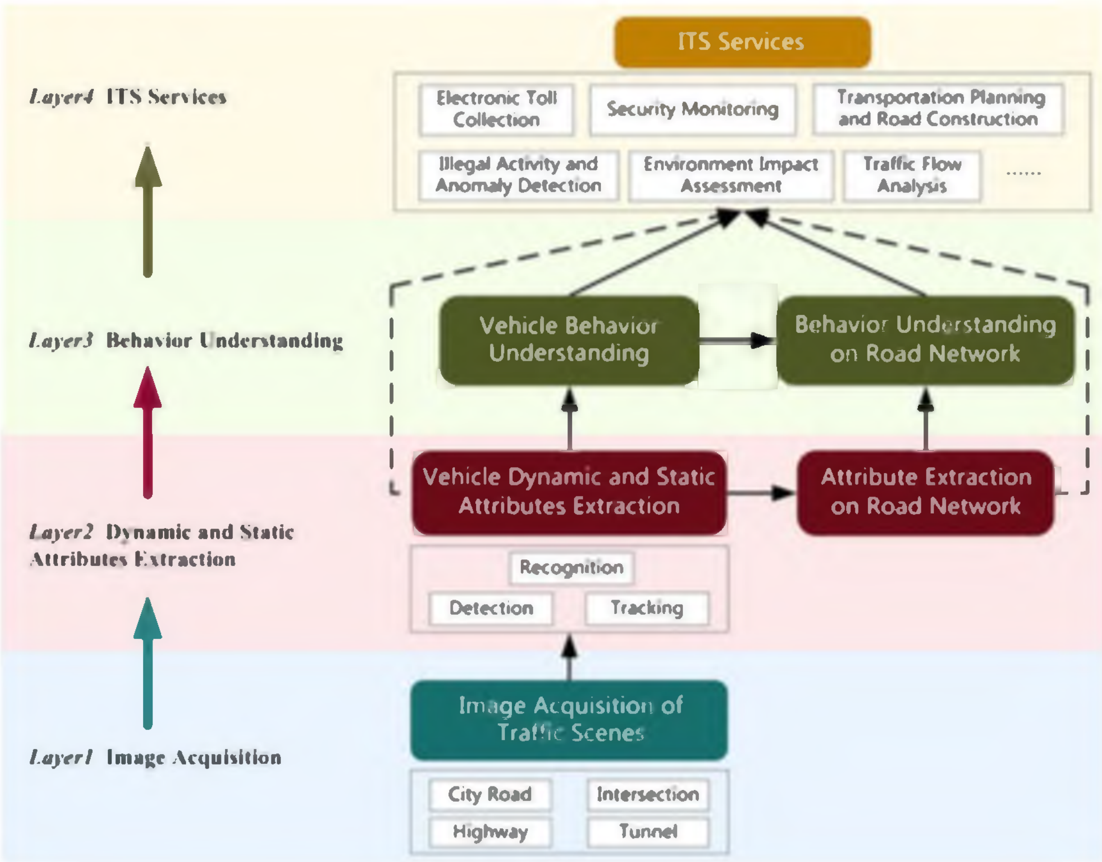

Figure 1.2 Main components of video surveillance systems [3].

Figure 1.2 illustrates the main components of a video surveillance system that consists of four layers:

- Layer 1: Image acquisition
- Layer 2: Dynamic and static attributes extraction
- Layer 3: Behavior understanding
- Layer 4: ITS services

The main function of layer 1 is to capture the traffic scene and extract images based on visual sensors. The purpose of layer 2 is to extract the dynamic attributes of vehicles such as velocity, vehicle trajectories and direction of movement, and static attributes of vehicles, which include its color, shape, and type. For layer 3, it aims to analyze and understand the dynamic and static attributes extracted from layer 2. Based on the extracted information, layer 4 provides ITS services such as traffic flow analysis, security monitoring, and transportation planning and road construction [3].

