PLANNING MALAYSIA:
Journal of the Malaysian Institute of Planners
VOLUME 21 ISSUE 4 (2023), Page 61 – 72

VIDEO CAMERA TECHNOLOGY FOR VEHICLE COUNTING IN TRAFFIC CENSUS: ISSUES, STRATEGIES AND OPPORTUNITIES

Khairul Khaizi Mohd Shariff[1], Megat Qamarul Zaffi Megat Ali[2], Aisyah Hartini Jahidin[3], Megat Syahirul Amin Megat Ali[4], Ahmad Ihsan Mohd Yassin[5]

[1,4,5]*Microwave Research Institute,*
UNIVERSITI TEKNOLOGI MARA
[2]*ITS Division,*
ZAF TRAFFIC PLANNERS
[3]*Centre for Foundation Studies in Science,*
UNIVERSITY OF MALAYA

Abstract

This study provides an overview of the sensor technologies commonly used for automated vehicle classification and counting, with a focus on non-intrusive sensors. Video cameras are found to be the most feasible solution for data collection in traffic census as it can operate in portable mode and used at any location. Several factors must be considered to ensure accurate counting. These involve optimum placement of the camera to ensure that all vehicles can be observed, and the lighting conditions must be considered to ensure good video quality. These further contributes to accurate classification and counting of vehicles by dedicated deep learning algorithm. As the data collection may involve location with poor access to cloud computing and storage, offline processing is therefore recommended. The study also revealed opportunities for solving issues related to strategic placement of video cameras, and development of dedicated deep learning algorithms.

Keywords: Video Cameras, Portable, Vehicle Classification, Vehicle Counting, Traffic Census

[4] Associate Professor at Universiti Teknologi MARA. Email: megatsyahirul@uitm.edu.my

INTRODUCTION

Traffic census is a vital tool used in road planning as it provides information on the volume and composition of traffic on roads and highways. Through a thorough analysis of traffic census data, road planners can identify areas of congestion and develop strategies to improve traffic flow (Lam et al., 2006). Moreover, the data can be used to inform decisions on the development of new roads and highways, and the placement of roadside facilities such as rest stops and gas stations (Gibbons et al., 2019). Data collection is an essential part of traffic census. It is an important process that allows researchers to gather a wide range of information related to traffic and road transportation. This information can then be used to create models, draw conclusions, and make decisions about traffic patterns and congestion (Mohd Yusoff et al., 2022). Traffic census data collection methods involve the use of both manual and automated methods.

Manual methods involve the use of direct observation and field surveys to collect data (Ogunyemi et al., 2021). This includes using traffic counters to count the number of vehicles at an intersection, observation of traffic patterns and speeds, and surveys of drivers and pedestrians. There is no need for costly equipment such as cameras or sensors, and the data collection process is relatively simple. Personnel can be stationed at a given location for a predetermined amount of time and record the number of passing vehicles (Sharma, 1981). This method can be used to measure traffic volumes on urban and rural roads. The accuracy of manual counting is dependent on the efficiency and consistency of the data collection process. Personnel must be adequately trained to accurately observe and record the passing vehicles and must be cognizant of any discrepancies or errors in their data collection. In addition, the data must be recorded in a timely manner to ensure that the count is accurate (Prabha et al., 2016).

Generally, manual counting is labour-intensive, time-consuming, and can be unreliable. Fortunately, there are several ways to overcome these limitations. Automated traffic counters can be used to collect more accurate and comprehensive data than manual counting (Hoxha et al., 2023). Specifically, both intrusive and non-intrusive sensor technologies can be used to automatically measure traffic volumes. Intrusive sensors are embedded in the road surface and use physical means, such as piezoelectric transducers and inductive loops. These sensors require physical installation and are best suited for measuring traffic volumes in a single location. Non-intrusive sensors are typically used to measure traffic volume over a larger area. These sensors use radar, cameras, and other devices to detect the presence of vehicles, which are then counted and converted into traffic volume data (Balid et al., 2018).

