Evaluating the impact of lane marking quality on the operations of autonomous vehicles

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ABSTRACT

The quality of lane markings is pivotal for safe operations and efficient trajectory generations of Connected and Autonomous Vehicles (AVs). However, most studies are devoted to enhancing in-vehicle detection systems and ignore the impact of faulty lane markings. An instrumented vehicle was employed to mimic the data input of an AV and real-world trials were conducted on (1) live motorways and (2) a controlled motorway facility. From the live motorway data, causal factors affecting computer vision lane detection and classification algorithms were examined and an enhanced lane classification algorithm was developed to overcome the limitations posed by poor lane markings. In the controlled motorway facility, experiments to modify the physical appearance of the lane markings were conducted to further test the performance of the developed algorithm. The detection rates of the developed lane classification algorithm were compared with the Lane Departure Warning (LDW) system already implemented in the vehicle. Findings revealed that the LDW system is accurate over 95% and 54% of time when lanes are faded by 50% and 75% respectively. Further testing on the quality of the lane markings was carried out virtually in such a way that the experiments were replicated in a simulation environment to: (1) identify lane marking conditions that can be reliably adopted for safe operations of AVs, (2) estimate the effect of adverse weather and lighting conditions on road markings detection and (3) address localisation issues for AVs. Simulation results show that poor lane markings have a significant negative impact on AV safety, especially in inclement weather and poor light conditions inducing an increase in conflicts, and delays. This can be compensated if more sophisticated sensors are employed in AVs, and the operators of road network develop lane-based digital road maps.

Keywords: lane markings, lane detection and classification, AVs, inclement weather, retro-reflectivity, simulation, lane-based digital maps

1. Introduction

Both government and industry have been focusing on developing AV technology for its potential to substantially improve road safety, traffic efficiency and promote environmental friendliness (Bajpai, 2016). In the UK, the government has invested heavily in the development of AVs and industry analysts predict that AVs will account for about 30% of sales in 2035 (Catapult Transport Systems UK, 2017). Much of the attention about AVs is currently devoted to technical developments of the vehicle. However, the ability of AVs to operate fully autonomously may not be entirely contained within the vehicle technology due to the inherent complexity in the road infrastructure (Liu et al., 2019).

Existing roadway designs and configurations are not intended for AV operations (Sanusi et al., 2022). Current design may not be suitable for mixed traffic operations with issues surrounding environmental sensing and trajectory planning. In terms of trajectory generation for AVs, sense-plan-act methodology is currently in place (Katrakazas et al., 2015). Nevertheless, this methodology cannot dynamically reflect changes in road geometry, road layout, and traffic dynamics (Katrakazas et al., 2019). To enrich the situational awareness of the trajectory generation method, it is important to take the elements of road infrastructure into consideration (e.g., lane markings, road signs, traffic lights, traffic controls, and variable message signs) (Katrakazas et al., 2019). Therefore, clear, and consistent road markings and signages are crucial for a safe and precise navigation for AVs under a dynamic environment.

Lane markings and signs are fundamental inputs for AV system (e.g., lane departure warning (LDW) and lane-keeping assistance systems (LKAS)) to maintain its position on the road through detecting lane markings accurately and timely. However, the performance of such systems can possible be jeopardised due to inexistent, confusing, obscured or non-compliant road markings (Khattak et al., 2021). Some factors affecting the quality of road markings are deposits on the roads such as oil and mud, adverse weather like sun glare, rain, snow can also obscure road markings (Khattak et al., 2021). As a result, the quality of lane markings need to be consistently monitored along the route to ensure the robustness of LDW and LKAS for AVs (Khan et al., 2019). If these major factors are ignored , the ability of AVs to plan safe trajectories would be limited since their sensors would not be able to detect the road markings with high integrity.