1.1.1 Vehicle Counting

Vehicle counting is a key feature in traffic flow estimation, which is one of the crucial features in the ITS [4]. Estimating the number of vehicles in ITS based on traffic video sequences is an important task, as it can provide reliable information for traffic management and control [11]. It can be used for understanding the traffic status, such as road-traffic density, lane occupancy, and congestion level, which helps drivers to avoid traffic congestion and spend less time in traffic. Subsequently, development authorities can use such information to design a better solution for road traffic.

1.1.2 Vehicle Detection

In any ITS, reliable vehicle detection is the first step to be achieved [12]. Subsequent applications such as vehicle counting, speed estimation and traffic flow depend on this first step. Hence, increasing the accuracy of the vehicle detection process will result in enhancing the efficiency of traffic control. Additionally, this will lead to improving the accuracy of other processes following it, such as vehicle tracking, vehicle trajectory, and behavior understanding, which is common in traffic surveillance systems [5].

1.2 Problem Statement

One of the main reasons for traffic congestion is the exponential increase in the number of vehicles concerning the number of roads [13]. In such a situation, developing a robust and reliable system that can estimate the traffic measurements in any weather conditions is necessary.

Vehicle detection can be considered as the first step for any ITS system. However, some challenges still remain particularly during adverse weather conditions. In such a situation, the exact shape or size of the moving vehicle may not be clearly detected leading to miscounting. The same problem is faced when one vehicle is being occluded by another vehicle.

Therefore, many approaches have been proposed for vehicle detection. However, a number of these approaches cannot be implemented in real-time due to their high computational complexity, such as the optical flow approach. On the other hand, some algorithms are so simple that they do not provide reliable reliable with a sufficient level of accuracy, such as the frame differencing approach. Additionally, the background subtraction (BS) approach still faces some challenges and the most challenging of all is in modeling of the background scene with acceptable degree of accuracy. Moreover, the performance of these algorithms decreases under unfavourable environment situations such as different weather conditions. As in many previous works, the worst accuracy for vehicle detection occurs when the visibility in the scene is poor or low such as during heavy rain condition.

Although there were many studies for vehicle detection, only a few methods dealt with the abnormal situation, especially in traffic jams [8,14,15]. In addition, evaluation under different weather conditions (Rainy, Foggy and Snowy) is so important for some countries, but unfortunately, it is rarely performed [8]. Furthermore, urban traffic is more challenging than highway traffic due to lower camera angles, which leads to occlusion and traffic density [8].

Moreover, the algorithm used for vehicle detection must be computationally efficient so that it can be implemented in real-time. This is essential so that the extracted information can be delivered to traffic users on time. Therefore, having an accurate algorithm, which can cope with these challenges and can be used in real-time, is very important.

1.3 Objectives

The undertaken research has the following objectives:

1. To propose an accurate vehicle detection and counting method that is robust under different conditions such as different weather conditions (sunny, rainy, foggy and snowy), and different traffic landscapes (urban and highway). An adaptive background modelling with feature representation techniques covering global and local approach is proposed.

2. To propose a detection model that is computationally efficient for possible real-time implementation. The proposed background method along with the local feature representation technique is further explored and analysed.

1.4 Scope

The scope of this research includes the followings:

a) This work will focus on vehicle detection and counting in urban and highway traffic under different illumination and weather conditions (Foggy, Rainy, Snowy and Sunny) using handcrafted methods.

b) The datasets used are standard datasets used by other researchers [17-20]. Additionally, data collected from urban roads in Malaysia, especially in the rainy condition, will also be used. This is because public dataset on different rainy condition is not currently available.

c) The collected videos were recorded from a stationary camera placed above the road so as to obtain two views; either the traffic is facing towards or away from the camera.

d) MATLAB software is used for testing the developed algorithms using Intel i5 core processor, 2.3 GHz speed and 4GB RAM operated under Windows 10.