Different sensor technologies offer a wide range of options for traffic counting. Each technology has its own advantages and disadvantages, so it is important to consider the specific requirements of the application and the

© 2023 by MIP

environment to choose the most suitable one. Ultimately, the most suitable sensor technology should be selected to achieve the best results for automatic traffic counting. This paper aims to compare and analyse the feasibility of intrusive and non-intrusive sensor technologies for vehicle counting in traffic census. Based on the current practice of vehicle counting practices, the most practical technology is proposed. These involve potential study on development of portable vehicle counting system based on video camera technology.

SENSOR TECHNOLOGIES

This paper has short-listed four intrusive sensors, and five non-intrusive sensors for traffic control. The respective technologies are summaries in terms of its working principles, and applications. Subsequently, the most suitable sensors are selected for use in vehicle classification and counting.

Intrusive Sensors

The installation of intrusive sensors on pavement surfaces has been demonstrated to provide a high degree of accuracy, although the associated costs for installation and maintenance are considerable. These sensors can be divided into three distinct categories, namely passive magnetic sensors connected to processing units via wired or wireless connection, pneumatic tube sensors transmitting data to processing units through wired or wireless media, and inductive loops composed of wire coils buried beneath the road and linked to processing units (Tasgaonkar et al., 2020).

The implementation of road sensors is advantageous due to their technology maturity and accuracy in detecting vehicles. However, their installation is costly and can cause disruption to traffic during installation, maintenance, or repairs. To address this issue, wireless battery-powered sensor nodes have been introduced to replace the intrusive sensors and are installed over the pavement. This technology is expected to revolutionize transportation sensors and improve the quality, quantity, accuracy, and trustworthiness of data collected from roads and avenues, while being more cost-effective compared to current solutions (Zhou et al., 2017). Table 1 summarizes the applications of pneumatic road tube, inductive loop detector, magnetic, and piezoelectric sensors.

Table 1: Intrusive Sensors and Applications

Sensor Type	**Applications**
Pneumatic Road Tube	Track the number of vehicles, vehicle classification and counting.
Inductive Loop Detector	Detect presence, count, movement, and lane occupancy.
Magnetic Sensors	Detect presence of vehicle and whether it is moving or stationary.
Piezoelectric Sensors	Vehicle classification, counting, measures weight and speed.

© 2023 by MIP

The use of pneumatic road tube sensors, which involve the placement of one or more tubes across traffic lanes, has been developed to enable the accurate counting and classification of vehicles. When a vehicle passes over the tube, the pressure exerted on the tube produces an electrical signal that is transmitted to a processing unit. Meanwhile, the inductive loop detector is a widely utilized sensor in traffic management, employed for data collection on vehicle flow, occupancy, length, and speed. This detector consists of a wire which is wound in a loop and installed into or beneath the surface of the road. The inductive loop detector works by measuring the change in the electrical properties of the circuit when a vehicle passes over the sensor, thereby generating an electrical current that is sent to the processing unit. Comparatively, magnetic sensors are utilized to detect vehicles by detecting a shift in the earth's magnetic field. They can be used to obtain flow, occupancy, vehicle length and speed data, and are appropriate for implementation on bridges. Likewise, piezoelectric sensors detect vehicles travelling at high speeds over a sensor via a change in the sensor's voltage and can monitor up to four lanes. Piezoelectric systems are most often composed of piezoelectric sensors and inductive loop detectors (Guerrero-Ibanez et al., 2018).

Non-Intrusive Sensors

Non-intrusive sensors are deployed in various locations off roads to detect vehicles, their speed, and the lane they are travelling on. Due to their cost and vulnerability to environmental conditions, they are primarily employed in applications that provide information on a particular site, such as traffic congestion at a traffic light, road weather conditions, and the condition of the pavement. For example, some sensors are mounted on masts to monitor a particular area, while others are placed on bridges with their monitoring area directly beneath. Other sensors are situated at ground level, using a beam that traverses the road and is primarily used for single lane traffic with unidirectional flow, as they are highly susceptible to interference from other objects (Zhou et al., 2017). Table 2 summarizes the applications of video cameras, radar sensors, infrared sensors, ultrasonic sensors, and acoustic array sensors.

