JOIV : Int. J. Inform. Visualization, 7(2) - June 2023 295-300

INTERNATIONAL JOURNAL ON INFORMATICS VISUALIZATION

journal homepage : www.joiv.org/index.php/joiv

Vehicles Speed Estimation Model from Video Streams for Automatic Traffic Flow Analysis Systems

Maizatul Najihah Arriffin [a], Salama A. Mostafa [a], Umar Farooq Khattak [b,1], Mustafa Musa Jaber [c,d]
Zirawani Baharum [e,2], Defni [f], Taufik Gusman [f]

[a] Faculty of Computer Science and Information Technology, Universiti Tun Hussein Onn Malaysia, Parit Raja 86400, Johor, Malaysia
[b] School of Information Technology, UNITAR International University, kelana jaya, 47301 Petaling Jaya, Selangor, Malaysia
[c] Department of Medical instruments engineering techniques, Dijlah University College, Baghdad,10021, Iraq
[d] Department of Medical instruments engineering techniques, Al-Farahidi University, Baghdad,10021, Iraq
[e] Malaysian Institute of Industrial Technology, Universiti Kuala Lumpur, Bandar Seri Alam, 81750 Johor Bahru, Malaysia
[f] Department of Information Technology, Politeknik Negeri Padang, Sumatera Barat, Indonesia
Corresponding author: [1] umar.farooq@unitar.my, [2] zirawani@unikl.edu.my

***Abstract*—Image and video processing have been widely used to provide traffic parameters, which will be used to improve certain areas of traffic operations. This research aims to develop a model for estimating vehicle speed from video streams to support traffic flow analysis (TFA) systems. Subsequently, this paper proposes a vehicle speed estimation model with three main stages of achieving speed estimation: (1) pre-processing, (2) segmentation, and (3) speed detection. The model uses a bilateral filter in the pre-processing strategy to provide free-shadow image quality and sharpen the image. Gaussian filter and active contour are used to detect and track objects of interest in the image. The Pinhole model is used to assess the real distance of the item within the image sequence for speed estimation. Kalman filter and optical flow are used to flatten vehicle speed and acceleration uncertainties. This model is evaluated with a dataset that consists of video recordings of moving vehicles at traffic light junctions on the urban roadway. The average percentage for speed estimation error is 20.86%. The average percentage for accuracy obtained is 79.14%, and the overall average precision of 0.08.**

***Keywords*— Traffic flow analysis; vehicle speed estimation; Kalman filter; Pinhole model; bilateral filter.**

Manuscript received 15 Oct. 2022; revised 19 Jan. 2023; accepted 12 Feb. 2023. Date of publication 30 Jun. 2023.

I. INTRODUCTION

Nowadays, the increase in population in big cities like Kuala Lumpur causes massive traffic congestion [1]. Intelligent traffic light control systems attempt to improve the traditional traffic light system. These types of systems are experimentally implemented in Malaysia, the UK, Germany, the USA, Australia, and Romania to handle traffic light systems management more efficiently and with less human intervention. With the evolution of technology and urbanization, various traffic parameters can be achieved from various sources of data, including radio detection and ranging (RADAR), radio frequency identification (RFID), microwave sensors, laser imaging detection and ranging (LIDAR), and camera [2].

Camera installation for traffic flow analysis (TFA) systems is now important to extract traffic flow features. Speed estimation is one of the variables that can be utilized to improve traffic light control operation, law enforcement, and incident management [3], [4], [5]. Several studies have used ready datasets with video revolution up to 1920 x 1080. Using datasets makes the job easier because the researchers don't have to film their own traffic flow videos [6].

Sochor et al. [5] produced visual speed measurements from a single monocular camera in free-flow traffic locations. In this study, they used LiDAR and GPS as reference tracks. Luvizon et al. [6] conducted a study on vehicle speed measurement using image processing, and they achieved 0.93 precision after testing for 5 hours with around 8000 vehicles associated. Sina et al. [7] conducted a study on speed estimation using headlight detection. This study managed to produce the closest speed estimation with ground truth for speed estimation. They came to the conclusion that the Pinhole model produces better speed estimation than the Euclidean distance approach.