1.5 Thesis Outline

This thesis is organized as follows: Chapter 1 presents an overview of the thesis. In this chapter the problem statement is presented along with the research objectives and scopes. Chapter 2 gives a survey of the existing techniques in vehicle detection and counting along with a summary of the existing methods. Chapter 3 details out the proposed background modeling in addition to the details of the two proposed feature representation techniques (global and local). The primary key technique is the adaptive background modelling based on Aproximate Median Filter (AMF). To proof the efficacy of the proposed method, it will then be applied to both global and local vehicle detection and counting methods. In the global method, the triangle threshold technique is implemented after the background subtraction operation to obtain foreground objects representing moving vehicles. While in the local method, two additional features are extracted from the background subtraction result performed in a predefined region. Next, k-means clustering technique is then applied for the vehicle detection and counting. Chapter 4 presents the results of the proposed adaptive background modelling accompanied by a comparison with some existing methods using existing benchmarks datasets and self-collected videos from different weather conditions. The results show the potential of the proposed methods compared to some existing methods in terms of accuracy and computational efficient. Finally, Chapter 5 summarizes the main contribution achieved by this thesis with suggestions for future work.

REFERENCES

[1] Asaidi, H., A. Aarab, and M. Bellouki. "Shadow elimination and vehicles classification approaches in traffic video surveillance context." *Journal of Visual Languages & Computing* 25.4 (2014): 333-345.

[2] Raghtate, Ganesh, and Abhilasha K. Tiwari. "Moving object counting in video signals." *International Journal of Engineering Research and General Science* 2.3 (2014): 215-220.

[3] Tian, Bin, Brendan Tran Morris, Ming Tang, Yuqiang Liu, Yanjie Yao, Chao Gou, Dayong Shen, and Shaohu Tang. "Hierarchical and networked vehicle surveillance in ITS: a survey." *IEEE transactions on intelligent transportation systems* 16.2 (2014): 557-580.

[4] Zhang, Yunsheng, Chihang Zhao, and Qiuge Zhang. "Counting vehicles in urban traffic scenes using foreground time-spatial images." *IET Intelligent Transport Systems* 11.2 (2016): 61-67.

[5] Wang, Yang. "Joint random field model for all-weather moving vehicle detection." *IEEE Transactions on Image Processing* 19.9 (2010): 2491-2501.

[6] Wang, Zilei, Xu Liu, Jiashi Feng, Jian Yang, and Hongsheng Xi "Compressed-domain Highway Vehicle Counting By Spatial and Temporal Regression." *IEEE Transactions on Circuits and Systems for Video Technology* 29.1 (2017): 263-274.

[7] Kurdi, Heba A. "Review of Closed Circuit Television (CCTV) Techniques for Vehicles Traffic Management." *International Journal of Computer Science & Information Technology* 6.2 (2014).

[8] Buch, Norbert, Sergio A. Velastin, and James Orwell. "A review of computer vision techniques for the analysis of urban traffic." *IEEE Transactions on Intelligent Transportation Systems* 12.3 (2011): 920-939.

[9] Van Pham, Huy, and Byung-Ryong Lee. "Front-view car detection and counting with occlusion in dense traffic flow." *International Journal of Control, Automation and Systems* 13.5 (2015): 1150-1160.

[10] Mandellos, Nicholas A., Iphigenia Keramitsoglou, and Chris T. Kiranoudis. "A background subtraction algorithm for detecting and tracking vehicles." *Expert Systems with Applications* 38.3 (2011): 1619-1631.

[11] Yang, Honghong, and Shiru Qu. "Real-time vehicle detection and counting in complex traffic scenes using background subtraction model with low-rank decomposition." *IET Intelligent Transport Systems* 12.1 (2017): 75-85.

[12] Dedeoglu, Yigithan. "*Moving object detection, tracking and classification for smart video surveillance*," Ph.D. dissertation, bilkent university, 2004.

[13] Dubey, Pooja P., and Prashant Borkar. "Review on techniques for traffic jam detection and congestion avoidance." *IEEE Conference on Electronics and Communication Systems*. 2015. 434-440.

[14] Wu, Bing-Fei, and Jhy-Hong Juang. "Adaptive vehicle detector approach for complex environments." *IEEE Transactions on Intelligent Transportation Systems* 13.2 (2012): 817-827.

[15] Feris, Rogerio, Russell Bobbitt, Sharath Pankanti, and Ming-Ting Sun. "Efficient 24/7 object detection in surveillance videos." *IEEE International Conference on Advanced Video and Signal Based Surveillance*. 2015. 1-6.