Table 2: Non-Intrusive Sensors and Applications

Sensor Type	Applications
Video Cameras	Multi-lane vehicle detection, vehicle classification, presence, flow rate, occupancy, and speed.
Radar Sensors	Measurement of volume, speed, and direction of vehicle for managing traffic lights.
Infrared Sensors	Measurement of speed, length, and volume of vehicle, as well as lane occupancy.
Ultrasonic Sensors	Track the number of vehicles, vehicle presence and lane occupancy.
Acoustic Array Sensors	Track vehicle passage, measurement of vehicle presence and speed.

Non-intrusive sensors offer many of the same capabilities as intrusive sensors, yet with fewer difficulties. However, their performance is highly dependent on environmental conditions such as snow, rain, and fog. Accurate traffic data is essential to making informed decisions regarding traffic management. Additionally, non-intrusive sensors are more visible to drivers, resulting in quicker responses, such as slowing down, when detected. The biggest challenge, however, is not just in the installation of these sensors, but in reducing driver reaction times, based on the collected data, and providing drivers with a more accurate view of the context and reality of the road (Guerrero-Ibanez et al., 2018).

A video image processor system comprises of numerous video cameras, a computer for the processing of images and a sophisticated algorithm-based software for the interpretation and translation of those images into traffic data. Specifically, the cameras located at the roadside capture and evaluate video images of the traffic scene to detect the variations between consecutive frames using traffic parameters such as flow volume and occupancy (Zhang et al., 2007). A limitation of video image processor systems is their susceptibility to decreased efficiency due to unfavourable weather conditions.

Radar sensors can transmit low-energy microwaves that reflect off objects within their detection range. Examples of radar sensor systems include Doppler systems that measure the frequency shift of the returned signal to track the number of vehicles and accurately calculate speed, as well as frequency-modulated continuous wave radar that utilizes a continuous transmission power to measure flow volume, speed, and presence (Yang et al., 2022). Generally, radar sensors are precise, easy to install, and can operate in most conditions. However, they are also highly susceptible to electromagnetic interferences.

Infrared sensors can detect the energy produced by vehicles, road surfaces, or other objects. These sensors work by transforming the reflected energy into electrical signals that are sent to a processing unit. There are two types of infrared sensors: passive infrared, which detects vehicles through the emission or reflection of infrared radiation to collect data such as flow volume, presence of vehicles, and occupancy; and active infrared, which utilizes light emitting diodes or laser diodes to measure the reflection time and collect data such as flow volume, speed, classification, presence of vehicles, and traffic density (Hussain et al., 1993).

Ultrasonic sensors are employed to measure the distance between two objects by calculating the amount of time which elapses between a sound wave at frequencies ranging from 25 kHz to 50 kHz being transmitted and reflected by the object back to the sensor. The electrical energy generated from the received energy is transmitted to the processor. These sensors are used to collect data related to vehicle flow and velocity (Appiah et al., 2020). However, one of the

© 2023 by MIP

major drawbacks of this type of sensor is its high susceptibility to external factors. Acoustic array sensors, which are composed of several microphones, are also used to detect sound energy produced by a vehicle entering their detection area (Chen et al, 2001). This is replacing magnetic induction loops as a method to determine traffic volume, occupancy, and average speed of vehicles.

Considerations

Both methods have their own strengths and weaknesses, which should be considered when deciding which technology to use. Intrusive sensors are installed in the road surface and directly measure the presence and passage of vehicles. They are reliable and accurate, making them suitable for measuring the exact number of vehicles passing through a given area. However, they are expensive to install and require ongoing maintenance. Furthermore, the installation process is disruptive to traffic, as the sensors are inserted into the road surface. Based on the review, pneumatic road tubes and piezoelectric sensors have been short-listed as suitable for vehicle classification and counting.