Geràt et al. [8] proposed a system that can measure vehicle speed in various conditions by considering the influence of weather, illumination, and overlays with other objects. The

Kalman filter and optical flow combination generate good results in high- and low-quality images captured by an industrial camera.

Table I shows some of the reviewed works of video-based speed detection models. Bilateral filter, Gaussian filter, Kalman Filter with optical flow, active contour, and Pinhole model are among the techniques used in these studies to estimate vehicle speed. In order to estimate speed from video recordings, each technique plays a significant role in each processing layer to achieve an accurate estimation of the speed goal.

TABLE I

EXAMPLES OF VIDEO-BASED SPEED DETECTION MODELS

Ref.	Model implementation		Evaluation
	Stage	Method	
[5]	Pre-processing	-	Dataset: 6 recording sessions in free-flowing traffic at various sites. Three videos were obtained for each session (approximately one hour long) from different positions by different video cameras. The videos were recorded in full-HD resolution and with 50 frames per second progressive scan. Result: Camera visual speed measurement. The average error of speed is 3.3km/h relative to the ground truth obtained by GPS.
	Segmentation	Background subtraction	
	Speed estimation	Acquired line markings	
	Tracking	Kalman Filter	
[6]	Pre-processing	Motion History Image (MHI)	Dataset: 20 videos captured by a low-cost 5-megapixel CMOS image sensor, with a frame resolution of 1920 × 1080 pixels, at 30.15 frames per second. The videos are divided into 5 sets according to weather and recording conditions. Each video has an associated ground truth file in a simple XML format. Result: Vehicle speed measurement in urban roadways. 0.5 km / h on average and in over 96% of the cases, within the maximum of [-3, +2] km / h set by regulators in a couple of countries.
	Segmentation	Edge extraction, edge filtering, and region grouping modules	
	Speed estimation	Direct blob analysis	
	Tracking	Kanade-Lucas-Tomasi (KLT)	
[7]	Pre-processing	Image binary conversion	Dataset: 5 videos with a duration between 4 to 6 minutes. The number of vehicles in each video has been manually counted, and each of them has a total of 100 vehicles. Result: Vehicle counting and speed measurement using headlight detection. The lowest average error of normalized cross-correlation and pinhole model is 33.25 km/h.
	Segmentation	Blob Detection	
	Speed detection	Euclidean Distance Pinhole Model	
	Tracking	Normalized cross-correlation	
[8]	Pre-processing	Density-based spatial clustering of application with noise (DBSCAN)	Dataset: Series of videos with constant vehicle speed (15 km/h and 20 km/h) recorded using Samsung iPOLinSSNP – 5200H with 10fps and 1280x1024 screen size. Result: Using image processing algorithms for vehicle speed detection.
	Segmentation	Gaussian Mixture Model	
	Speed estimation	Optical flow	
	Tracking	Kalman Filter	

This study intended to provide a vision-based system for road vehicle speed measurement and explore the speed detection domain, pre-processing, segmentation, and speed detection as the main components [5]. Subsequently, this research proposes a vehicle speed estimation model from a video stream for automatic TFA systems. It utilizes a bilateral filter for image pre-processing and Gaussian blur for segmentation that detects foreground pixels corresponding to moving vehicles. The model processes each pixel of the background with the Gaussian distribution. Vehicles are spotted using active contour during speed detection. A Kalman filter then tracks the vehicles with optical flow, and the speed is measured with a pinhole model. Our suggested model aims to reduce redundancy in vehicle detection and improve the overall performance of vehicle speed estimation. Lastly, evaluate the model's application in terms of speed detection accuracy and precision. A free dataset available from previous research conducted by Luvizon et al. [6] has been utilized. The research results suggest that convenient video-based speed measurement can be found even in critical scenarios.