[16] Sivaraman, Sayanan, and Mohan Manubhai Trivedi. "Looking at vehicles on the road: A survey of vision-based vehicle detection, tracking, and behavior analysis." *IEEE Transactions on Intelligent Transportation Systems* 14.4 (2013): 1773-1795.

[17] A video database for testing changes detection algorithms. [Online]. Available: http://changedetection.net/ Last accessed: 22-4- 2019.

[18] Campus Sequence. [Online]. Available: http://perception.i2r.a-star.edu.sg/bk_model/bk_index.html

[19] Video Surveillance Online Repository. [Online]. Available: http://imagelab.ing.unimore.it/visor/video_details.asp?idvideo=111

[20] Image Sequence Server at Universität Karlsruhe. [Online]. Available: http://i21www.ira.uka.de/image_sequences/

[21] Xia, Yingjie, Chunhui Wang, Xingmin Shi, and Luming Zhang. "Vehicles overtaking detection using RGB-D data." *Signal Processing* 112 (2015): 98-109.

[22] Yao, Fan, and Chu Yanli. "Study of a new vehicle detection algorithm based

on linear CCD images." *Optik-International Journal for Light and Electron Optics* 126.24 (2015): 5932-5935.

[23] Gangodkar, Durgaprasad, Padam Kumar, and Ankush Mittal. "Robust segmentation of moving vehicles under complex outdoor conditions." *IEEE Transactions on intelligent transportation systems* 13.4 (2012): 1738-1752.

[24] Shukla, A. P., and Mona Saini. "“Moving Object Tracking of Vehicle Detection”: A Concise Review." *International Journal of Signal Processing, Image Processing and Pattern Recognition* 8.3 (2015): 169-176.

[25] Hadi, Raad Ahmed, Ghazali Sulong, and Loay Edwar George. "Vehicle detection and tracking techniques: a concise review." *International Journal of Signal & Image Processing 5.1 (2014): 1-12.*

[26] Chen, Yen-Lin, Bing-Fei Wu, Hao-Yu Huang, and Chung-Jui Fan. "A real-time vision system for nighttime vehicle detection and traffic surveillance." *IEEE Transactions on Industrial Electronics* 58.5 (2011): 2030-2044.

[27] Buch, Norbert, James Orwell, and Sergio A. Velastin. "Detection and classification of vehicles for urban traffic scenes." *IET International Conference on Visual Information Engineering.* 2008. 182-187.

[28] Brutzer, Sebastian, Benjamin Höferlin, and Gunther Heidemann. "Evaluation of background subtraction techniques for video surveillance." *IEEE Conference on Computer Vision and Pattern Recognition.* 2011. 1937-1944.

[29] Zhou, Jie, Dashan Gao, and David Zhang. "Moving vehicle detection for automatic traffic monitoring." *IEEE transactions on vehicular technology* 56.1 (2007): 51-59.

[30] Wu, K., Xu, T., Zhang, H., & Song, J. "Overview of video-based vehicle detection technologies. " IEEE *International Conference on Computer Science & Education.* 2011. 821-825.

[31] Huang, Shih-Chia, and Bo-Hao Chen. "Highly accurate moving object detection in variable bit rate video-based traffic monitoring systems." *IEEE transactions on neural networks and learning systems* 24.12 (2013): 1920-1931.

[32] Liu, Yuqiang, Bin Tian, Songhang Chen, Fenghua Zhu, and Kunfeng Wang. "A survey of vision-based vehicle detection and tracking techniques in ITS."

IEEE International Conference on Vehicular Electronics and Safety. 2013. 72-77.

[33] Parks, Donovan H., and Sidney S. Fels. "Evaluation of background subtraction algorithms with post-processing." *IEEE International Conference on Advanced Video and Signal Based Surveillance.* 2008. 192-199.

[34] Nunes, E., A. Conci, and A. Sanchez. "Robust background subtraction on traffic videos." *IEEE International Conference on Systems, Signals and Image Processing.* 2011. 1-4.

[35] Yaghoobi Ershadi, Nastaran, and José Manuel Menéndez. "Vehicle Tracking and Counting System in Dusty Weather with Vibrating Camera Conditions." *Journal of Sensors* 2017.