Meanwhile, non-intrusive sensors are placed above the road surface and measure the presence of vehicles using video cameras, radar, infrared, ultrasonic or acoustic technologies. They are relatively inexpensive to install and require minimal maintenance. Additionally, they can be used to measure the speed of vehicles, as well as the number of vehicles passing through an area. However, they are not as accurate as intrusive sensors and may be affected by environmental conditions, such as rain or snow. Generally, only video camera can perform both vehicle classification and counting.

Both intrusive and non-intrusive sensors require installation, although the former in the road surface and the later above it. These are usually installed at traffic hotspots throughout the city. However, for planners who perform feasibility studies, these may not be suitable as the data collection may involve new road locations that are not equipped with these fixed technologies. Therefore, an alternative solution that is portable, but can perform vehicle classification and counting efficiently should be considered. In this case, intrusive sensors are not practical as the technology is fixed to the road or pavements. Hence, video cameras are deemed the most feasible as it can also function in portable mode.

VIDEO CAMERA BASED VEHICLE COUNTING

A portable system for vehicle counting will greatly improve the efficiency of data collection for traffic census. These should be based on suitable placement of video cameras and the use of intelligent algorithms for counting vehicles offline.

© 2023 by MIP

Placement Strategies and Device Specifications

The placement of video cameras on the road for vehicle counting is an important factor for efficient and accurate data collection. It is important to ensure that camera placement is optimal to ensure that the vehicles passing by are not obscured or misrepresented in the footage (Grant et al., 2000). An example of a vehicle that is potentially obscured by another vehicle is shown in Figure 1.

Figure 1: An Example of Vehicle that is Potentially Obscured by Another Vehicle

The most important factor to be considered is the type of road and lane configuration. On a multi-lane road, the camera should be placed on the shoulder of the lane. Another factor to consider is the angle of the camera (Zhang et al., 2007). A wide-angle lens can be used to capture a large area, while a narrow-angle lens can be used to focus on specific lanes. It is important to ensure that the camera is not obstructed by foliage or other objects, and that its field of view is not too wide or too narrow. Figure 2 shows an example of video recording with tree branches covering the later end of the road.

 © 2023 by MIP

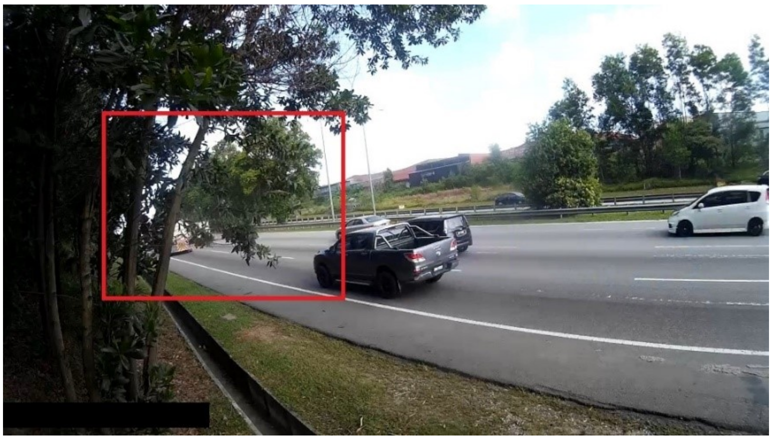

Figure 2: An Example of Tree Branches Covering the Later End of the Road

It is also important to consider the lighting conditions when determining the best placement for the camera. A camera placed in an area with direct sunlight will produce higher quality footage than one placed in a shaded area (Kamkar et al., 2016). Additionally, placing the camera in an area where there is minimal vehicle traffic will reduce the risk of the footage being obscured by passing vehicles. Finally, the location of the camera should be chosen to ensure that the footage collected is representative of the local traffic patterns. For example, if the camera is placed too close to a traffic light or intersection, the footage may not accurately reflect the overall traffic patterns in the area.