This paper is organized as follows: Section I gives an overview of the research conducted, while Section II focuses on the implementation of the material and research model. Section III discusses the result, and Section IV wraps up the paper presentation.

II. MATERIAL AND METHOD

This project intends to propose vehicle speed detection based on an artificial vision based on video stream processing. Fig.1 shows the overview of the research methodology.

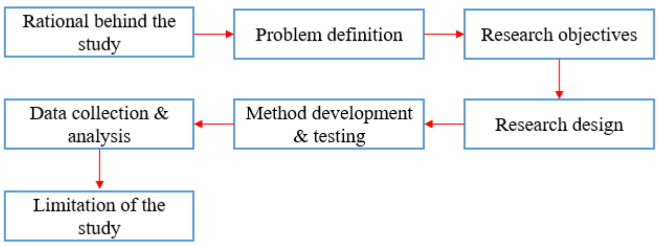

Fig. 1 Research methodology

A. Dataset

The dataset implemented in this study is taken from existing research conducted by Luvizon et al. [6]. This dataset consists of 20 videos captured by a low-cost 5-megapixel CMOS image sensor, with a frame resolution of 1920 × 1080 pixels, at 30.15 frames per second. Each video has an associated ground truth (GT), and the dataset consists of moving vehicles collected via camera at a traffic light intersection on an urban roadway. The video was taken for 5 hours. The features available for study purposes include (1) the number of lanes, (2) the timing of the video, (3) the number of valid speed estimations, (4) actual speed, and (5) speed measurement.

B. Evaluation Criteria

There are a few evaluation criteria for our model performance proposed in this work. They are error (Err), average error (AvE), Accuracy (Acc), and precision (Pre). Error percentage is calculated based on the comparison to the GT value. The calculation result reveals the suggested model's error as in (1).

$$Err(\%) = (|GT - found|/GT)100 \quad (1)$$

The average error (AvE) is obtained after calculating the percentage error using (2). This error percentage is used to determine the accuracy of vehicle speed.

$$\text{AvE} = (\Sigma\, error)/n \quad (2)$$

The accuracy (Acc) calculation is shown in (3).

$$Acc = 100 - average\ error \quad (3)$$

Subsequently, the precision (Pre) is calculated as in (4).

$$Pre = \sqrt{\frac{\sum_i^n (xi - \dot{x})^2}{n-1}} \quad (4)$$

C. Method

Three processes are involved in measuring the speed of moving vehicles: (1) pre-processing, (2) segmentation, and (3) speed detection. A bilateral filter is chosen for classification in the pre-processing stage, while Gaussian mixture distribution is selected for segmentation purposes. Active contour is used in detecting the speed, while the Kalman filter and optical flow are used for vehicle tracking. The pinhole model is used to estimate speed. Fig.2 shows the speed estimation model design proposed in this study.