To detect lane markings, most AVs rely on camera-based, Light Detection and Ranging (LiDAR)-based and fusion approaches (Zhang et al., 2021). Solely relying on image or LiDAR sensors might not guarantee safe driving performances under poor driving conditions (Khattak et al., 2021). For example, cameras provide rich information working at high framerate and low-cost but are sensitive to light conditions and cannot capture depth information directly. For LiDAR, accurate depth information of the surroundings of AVs are provided from the 3D point clouds but it has a limited range and does not support colour information. Sensor fusion can compensate the respective drawbacks from camera and LiDAR. A more sophisticated measure is to ensure that the information gathered from the in-vehicle sensors is integrated with a combination of data from road side beacons (Kuutti et al., 2018) and highly detailed road maps (Katrakazas et al., 2015). AVs require a higher level of detail of maps for self-position estimation than the static road centre-line maps used for conventional vehicles (Watanabe et al., 2020). Additionally, navigational dynamic maps are necessary to provide centimetres accurate references.

To appraise how lane markings impact AV operations, a virtual simulation environment can be a highly effective solution. Through simulation, the effect of the condition and visibility of lane markings leading to the disengagement of AVs can be verified through a controlled experiment without the need of real-world testing. The outcomes of such simulations can be used to prevent the same disengagement reoccurrence and modify existing infrastructure to prevent further disengagements. A sub-microscopic traffic simulator environment (e.g., PreScan (Formosa et al., 2022)) could provide an appropriate testbed to accurately represent the AV functionality, communication, mixed fleets and varying road, weather and light conditions. To obtain more realistic values, the surrounding dynamic traffic can be generated via a microscopic simulator (e.g. PTV VISSIM) and integrated with the sub-microscopic simulator (Formosa et al., 2022). Despite the robustness of the integrated simulation platform, this approach can prove to be complex and challenging since all possible combinations of traffic situations are time and computationally exhaustive to be modelled, so a number of 'benchmark' scenarios have to be developed.

In conclusion, lane markings are essential for safe operations of AVs. However, sporadic attention has been given to examining the impact between lane marking quality on lane marking detection and AV operations. Therefore, this study used an instrumented vehicle equipped with a suite of sensors, mimicking the data input of an AV, to conduct real-world trials at: (1) live motorways and (2) a controlled motorway facility operated by National Highways (UK). From the live motorway data, causal factors affecting computer vision lane detection and classification algorithms were examined and an enhanced lane classification algorithm was developed to overcome the limitations posed by poor lane markings. In the controlled motorway facility, experiments to modify the physical appearance of the lane markings were conducted to further test the performance of the developed algorithm. The detection rates from the developed algorithm were compared to detection rates obtained by the MobilEye 630 PRO sensor. MobilEye provides a cost-effective approach to appraise lane marking quality (Mahlberg et al., 2021) but their performance is limited due to the lack of robustness in harsh operational environments (Kuutti et al., 2018). Further testing on the quality of the lane markings was carried out virtually such that the experiments were replicated in an integrated simulation platform using data collected from the real-world trials. This platform provides an approach to: (1) identify the road markings condition that can be reliably adopted for safe operations of AVs, (2) the effect of adverse weather and lighting conditions on road markings detection and (3) the importance of adopting lane-level digital maps for AVs.

To the authors' knowledge, no research has holistically reviewed the impact of road markings on AV operations through both real-world trials and simulations. This study is essential given that the ability of AVs can be severely impaired by the roadway infrastructure's design and maintenance. Therefore, this study provides guidance to AV developers and infrastructure providers regarding the quality of lane markings to expect in real-world conditions. Additionally, safe AV implementation would not be achieved by solely focusing on developing vehicular technologies because: (1) the road infrastructure has a pivotal role to play in ensuring AV safety and (2) there is a long transition period to automation and the co-existence of conventional vehicles and AVs on the same network.

2. Literature Review

AVs rely on a suite of sensors which collect large streams of data continuously to internalise the surroundings, for example, identification of lane markings so the vehicle stays in a lane. Lane markings are considered to be an important road safety feature since the quality of lane markings positively correlate with driving safety (Burghardt et al., 2021). Therefore, this section reviews the literature by investigating the lane detection and classification technology for AVs and the factors affecting lane marking quality and detection rates.

2.1 Computer vision-based lane detection and classification algorithms

Park, Kim and Yi (2016) make use of four fish-eyed cameras on each side of the vehicle to capture the top-view images for lane detection. The proposed algorithm first filtered the images by a 2-dimensional (2D) Gaussian kernel and then binarized by setting a threshold value. Random sample consensus (RANSAC) was adopted and found that lane markings from images can be sufficiently represented by a second-order polynomial. Niu *et al.* (2016) used modified Hough Transform to extract small line segments. These line segments were then clustered into groups using DBSCAN clustering and identified as lanes through curve fitting. Gupta and Choudhary (2018) show that their method achieved an increase in true positive and a decrease in false positive results. This was achieved by clustering connected components using a spatio-temporal incremental clustering algorithm coupled with curve fitting.