[36] Engel, Juan Isaac, Juan Martín, and Raquel Barco. "A low-complexity vision-based system for real-time traffic monitoring." *IEEE Transactions on Intelligent Transportation Systems* 18.5 (2017): 1279-1288.

[37] Sureshkumar, C. "Background subtraction in dynamic environment based on Modified Adaptive GMM with TTD for moving object detection." *Journal of Electrical Engineering & Technology* 10.1 (2015): 372-378.

[38] Xia, Yingjie, Xingmin Shi, Guanghua Song, Qiaolei Geng, and Yuncai Liu. "Towards improving quality of video-based vehicle counting method for traffic flow estimation." *Signal Processing* 120 (2016): 672-681.

[39] El Harrouss, Omar, Driss Moujahid, and Hamid Tairi. "Motion detection based on the combining of the background subtraction and spatial color information." *IEEE International Conference in Intelligent Systems and Computer Vision.* 2015. 1-4.

[40] Panda, Deepak Kumar, and Sukadev Meher. "Detection of moving objects using fuzzy color difference histogram based background subtraction." *IEEE Signal Processing Letters* 23.1 (2015): 45-49.

[41] Yang, Yizhong, Qiang Zhang, Pengfei Wang, Xionglou Hu, and Nengju Wu. "Moving object detection for dynamic background scenes based on spatiotemporal model." *Advances in Multimedia* 2017.

[42] Chen, Xiaorong, Chuanli Xi, and Jianghui Cao. "Research on moving object detection based on improved mixture Gaussian model." *Optik* 126.20 (2015): 2256-2259.

[43] Cheng, Hsu-Yung, Chih-Chia Weng, and Yi-Ying Chen. "Vehicle detection in aerial surveillance using dynamic Bayesian networks." *IEEE transactions on image processing* 21.4 (2012): 2152-2159.

[44] Sivaraman, Sayanan, and Mohan M. Trivedi. "A review of recent developments in vision-based vehicle detection." *Intelligent Vehicles Symposium*. (2013): 310-315.

[45] Mohamed, Atibi, Atouf Issam, Boussaa Mohamed, and Bennis Abdellatif. "Real-time Detection of Vehicles Using the Haar-like Features and Artificial Neuron Networks." *Procedia Computer Science* 73 (2015): 24-31.

[46] Robert, Kostia. "Video-based traffic monitoring at day and night vehicle features detection tracking." *IEEE International Conference on Intelligent Transportation Systems*. 2009. 1-6.

[47] Moghimi, Mohammad Mahdi, Maryam Nayeri, Majid Pourahmadi, and Mohammad Kazem Moghimi. "Moving vehicle detection using Adaboost and haar-like feature in surveillance videos." *International Journal of Imaging and Robotics*. 18.1 (2018): 94–106.

[48] Nur, Shazwani A., M. M. Ibrahim, N. M. Ali, and Fatin Izzati Y. Nur. "Vehicle detection based on underneath vehicle shadow using edge features." *IEEE International Conference on Control System, Computing and Engineering*. 2016. 407-412.

[49] Sale, P. D., Namrata Bhole, and P. S. D. Chavan. "Multiclass Vehicle Detection and Tracking Using Local Visual Features." *International Journal of Computer Science and Information Technologies*. 7.1 (2016): 249-253.

[50] Tian, Ye, Yangli Wang, Rui Song, and Huansheng Song. "Accurate vehicle detection and counting algorithm for traffic data collection." *IEEE International Conference on Connected Vehicles and Expo*. 2015. 285-290.

[51] Moutakki, Zakaria, Imad Mohamed Ouloul, Karim Afdel, and Abdellah Amghar. "Real-time system based on feature extraction for vehicle detection and classification." *Transport and Telecommunication Journal* 19.2 (2018): 93-102.

[52] Lipton, Alan J., Hironobu Fujiyoshi, and Raju S. Patil. "Moving target classification and tracking from real-time video." *IEEE Workshop on Applications of Computer Vision*. 1998. 8-14.