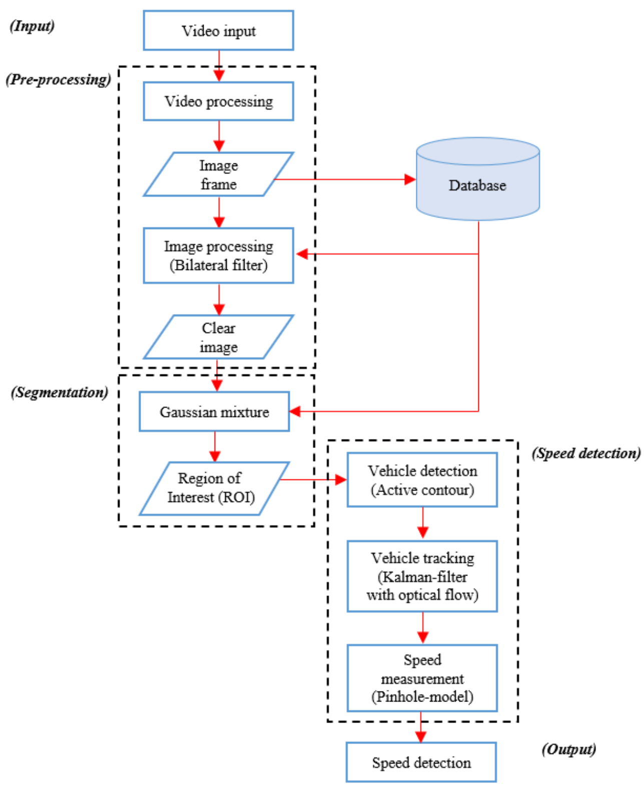

Fig. 2 The proposed speed estimation model design

The pre-processing stage is used to boost the precision and interpretability of an image, including several techniques like cleaning, integration, transformation, and reduction [9]. There are two steps involved in pre-processing, (1) video pre-processing (2) and image pre-processing. Video pre-processing focuses on the image frame. A max frame per second (fps) is set to be analyzed using the maxWaitingFPS method. The image sequence is read from the video by using openCV.videoio. VideoCapture and the resized image size is (640,360). In this step, the clone image is done by making copies of the image to track many vehicles simultaneously and in the same place.

On the other hand, image pre-processing aims to enhance image data, remove unwanted distortions, and improve certain essential image features for further processing. The bilateral filter is a non-linear, edge-preserving, and noise-reducing smoothing filter for image processing. It manages to smooth out the signal while keeping the edges sharp. It replaces the intensity of each pixel with a weighted average of intensity values from nearby pixels. This filter is also used to improve the accuracy of the coming process. The bilateral filter can be extended to treat more general reconstruction problems such as image restoration, image scaling, and super-resolution.

Image segmentation divides an object into relevant sections with similar characteristics and properties [10]. Image segmentation aims to extract object features with the least amount of data that differs from the input sequence possible. It allows for a more consistent and better image representation. The Gaussian mixture model filter is used for background subtraction and to recognize moving objects in static image frames. Subsequently, image segmentation manages to create the region of interest (ROI) to detect vehicle speed.

During the speed detection stage, the active contour is chosen as the speed detection technique by comparing the current image with the background image. Three output parameters can be achieved from this technique: (1) vehicle detection, (2) vehicle tracking, and (3) speed measurement. Vehicle detection identifies the instant detection of moving vehicles from the image segmentation or video stream [11], [12]. It is used to obtain deformable models or structures with constraints in image objects. To meet the match criteria, the contour position and size must be within the tracking tolerance setting. If the matching is found, the detected object will be updated accordingly [13]. If a vehicle moves out of the detecting region, the tracking process will be created to avoid duplication. The object that has been identified as a vehicle will be tracked over sequential frames retrieved from video streams [14], [15]. The tracked vehicle information will be sent to the vehicle detection module for volume counting purposes.

Vehicles can be tracked when the contours model describes the object boundaries to form a parametric curve or contour. The vehicle tracking process uses a Kalman filter with an optical flow method. An object matching scheme calculates the distance between vehicle features saved in prior storage and immediate frame features. This tracking is also used to prevent redundancy in measurement [16], [17]. After detecting the moving object, speed measurement is computed based on contour movement with the real-time video [18], [19]. A pinhole model is used to estimate the object's actual distance within the sequence of images. Vehicle speed measurement is shown in (5).

$$Speed = (Distance)/(Total\ Frames * Frame\ Rat \quad (5)$$

For the pinhole model to calculate speed measurement: K is the distance between the camera and ground (meter), and f is the distance between the camera projection and focus point. This paper uses the pixels' unit, which is converted from mm, and θ is the angle created by the camera's blind spot. Then Lp is the estimation of the actual distance on the surface of the road depending on the distance in the image [20], [21]. Lp is calculated using equations in (6) and (7).