Experimental results show that their work can be adopted in real-time and can recognize road surface markings viewed from different orientations, conditions and of different sizes.

A common hinderance to recognising lane marking is the obstruction of the marking by other vehicles in traffic as well as environmental factors. To overcome the issue of obstruction by other vehicles, Kim, Yoo and Koo, (2018) used a 3-dimensional (3D) disparity map of the road to remove all vehicles and the Kalman filter to recognise the lane markings. When considering challenging environmental conditions, including weather-induced challenges such as rain and heat, Taubel, Sharma and Yang, (2014), develop a lane detection algorithm by integrating the Lucas-Kanade (L-K) optimal flow method (to determine the lateral position and heading angle of the vehicle between consecutive images when the lane boundaries cannot be found) and the Hough transform method (when they become apparent again). Based on road tests, a false reading was only recorded 1.18% of the time.

A fast and robust approach for lane detection based on multi-source camera fusion system was developed by Xiong *et al.*, (2020). A B-spline lane line was fitted based on the strength of the RANSAC algorithm for the front view image detection. This was improved by adopting the Hough algorithm for the two rear-view images correspondingly. When the front-view image detected a valid lane marking, it was not necessary to integrate the top-view information. Only when there is uncertain, missing, or false detection, were the two sides and top-view information used for compensation. Experimental results show that the multi-camera fusion framework contributes to significant improvement in accuracy and robustness in comparison with traditional methods.

2.2 Lane marking impact evaluation

Expert observation is a commonly adopted technique to evaluate the impact of lane markings (Stacy, 2019). In various standards such as ASTM E1710, E2176, and E2177 methods to evaluate the impact of lane markings take into consideration the physical appearance and retro-reflectivity in different weather conditions (Pike et al., 2007). However, this approach is difficult to adopt as it requires subjective judgements.

With the advancements in technology, image processing techniques are nowadays used to evaluate pavement markings. In fact, Zhang et al., (2012) confirms that these techniques are consistent with expert judgement. Consequently, evaluation characteristics using machine vision of current lane markings can also be examined by the same set of defined pavement markings factors (i.e., retro-reflectivity, weather, and luminance) (Stacy, 2019). Additionally, particular performance measures from image processing techniques can also be adopted for evaluating results such as precision, recall, true/false positives have also been adopted (Mamun et al., 2022).

Several studies have shown that safety is influenced by lane markings (Hatfield et al., 2009; Wu et al., 2018) which in turn are also highly affected by weather conditions. As a result, another recognised evaluation design of lane marking impact is due to crash incidences such as traffic conflicts and road usage patterns (e.g., traffic delays) (Hatfield et al., 2009).

2.3 Lane marking factors affecting computer vision detection algorithms

Little attention has been paid to understand the relationships between lane marking quality and the lane detection rates (Carreras et al., 2018) and their effect on AVs. This section explores factors which AVs might face from poor lane markings: (i) visibility issues due to adverse weather conditions, (ii) lane marking physical properties and (iii) localisation in uncertain driving conditions due to weather conditions and physical change.

2.3.1 Visibility issues during adverse weather conditions

AVs gather surrounding data from different sensors. Their functionality of each sensor can be affected by weather conditions (Yoneda et al., 2019). To determine the perception and navigation performance of sensors under inclement weather conditions, Neumeister et al., (2019) carried out an experiment on LDW and LKAS. Their results show that rain had a negative impact on the LDW in a vision-based system only, whilst the effect of ice and snow on camera and radar sensors affected all systems. Hadj-bachir et al., (2019) simulated that the measurable distance of LiDAR would be halved if the intensity of rain is greater than 30mm/h. Moreover, the splashes from water puddles as vehicles drive through, could also confuse a LiDAR by falsely identifying the splashes as objects (Yoneda et al., 2019). In snowy conditions, the lane markings are often obscured, making it impossible to be detected (Yoneda et al., 2019). These conclusions were also confirmed by Vargas et al., (2021) where sensors were tested in conditions with rain, fog, snow and lightning. On the other hand, Zhang et al., (2020) showed that the positioning performance of Global Navigation Satellite System (GNSS) are not dependent on local weather. Thus, by fusing multiple sensors together (e.g., LiDAR with GNSS), can compensate for the shortcomings of another sensor, providing an enhanced detection result. This brings a more trustworthy and safe detection system with additional redundancy compared with a single sensor system (Kmiotek et al., 2008).