Deep Learning Algorithms for Vehicle Counting

Video camera placement can have a significant impact on the performance of deep learning algorithms used for vehicle counting. The placement of the camera affects the quality of the image data that is collected and used for training, and thus affects the accuracy of the model. For example, if the camera is placed too high or too low, the resulting images may not capture the full view of the vehicles, making it difficult for the deep learning algorithms to accurately identify and count the vehicles. Additionally, if the camera is placed too far away from the area of interest, the images may be too blurry or have insufficient resolution, leading to misclassified objects and inaccurate vehicle counts.

To maximize the accuracy of deep learning models for vehicle counting, the camera should be placed in an ideal location in terms of height, angle, and distance. The camera should be placed at a height that is tall enough to capture the entire view of the vehicles, yet not too high to cause a loss of detail and resolution. The angle should be chosen so that it provides the best view of the vehicles, while avoiding any obstructions or shadows. Hence, the camera should be placed close enough that the resolution is sufficient to properly identify and count the vehicles.

Vehicle counting from video is a challenging task, as it requires the algorithm to be able to detect and track vehicles over multiple frames and make accurate predictions about their number. This task is typically performed using convolutional neural networks (CNN), which can extract features from images and videos and learn to recognize vehicles in a scene across frames. CNN can be trained on large datasets of videos with labelled images of vehicles to learn how to recognize and count them. This is done by providing the network with several examples of vehicles, and then training it to recognize their presence in different scenes. Once trained, the CNN can be used to detect and count vehicles in a video by analysing each frame of the video. The algorithm can then use its knowledge of the vehicles' features to accurately identify them and track them across frames. This allows the algorithm to accurately count the number of vehicles in a scene, even if there are multiple vehicles present (Liang et al., 2020).

You Only Look Once (YOLO) is a state-of-the-art convolutional neural network-based approach that can detect objects in an image and classify them into different categories. YOLO has been applied to a wide range of applications, including vehicle classification, and counting. In vehicle classification and counting, YOLO is used to detect vehicles in an image or video and then classify them into different categories, such as cars, trucks, buses, and motorcycles. YOLO uses a single deep neural network to simultaneously detect objects and classify them into the specified categories. It can detect objects of various sizes and shapes and can be used to count the number of vehicles in each image or video (Lin et al., 2021).

Access to Cloud Computing and Processing Issues

Cloud computing has become a critical tool for vehicle classification and counting in recent years. By providing access to big data, the cloud has enabled more accurate and efficient analysis of vehicle data. This has resulted in improved accuracy and precision for vehicle classification and counting. The cloud provides access to vast amounts of data that can be used for vehicle classification and counting. With the ability to store large amounts of data, the cloud can be used to aggregate multiple data sources from different locations and enable real-time analysis. This in turn enables the development of predictive models for vehicle classification and counting, which can be used to identify patterns in vehicle behaviour. This can be used to improve the accuracy of vehicle classification and counting (Qiao et al, 2018).

However, the use of video data for vehicle classification and counting poses some significant challenges when it comes to sending this data to the cloud. As video is typically high resolution and can involve large volumes of data, it

 © 2023 by MIP

may require a high bandwidth connection with a fast upload speed to send it to the cloud. This can be a problem in places with limited internet access or in areas with a low population density, where the available connection speeds may be slow or even non-existent. In addition, the process of transferring the video data may introduce latency, which can be an issue when it comes to gathering accurate data in real-time. This delay can cause problems with the accuracy of the data and make it difficult to capture vehicles moving at high speeds. Furthermore, the cost associated with sending large volumes of video data to the cloud can be prohibitive for some applications.

A feasible approach to solve this is to perform offline processing of the video data. In addition, deep learning algorithms can be used to process video recordings even when the recording is offline. This makes it possible to count vehicles in recordings even if they were made in the past. This enables long-term vehicle counting and monitoring of traffic patterns and congestion. The advantages of using offline processing for vehicle counting are numerous. First, it is much more cost-effective than traditional methods of vehicle counting, as it does not require the use of expensive equipment and personnel. Additionally, the data collected is much more accurate, as the software can detect subtle differences in the video recordings. Additionally, the data collected is much more comprehensive, as it can provide a detailed analysis of the vehicles travelling on a given stretch of road.