$$Lp = K\tan(\delta + \theta) \tag{6}$$

$$\delta = \arctan\left(\frac{\frac{P}{2}}{f}\right) - \arctan\frac{p - \left(\frac{P}{2}\right)}{f} \tag{7}$$

where P is the pixel number in the image, and p is a pixel index row in the image. Pinhole design is implemented using a formula in (8). P2 is frame index position f2= n, and p1 is frame index position f2= n−1. $Lp1$ is the result of the pixel-pinhole model that represents the distance, and Fr is the frame rate of the video [22]. The constant 3.6 is used to change the km / h (kilometer/hour) units from m / s (meter / second).

$$S_{vehicle} = \frac{(Lp1 - Lp2) * Fr * 3.6}{f2 - f1} \tag{8}$$

III. Results and Discussion

This section discusses the implementation of the proposed speed estimation model. Various parameters need to be considered for the obtained images from the video to obtain the application result. The parameter of the video threshold in this dataset was approximately 0 to 5. The area threshold used was approximately 600 to 750, and for a vehicle, the size threshold used was approximately about 40000. To obtain the speed result, the distance between two boundary lines is approximately 6m.

Table II shows samples of the vehicle speed estimation experimental data collection. There are three result sub-tables from the three videos used in this work. The sub-tables show the results for vehicle speed estimation based on the GT and the detected speed of vehicles in a particular lane. Then the valid estimation indicator shows whether a vehicle has been detected and has a valid vehicle speed measure. The experiment was repeated three times to find the average results.

TABLE II
VEHICLE SPEED ESTIMATION

Vehicle	Lane	Frame	GT	Obtained speed	Valid estimation
			Video 1		
1	1	2	20.52	21.6	Yes
2	3	20	19.76	17.51	Yes
3	3	27	23.21	-	No
4	2	60	18.33	18.64	Yes
5	1	76	23.85	23.2	Yes
			Video 2		
144	2	7992	52.86	-	No
145	3	8029	51.22	43.2	Yes
146	3	8052	53.9	-	No
147	3	8081	48.42	48.22	Yes
148	2	8093	54.13	54.18	Yes
			Video 3		
287	3	16985	25.26	25.46	Yes
288	1	16989	30.54	22.71	Yes
289	2	17026	42.42	41.72	Yes
290	1	17055	41.38	-	No
291	3	17055	44.83	43.81	Yes

Table III shows the average error (AvE), accuracy (Acc), and precision (Pre) for Video 1 speed estimation. The results of this video show that lane 1 has the highest average speed of 47.57Km/h compared to lane 3 (40.78Km/h) and lane 2 (46.88Km/h). In terms of vehicle minimum speed, lane 3 minimum speed is 11.12Km/h, while lane 2 and lane 3 both have higher minimum speeds of 17.63Km/h and 12.46Km/h. Lane 3 has the highest speed estimation error of 36.54% as compared to the other 2 lanes. The average error obtained from this video is 31.28%, which is the highest among the three videos. Subsequently, the model in video 1 has the lowest accuracy result of 68.71% compared to videos 1 and 2 and a precision of 0.1054.

TABLE III
EVALUATION RESULTS OF VIDEO 1

Speed parameter	Video 1					
	Lane 1	**Lane 2**	**Lane 3**	**AvE**	**Acc**	**Pre**
Error	22.39	35.83	36.53	31.28		
Slow lane			√			
Fast lane	√					
Avg speed	47.57	46.88	40.78	45.46	68.71	0.1054
Max speed	81.00	62.18	68.72	70.64		
Min speed	12.46	17.62	11.11	13.73		