2.3.2 Lane markings physical properties

Visibility of lane markings is an important physical property which can adversely affect the ability of lane detection and the safety of AVs (Austroads, 2019). Retro-reflectivity is used to measure the quality of lane marking in terms of its visibility to drivers or AVs. It can be formalised as a ratio between luminance of an object with illuminance from the light source (Choubane et al., 2018). Retro-reflectivity of lane markings are standardised and in speeds over 70mph, it must be above 100 mcd/m^2/lux in lit areas and above 150 mcd/m^2/lux in unlit areas (Highways England, 2020).

Lv et al., (2018) shows that passive disengagements impairing the navigation of AVs can occur, under the circumstance of degraded lane marking retro-reflectivity. Carlson et al., (2013) showed that a decrease in retro-reflectivity to 100 mcd/m^2/lux, leads to an increase in traffic accidents by 23% when conventional vehicles are considered. Matowicki et al., (2016) also agreed that retro-reflectivity is an important factor for correct lane recognition from the experimental result of testing LKAS. Several factors can possibly impair the retro-reflectivity of lane markings such as higher traffic volume, lane markings location (centre line or edge line) and geometry (horizontal curvature) because of vehicle crossovers can scatter the retroreflective beads or abrade them (MacEacheron et al., 2019).

2.3.3 Localization issues in uncertain driving conditions

Precise localisation for AVs requires the construction of detailed maps containing landmarks such as lane markings. However, it is possible that vehicles cannot self-localise in scenarios such as adverse weather, poor retro-reflectivity of lane markings and inconsistent lane markings. Under these circumstances, the data collected by sensors are inconsistent with the map data, limiting the AV's ability to identify the correct lane of driving (Vivacqua et al., 2018).

To overcome these limitations, the use of GNSS with high-definition (HD) maps is the typical methodology for AVs self-localisation (Kang et al., 2020). These maps consist of layers ranging from road-level map, lane-based map and a localisation model (Zheng et al., 2019). While the road-level map proved not to be comprehensive enough for lane keeping function, lane-level map proved to be crucial in enhancing vehicle's ability in autonomous driving. This layer can assist the vehicle localisation system when the lane markings are not visible. The localisation model compliments the lane-level map by providing features or 3D point cloud information for the surrounding area that the vehicle is driving on. Moreover, V2I can also be used to inform the vehicle about the current road markings from the infrastructure, which gathers local or global information.

In summary, AVs are equipped with multiple sensors to navigate the road network with the assistance of pavement markings (Hallmark et al., 2019). However, lane marking inconsistency, visibility issues, and adverse weather conditions can severely limit the functionality of the sensory units of AVs. Detection errors and reduced sensor detection range pose challenges for AVs to perform optimally under these conditions. To compensate for this limitation, AVs can fuse data from the GNSS and HD maps to keep in lane (Ukkusuri et al., 2019).

3. Data

An instrumented car with various sensors was utilised to acquire real-time traffic, location, and infrastructure data, mimicking the data an AV receives on a roadway. From this data, an enhanced lane detection and classification algorithm was developed. Real-world tests were also undertaken at a controlled freeway facility. This feature allows for testing without interrupting real traffic. The trials collect data from the instrumented vehicle to test the performance of the developed algorithm with fading lane markings. This study utilised the controlled real-world data to develop the network in the simulation environment to further evaluate the impact of lane markings on an AV in different conditions. More specifically, this data was used as input to develop the network in the simulator to ensure realistic scenarios are developed.

3.1 Vehicle Instrumentation and Data Collection Process

Multiple sensors, including a LiDAR sensor, two radar sensors (front and back), two camera sensors (front and rear), localisation sensor, weather sensor, gyroscope, accelerometer, and a MobilEye camera sensor, were put in the instrumented car to collect data. A data integration design aggregated all the data on a central computer. A schematic diagram of the instrumented vehicle is shown in Fig. 1.