[53] Salvi, G. "An automated nighttime vehicle counting and detection system for traffic surveillance." *IEEE International Conference on Computational Science and Computational Intelligence*. 2014. 131-136.

[54] Joshi, Kinjal A., and Darshak G. Thakore. "A survey on moving object detection and tracking in video surveillance system." *International Journal of Soft Computing and Engineering* 2.3 (2012): 44-48.

[55] C. SrinivasRao, P. Darwin, "Frame Difference And Kalman Filter Techniques For Detection Of Moving Vehicles In Video Surveillance", *International Journal of Engineering Research and Applications* 2.6 (2012): 1168-1170.

[56] Han, Xiaowei, Yuan Gao, Zheng Lu, Zhimin Zhang, and Dun Niu. "Research on moving object detection algorithm based on improved three-frame difference method and optical flow." *IEEE International Conference on Instrumentation and Measurement, Computer, Communication and Control*. 2015. 580-584.

[57] Lin, Yao, Ma Fang, and Duan Shihong. "An object reconstruction algorithm for moving vehicle detection based on three-frame differencing." *IEEE International Conference on Ubiquitous Intelligence and Computing*. 2015. 1864-1868.

[58] Abdulrahim, Khairi, and Rosalina Abdul Salam. "Cumulative frame differencing for urban vehicle detection." *International Workshop on Pattern Recognition*. Vol. 10011. International Society for Optics and Photonics, 2016.

[59] Sengar, Sandeep Singh, and Susanta Mukhopadhyay. "Foreground detection via background subtraction and improved three-frame differencing." *Arabian Journal for Science and Engineering* 42.8 (2017): 3621-3633.

[60] Sengar, Sandeep Singh, and Susanta Mukhopadhyay. "Moving object detection based on frame difference and W4." *Signal, Image and Video Processing* 11.7 (2017): 1357-1364.

[61] Chen, Yanfeng, and Qingxiang Wu. "Moving vehicle detection based on optical flow estimation of edge." *IEEE International Conference on Natural Computation*. 2015. 754-758.

[62] Tu, Chun-Ling, and Sheng-Zhi Du. "Moving vehicle detection in dynamic traffic contexts." *Electronics, Communications and Networks V*. Springer, Singapore, 2016. 263-269.

[63] [Tsai, Luo-Wei, Jun-Wei Hsieh, and Kuo-Chin Fan. "Vehicle detection using normalized color and edge map." *IEEE transactions on Image Processing*16.3 (2007): 850-864.

[64] Li, Shuguang, Hongkai Yu, Jingru Zhang, Kaixin Yang, and Ran Bin. "Video-based traffic data collection system for multiple vehicle types." *IET Intelligent Transport Systems* 8.2 (2013): 164-174.

[65] Mu, Kenan, Fei Hui, Xiangmo Zhao, and Christian Prehofer. "Multiscale edge fusion for vehicle detection based on difference of Gaussian." *Optik* 127.11 (2016): 4794-4798.

[66] https://towardsdatascience.com/support-vector-machine-introduction-to-machine-learning-algorithms-934a444fca47

[67] McFarlane, Nigel JB, and C. Paddy Schofield. "Segmentation and tracking of piglets in images." *Machine vision and applications*., vol. 8, no. 3, pp. 187-193, May. 1995.

[68] Zack, G. W., W. E. Rogers, and S. A. Latt. "Automatic measurement of sister chromatid exchange frequency." *Journal of Histochemistry & Cytochemistry*., vol. 25, no. 7, pp. 741-753, Jul. 1977.

[69] P. Chiranjeevi and S. Sengupta, “New fuzzy texture features for robust detection of moving objects,” IEEE Signal Process. Lett., vol. 19, no. 10, pp. 603–606, 2012.

[70] S. Zhang, H. Yao, and S. Liu, “Dynamic background modeling and subtraction using spatio-temporal local binary patterns,” in Proc. ICIP, 2008, pp. 1556–1559.

[71] M. Heikkilä and M. Pietikäinen, “A texture-based method for modeling the background and detecting moving objects,” IEEE Trans. Patt. Anal. Mach. Intell., vol. 28, no. 4, pp. 657–662, 2006.