WAY FORWARD

This study provides an overview on the sensor technologies commonly used for vehicle classification and counting. The intrusive type provides more variation in sensor technology. However, for the non-intrusive sensor type, only video camera is considered feasible. Meanwhile, a more specialized data collection for traffic census requires reconsideration on the technologies used since it may involve roads that do not have access to the conventional sensing devices. Therefore, intrusive sensors are ruled out as it requires installation with high maintenance cost. This leaves video cameras which can also operate in portable mode. To ensure accurate count of the vehicle types, several additional factors must be considered.

The placement of video camera by the roadside has to be optimized so that every vehicle can be observed by the recording video frames. Hence, installation of the portable device on a pole of optimum height angle will minimize the risk of a vehicle being obscured by another vehicle. Furthermore, a strategically placed video camera should avoid foliage of other objects covering the camera view. Furthermore, the lighting conditions that can also affect the quality of video being recorded. These are important as a good quality video data will result in accurate vehicle classification and counting by the deep learning algorithms. In this situation, access to cloud for real-time computing and storage is also considered not feasible as this requires large bandwidth and fast upload speed. Hence, offline processing by dedicated machine is recommended.

The strategies to be adopted will result in optimum use of resources. However, optimum settings can further be assessed through extended research. Based on the discussed strategies, two of issues can potentially be solved through a structured study. The first involves optimum placement of video camera by the roadside. The scopes to be considered include the elevation and angle of the device, as well as impact of lighting conditions on the quality of the video data. Meanwhile, the second issue can be solved through a dedicated study on the development of deep learning algorithm for accurate vehicle counting.

ACKNOWLEDGEMENT

The study is supported by Universiti Teknologi MARA through the Sustainable Research Collaboration Grant (600-RMC/SRC/5/3 (049/2020)).

REFERENCES

Appiah, O., Quayson, E., & Opoku, E. (2020). Ultrasonic Sensor based Traffic Information Acquisition System; A Cheaper Alternative for ITS Application in Developing Countries. *Scientific African*, *9*, e00487. https://doi.org/10.1016/j.sciaf.2020.e00487

Balid, W., Tafish, H., & Refai, H.H (2018). Intelligent Vehicle Counting and Classification Sensor for Real-Time Traffic Surveillance. *IEEE Transactions on Intelligent Transportation Systems*, *19*(6), 1784–1794. https://doi.org/10.1109/TITS.2017.2741507

Chen, S., Sun, Z., & Bridge, B. (2001). Traffic Monitoring using Digital Sound Field Mapping. *IEEE Transactions on Vehicular Technology*, *50*(6), 1582–1589. https://doi.org/10.1109/25.966587

Grant, C., Gillis, B., & Guensler, R. (2000). Collection of Vehicle Activity Data by Video Detection for Use in Transportation Planning. *Intelligent Transportation Systems Journal*, *5*(4), 343–361. https://doi.org/10.1080/10248070008903775

Guerrero-Ibanez, J., Zeadally, S., & Contreras-Castillo, J. (2018). Sensor Technologies for Intelligent Transportation Systems. *Sensors*, *18*(4), 1212. https://doi.org/10.3390/s18041212

Hoxha, G., Fandaj, A., & Bajrami, X. (2023). Quality aof Automatic Traffic Volume Counting by Cameras and Impact on the Qualitative Indicators of Traffic. *Infrastructures*, *8*(3), 44. https://doi.org/10.3390/infrastructures8030044

Hussain, T.M., Saadawi, T.N., & Ahmed, S.A. (1993). Overhead Infrared Sensor for Monitoring Vehicular Traffic. *IEEE Transactions on Vehicular Technology*, *42*(4), 477–483. https://doi.org/10.1109/25.260764

Gibbons, S., Lyytikainen, T., Overman, H.G., & Sanchis-Guarner, R. (2019). New Road Infrastructure: The Effects on Firms. *Journal of Urban Economics*, *110*, 35–50. https://doi.org/10.1016/j.jue.2019.01.002

Kamkar, S., & Safabakhsh. (2016). Vehicle Detection, Counting and Classification in Various Conditions. *IET Intelligent Transport Systems*, *10*(6), 406–413.