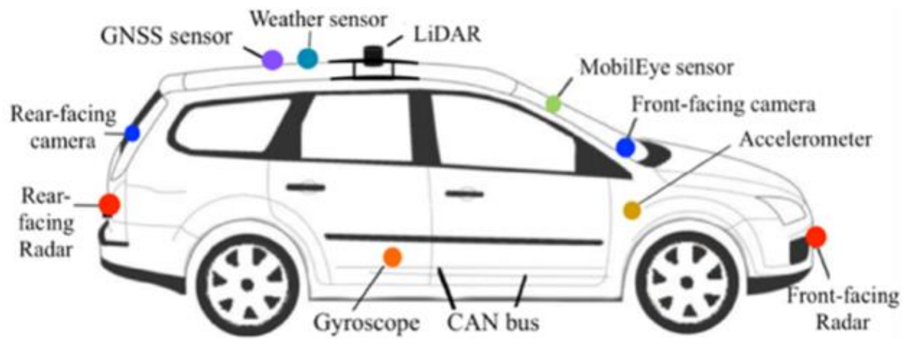


Fig. 1. Sensor configuration on instrumented vehicle

This study used detailed data from collected from:

i. Live motorways

To identify causal factors affecting computer vision lane detection and classification algorithms, data was collected from live motorway sections in the UK (M1 (J23 to J12), M25 (J19 to J16), M40 (J1 to J15) and M69 (J1 to J3)). A total of 9 trials, equivalent to 1062 miles travelled were conducted. Additionally, during these trials, 902 lane change events were manually recorded and matched with the events recorded by LDW System. For every lane change by the LDW system, the time, left/right indicator status, issues warning messages were recorded.

ii. A controlled motorway facility

To evaluate the impact of lane marking quality, data was collected at a controlled highway facility. Two experiments were set up and each experiment was conducted in dry daylight without sun glare. The driver was told to drive in the centre of the lane and avoid harsh braking and accelerating outside the acceleration zone.

iii. An integrated simulation platform

To evaluate the lane markings condition that can be reliably identified for safe operations of AVs and to provide guidance to AV developers and infrastructure providers regarding the quality of lane markings to expect in real-world conditions, an integrated simulation platform was developed. From this platform the factors affecting computer vision detection algorithms discussed in Section 2.2 were tested.

In summary, the data extracted from the field experiments include microscopic data collected from in-vehicle sensors as well as headways, speed, acceleration, and deceleration profiles. Traffic volume data such as speed and flow were also collected from inductive loop detectors on the motorways to calibrate and validate the simulation model. More details about the data used in the study for calibration and validation is given by Singh et al., (2023). This data guarantees that the output from the simulators is realistic such that the conclusions drawn are accepted for a real-world scenario. From this data, the key performance indicators such as: (1) traffic safety by estimating traffic conflicts and (2) efficiency by measuring delays of AVs were estimated.

4. Methodology

This section describes the paper's methodological approach. Real-world and simulated studies were conducted to assess and evaluate the influence of lane markings on AVs safety and efficiency. Live motorway data was collected to identify causal factors for affecting computer vision algorithms and to develop an enhanced lane detection and classification algorithm (Section 4.1). Based on the causal factors identified, two experiments were developed at a controlled motorway facility (Section 4.2). These experiments were developed to evaluate the impact of lane change events under any changes in lane markings. Simulation studies complement the real-world experiment which evaluates the impact of safe and efficient navigation of AVs when the lane markings are impacted by poor weather, change in physical properties of lane markings, and the necessity of using lane-based digital maps in the safety and efficiency of AVs (Section 4.3). From the data collected, a comprehensive assessment on the quality of lane markings was evaluated in terms of their impact on the traffic efficiency and safety. An overall framework interlinking the different components of the methodology was developed (Hu et al., 2023; Lai et al., 2020; Li et al., 2018; Matowicki et al., 2016b). In this paper the framework for evaluation of the impact of lane marking quality on the operations of AVs is presented in Fig. 2.