[72] P. Chiranjeevi and S. Sengupta, “Detection of moving objects using multi-channel kernel fuzzy correlogram based background subtraction,” IEEE Trans. Cybern., vol. 44, no. 6, pp. 870–881, 2014.

[73] K. K. Hati, P. K. Sa, and B. Majhi, “Intensity range based background subtraction for effective object detection,” IEEE Signal Process. Lett., vol. 20, no. 8, pp. 759–762, 2013.

[74] F. E. Baf, T. Bouwmans, and B. Vachon, “A fuzzy approach for background subtraction,” in Proc. ICIP, 2008, pp. 2648–2651, IEEE.

[75] C. Stauffer and W. E. L. Grimson, “Learning patterns of activity using real-time tracking,” IEEE Trans. Patt. Anal. Mach. Intell., vol. 22, no. 8, pp. 747–757, 2000.

[76] Long J, Shelhamer E, Darrell T (2015) Fully convolutional networks for semantic segmentation. In: Proceedings of the IEEE conference on computer vision and pattern recognition (CVPR), pp 3431– 3440

[77] Dai J, He K, Sun J (2016) Instance-aware semantic segmentation via multi-task network cascades. In: Proceedings of the IEEE conference on computer vision and pattern recognition (CVPR), pp 3150– 3158

[78] BengioY, CourvilleA, VincentP (2013) Representation learning: a review and new perspectives. IEEE Transactions on Pattern Analysis and Machine Intelligence 35(8):1798–1828.

[79] Kavukcuoglu K, Sermanet P, Boureau Y-L, Gregor K, Mathieu M, Cun YL (2010) Learning convolutional feature hierarchies for visual recognition. In: Advances in neural information processing systems (NIPS), pp 1090–1098

[80] Oquab M, Bottou L, Laptev I, Sivic J (2014) Learning and transferring mid-level image representations using convolutional neural networks. In: Proceedings of the IEEE conference on computer vision and pattern recognition (CVPR), pp 1717–1724

[81] Song, Huansheng, et al. "Vision-based vehicle detection and counting system using deep learning in highway scenes." *European Transport Research Review* 11.1 (2019): 1-16.

[82] Wang, Lixin, Junguo Liao, and Chaoqian Xu. "Vehicle detection based on drone images with the improved faster R-CNN." *Proceedings of the 2019 11th International Conference on Machine Learning and Computing*. 2019.

[83] M. Seki, H. Fujiwara, and K. Sumi, “A robust background subtraction method for changing background”, Fifth IEEE Workshop on Applications of Computer Vision, 2000.

[84] R.T. Collins, et al., “A system for video surveillance and monitoring”, VASM final Report, Robotics Institute, Carnegie Mellon University, 2000, pp.1-68.

[85] J.J. Gibson, "The perception of the visual world", 1950.

[86] K. Wu, et al., "Overview of video-based vehicle detection technologies", 2011.

LIST OF PUBLICATIONS

1. El-Khoreby, Mohamed A., Syed Abd Rahman Abu-Bakar, Musa Mohd Mokji, and Syaril Nizam Omar. Vehicle detection and counting using adaptive background model based on approximate median filter and triangulation threshold techniques. *Automatic Control And Computer Sciences*. 2020.

2. El-Khoreby, Mohamed A., and Syed Abd Rahman Abu-Bakar. Vehicle detection and counting for complex weather conditions. *IEEE International Conference on Signal and Image Processing Applications (ICSIPA)*. 2017. 425-428.

3. El-Khoreby, Mohamed A., Syed Abd Rahman Abu-Bakar, Musa Mohd Mokji, Syaril Nizam Omar, and Najeeb Ur Rehman Malik. Localized background subtraction feature-based approach for vehicle counting. *IEEE International Conference on Signal and Image Processing Applications (ICSIPA). 2019.* 324-328.

4. El-Khoreby, Mohamed A., Syed Abd Rahman Abu-Bakar, Musa Mohd Mokji, and Syaril Nizam Omar. Performance comparison between SVM and K-means for vehicle counting. *Sustainable & Integrated Engineering International Conference*. 2019