From the evaluation results of video 2 in Table IV, lane 1 is the fastest lane, while the slowest lane is lane 3. Lane 1 has the highest average speed of 43.3091Km/h, as compared to both lane 2 and lane 3, with an average speed value of 43.28Km/h and 40.77Km/h. Lane 2 shows the maximum speed value 85.71Km/h, followed by lane 1 62.99Km/h, and lane 3 56.57Km/h. Lane 1 also has a low minimum speed of 10.38m/h, while lane 2 and lane 3 both show minimum speeds of 12.72Km/h and 16.35Km/h, respectively. Lane 1 has the least speed estimation error of 14.70% as compared to lane 2 (21.06%) and lane 3 (29.36%). The average error obtained from this video is 21.71%, which is intermediate as compared to video 1 and video 3. Furthermore, the model in video 2 has higher accuracy than in video 1, which is 78.29%, and better precision of 0.0404.

TABLE IV
EVALUATION RESULTS OF VIDEO 2

Speed parameter	Video 2					
	Lane 1	**Lane 2**	**Lane 3**	**AvE**	**Acc**	**Pre**
Error	14.69	21.06	29.36	21.70		
Slow lane			√			
Fast lane	√					
Avg speed	43.30	43.28	40.71	42.44	78.29	0.0404
Max speed	62.98	85.71	56.57	68.42		
Min speed	10.37	12.72	16.34	13.15		

The evaluation results of video 3 in Table V show that lane 3 is the slowest lane and has the least value of the average speed of 41.84Km/h. Lane 2 indicates the fastest lane, with an average speed of 47.37 Km/h. Meanwhile, lane 1 has an average speed of 44.27 Km/h. lane 1 has the highest maximum speed of 84.07Km/h as compared to lane 2 (59.97 Km/h) and lane 3 (56.62Km/h). Lane 1 marked a minimum speed of 16.79 Km/h while lane 2 and lane 3 minimum speeds are 42.42Km/h and 17.6 Km/h, respectively. Lane 3 has the highest value of speed estimation error of 16.899%, with lanes 1 and 2 having low speed estimation errors of 3.77 and 8.04%. This video's average error is 9.57%, which has better accuracy than video 1 and video 2. The accuracy of video 3 is 90.43%, and the precision is 0.1062.

TABLE V
EVALUATION RESULTS OF VIDEO 3

Speed parameter	Video 3					
	Lane 1	Lane 2	Lane 3	AvE	Acc	Pre
Error	3.77	8.04	16.89	9.57	90.42	0.1062
Slow lane			√			
Fast lane		√				
Avg speed	44.27	47.37	41.84	44.99		
Max speed	84.07	59.97	56.62	66.89		
Min speed	16.79	42.42	17.65	25.62		

Subsequently, the overall accuracy obtained in each video 1, video 2, and video 3 is 68.71%, 78.29%, and 90.43%, respectively. The average percentage for accuracy is 79.14%. The precision obtained in each video 1, video 2, and video 3 is 0.105, 0.040, and 0.106, respectively. The overall average precision is 0.08. The model implementing video 3 has produced results closer to the actual GT speed values. The model can detect only 376 vehicles compared with 429 of the ground truth (87.64%). Table VI shows the overall results of the testing parameters.

TABLE VI
TESTING PARAMETERS

TFA parameter	Video 1	Video 2	Video 3
Speed Estimation	115	137	124
Ground Truth	143	143	143
Error	31.29	21.71	9.57
Slow Lane	lane 3	lane 3	lane 3
Fast lane	lane 1	lane 1	lane 2
Average Speed	45.46	42.44	44.99
GT average speed	44.20	41.95	43.72
Maximum speed	70.64	68.42	66.89
Minimum speed	13.73	13.15	25.62
Accuracy	68.71	78.29	90.43
Precision	0.105	0.040	0.106