© 2023 by MIP

https://doi.org/10.1049/iet-its.2015.0157

Lam, W.H.K., Tang, Y.F., Chan, K.S., & Tam, M.-L. (2006). Short-term Hourly Traffic Forecasts using Hong Kong Annual Traffic Census. *Transportation*, *33*, 291–310. https://doi.org/10.1007/s11116-005-0327-8

Liang, H., Song, H., Li, H., & Dai, Z. (2020). Vehicle Counting System using Deep Learning and Multi-Object Tracking Methods. *Transportation Research Record: Journal of the Transportation Research Board*, *2674*(4), 114–128. https://doi.org/10.1177/0361198120912 74

Lin, C.-J., Jeng, S.-Y., & Lioa, H.-W. (2021). A Real-Time Vehicle Counting, Speed Estimation, and Classification System Based on Virtual Detection Zone and YOLO. *Mathematical Problems in Engineering*, *2021*, 1577614. https://doi.org/10.1155/2021/1577614

Mohd Yusoff, Z., Aziz, I.S., Naharudin, N., Abdul Rasam, A.R., Ling, O.H.L., & Nasrudin, N. (2022). Mobility and Proximity Coefficient to High-Traffic Volume in Daily School Operations. *Planning Malaysia*, *20*(2), 321–332. https://doi.org/10.21837/pm.v20i21.1116

Ogunyemi, O.F., Mohamad, D.B., Badarulzaman, N., & Othman, A.G. (2021). Traffic Congestions, Time Spent at the Expressway Junctions, and Its Impact on Individual Productivity: A Perception Study of Ilesa-Owo-Benin Expressway in Akure Ondo State, Nigeria. *Planning Malaysia*, *19*(5), 14–25. https://doi.org/10.21837/pm.v19i19.1056

Prabha, R., & Kabadi, M.G. (2016). Overview of Data Collection Methods for Intelligent Transportation Systems. *The International Journal of Engineering and Science*, *5*(3), 16–20. https://doi.org/10.1007/s11116-005-0327-8

Qiao, J., He, Y., & Shen, X.S. (2018). Improving Video Streaming Quality in 5G Enabled Vehicular Networks. *IEEE Wireless Communications*, *25*(2), 133–139. https://doi.org/10.1109/MWC.2018.1700173

Sharma, S.C. (1981). Minimizing Cost of Manual Traffic Counts: Canadian Example. *Transportation Research Record*, *905*, 1–7.

Tasgaonkar, P.P., Garg, R.D., & Garg, P.K. (2020). Vehicle Detection and Traffic Estimation with Sensors Technologies for Intelligent Transportation Systems. *Sensing and Imaging*, *21*, 29. https://doi.org/10.1007/s11220-020-00295-2

Yang, Z., Shi, F., & Liang, H. (2022). A Portable Traffic Counting, Speed Estimation, and Classification Terminal Using IR-UWB Radar. *IEEE Sensors Journal*, *22*(13), 13365–13374. https://doi.org/10.1109/JSEN.2022.3181215

Zhang, G., Avery, R.P., & Wang, Y. (2007). Video-Based Vehicle Detection and Classification System for Real-Time Traffic Data Collection Using Uncalibrated Video Cameras. *Transportation Research Record: Journal of the Transportation Research Board*, *1993*(1), 138–147. https://doi.org/10.3141/1993-19

Zhou, Y., Dey, K.C., Chowdhury, M., & Wang, K.-C. (2017). Process for Evaluating the Data Transfer Performance of Wireless Traffic Sensors for Real-Time Intelligent Transportation Systems Applications. *IET Intelligent Transport System*, *11*(1), 18–27. https://doi.org/10.1049/iet-its.2015.0250

Received: 24th Jan 2023. Accepted: 20th July 2023

© 2023 by MIP