We can conclude from all the results of the three videos that video 1 has the highest speed estimation error, which is 31.29%, followed by video 2 (21.71%) and video 3 (9.57%). Then, the average percentage for speed estimation error is 20.86%. Lane 3 has the slowest speed, and lane 1 has the fastest speed. The average speed detection in video 1 is 45.46Km/h which is 1.23Km/h more than the GT, 44.20Km/h. video 2 obtained 42.44Km/h, which is 0.485Km/h more than the GT, 41.96Km/h. Video 3 obtained 44.99Km/h, which is 1.27Km/h more than the GT, 43.72Km/h. The average speed detection is 43.30Km/h, which is 0.10 Km/h more than the GT, 43.29Km/h. The average maximum speed obtained is 68.65Km/h, while the average minimum speed obtained is 17.5 Km/h. This work considers applying software agent architecture adapted from [23] [24] to the vehicle speed estimation model to adjust the model's operational parameters based on the detected objects' size and dimensions.

IV. CONCLUSIONS

This paper proposed a vehicle speed estimation model from video streams. This model utilized video and image processing capability to produce linear speed estimation value by integrating various techniques, including the bilateral filter, Kalman filter, optical flow, and pinhole model. This study uses video streams of vehicles from an existing dataset to provide accurate speed measurements by vehicle detection at a given location. The dataset implemented in this study is based on urban roadways and is freely available. As a result, the average percentage for speed estimation error of the model is 20.86%, while the average accuracy percentage is 79.14%, and the overall average precision is 0.08. Future work considers software agent-based adaptive model that can improve object segmentation and speed estimation.

ACKNOWLEDGMENT

Special thanks to UNITAR International University for funding this research. This research also supported by the Ministry of Higher Education (MoHE) through the Fundamental Research Grant Scheme (FRGS/1/2021/ICT01/UTHM/02/1) grant vot number K389.

REFERENCES

[1] J. L. Zambrano-Martinez, C. T. Calafate, D. Soler, J. C. Cano, and P. Manzoni, “Modeling and characterization of traffic flows in urban environments,” Sensors (Switzerland), vol. 18, no. 7, pp. 1–19, 2018.

[2] S. A. Kashinath et al., “Review of data fusion methods for real-time and multi-sensor traffic flow analysis,” IEEE Access, vol. 9, pp. 51258–51276, 2021.

[3] S. A. Kashinath, S. A. Mostafa, D. Lim, A. Mustapha, H. Hafit, and R. Darman, “A general framework of multiple coordinative data fusion modules for real-time and heterogeneous data sources,” J. Intell. Syst., vol. 30, no. 1, pp. 947–965, 2021.

[4] S. S. Wardha, S. M. Deokar, S. S. Patankar, and J. V. Kulkarni, “Development of automated technique for vehicle speed estimation and tracking in video stream,” RTEICT 2017 - 2nd IEEE Int. Conf. Recent Trends Electron. Inf. Commun. Technol. Proc., vol. 2018-January, pp. 940–944, 2017.

[5] J. Sochor et al., “Comprehensive Data Set for Automatic Single Camera Visual Speed Measurement,” IEEE Trans. Intell. Transp. Syst., vol. 20, no. 5, pp. 1633–1643, 2019.

[6] D. C. Luvizon, B. T. Nassu, and R. Minetto, “A Video-Based System for Vehicle Speed Measurement in Urban Roadways,” IEEE Trans. Intell. Transp. Syst., vol. 18, no. 6, pp. 1393–1404, 2017.

[7] I. Sina, A. Wibisono, A. Nurhadiyatna, B. Hardjono, W. Jatmiko, and P. Mursanto, “Vehicle counting and speed measurement using headlight detection,” 2013 Int. Conf. Adv. Comput. Sci. Inf. Syst. ICACSIS 2013, no. April 2015, pp. 149–154, 2013.

[8] J. Gerat, D. Sopiak, M. Oravec, and J. Pavlovicova, “Vehicle speed detection from camera stream using image processing methods,” Proc. Elmar - Int. Symp. Electron. Mar., vol. 2017-September, no. September, pp. 201–204, 2017.

[9] L. Zhang, Y. Xie, L. Xidao, and X. Zhang, “Multi-source heterogeneous data fusion,” 2018 Int. Conf. Artif. Intell. Big Data, ICAIBD 2018, pp. 47–51, 2018.

[10] K. Dilpreet and K. Yadwinder, “Various Image Segmentation Techniques: A Review,” Int. J. Comput. Sci. Mob. Comput., vol. 3, no. 5, pp. 809–814, 2014.

[11] R. Ke, S. Kim, Z. Li, and Y. Wang, “Motion-vector clustering for traffic speed detection from UAV video,” 2015 IEEE 1st Int. Smart Cities Conf. ISC2 2015, no. October, 2015.

[12] N. A. Mohd, S. A. Mostafa, A. Mustapha, A. A. Ramli, M. A. Mohammed, and N. M. Kumar, "Vehicles counting from video stream for automatic traffic flow analysis systems," Int. J. Emerg. Trends Eng. Res., vol. 8, no. 1 Special Issue 1, pp. 142–146, 2020.

[13] J. Al-Azzeh, B. Zahran, and Z. Alqadi, "Salt and pepper noise: Effects and removal," Int. J. Informatics Vis., vol. 2, no. 4, pp. 252–256, 2018.

[14] C. Yi and J. Cho, "Real-time Estimation of Road Surfaces using Fast Monocular Depth Estimation and Normal Vector Clustering," vol. 5, no. September, pp. 206–211, 2021.

[15] M. A. Aljamal, H. M. Abdelghaffar, and H. A. Rakha, "Developing a neural–kalman filtering approach for estimating traffic stream density using probe vehicle data," Sensors (Switzerland), vol. 19, no. 19, pp. 1–18, 2019.

[16] R. Krishnapuram, S. Shorewala, and P. Rao, "Link Speed Estimation for Traffic Flow Modelling Based on Video Feeds from Monocular Cameras," 2020 IEEE 23rd Int. Conf. Intell. Transp. Syst. ITSC 2020, pp. 1–6, 2020.

[17] D. Biswas, H. Su, C. Wang, and A. Stevanovic, "Speed estimation of multiple moving objects from a moving UAV platform," ISPRS Int. J. Geo-Information, vol. 8, no. 6, 2019.

[18] Z. Czapla, "S Pa 2017 Vehicle Speed Estimation with the Use of Gradient- Based Image Conversion into Binary Form," pp. 213–216, 2017.

[19] T. V. Mini and T. Vijayakumar, "Speed estimation and detection of moving vehicles based on probabilistic principal component analysis and new digital image processing approach," in AI International Conference on Big Data Innovation for Sustainable Cognitive Computing: BDCC 2018, pp. 221–230.

[20] A. Raj et al., "Semi-Geometrical approach to estimate the speed of the vehicle through a surveillance video stream," Int. J. Comput. Sci. Eng., vol. 7, no. 3, pp. 741–748, 2019.

[21] S. Hua, M. Kapoor, and D. C. Anastasiu, "Vehicle tracking and speed estimation from traffic videos," IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. Work., vol. 2018-June, pp. 153–160, 2018.

[22] H. K. Gauttam and R. K. Mohapatra, "Speed prediction of fast approaching vehicle using moving camera," Commun. Comput. Inf. Sci., vol. 1148 CCIS, pp. 423–431, 2020.

[23] S. A. Mostafa, M. S. Ahmad, M. Annamalai, A. Ahmad, and S. S. Gunasekaran, "A conceptual model of layered adjustable autonomy," In *Advances in information systems and technologies* (pp. 619-630). Springer, Berlin, Heidelberg, 2013.

[24] S. A. Mostafa, S. S. Gunasekaran, A. Mustapha, M. A, Mohammed, and W. M. Abduallah, "Modelling an adjustable autonomous multi-agent internet of things system for elderly smart home," In *International Conference on Applied Human Factors and Ergonomics* (pp. 301-311). Springer, Cham, 2019.