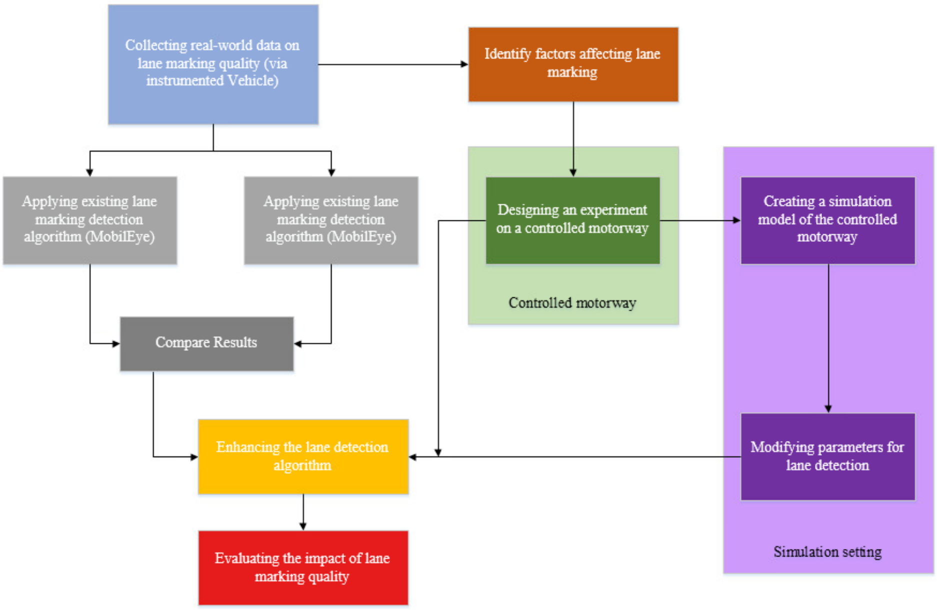
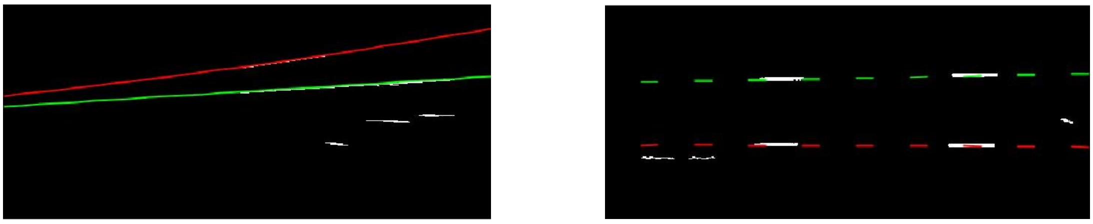


Fig. 2. A framework for the methodology for evaluation of the impact of lane marking quality on the operations of AVs

4.1 Enhanced lane detection and classification algorithm

The lane detection and classification algorithm use each video frame to detect lane makings. The algorithm starts by warping a binary image to birds-eye-view (BEV) (Formosa et al., 2020). From the video data collected, each frame was recorded approximately every 66ms. In each frame, the forward-facing images were transformed into BEV image through inverse perspective mapping (IPM) technique using the intrinsic camera parameters. The IPM algorithm utilised the camera settings parameters such as the location of the camera (x, y, z) coordinate, focal length, yaw, roll and pitch angle of the camera to translate between the world coordinate system with camera coordinate system. BEV image assists in lane detection as the lane markings are transformed from two converging lines into two parallel lane markings. The images are then binarized, which signifies the pixels of the lane markings. To detect lanes from the frames, a random sample consensus (RANSAC) is used to fit second order polynomials from the image. This algorithm produces the results of left lane, right lane, intersecting lines, lanes below threshold, two lanes detected.

In this study, a lane marking is detected by a colour coded approach: red pixels for detecting the left lane and green pixels for detecting the right lane. If no red or green pixels are detected from the image, it indicates that there is an issue with lane markings at that location. In the case where both lanes are detected, second order polynomials are fitted to the red and green pixels respectively. Fig. 3 shows an example of rejected and accepted detected lanes. The detected lane markings are also tracked using Kalman Filter (KF) using the rate of change of position and size of the lane markings through a two-staged prediction and correction model (Formosa et al., 2020). The pseudocode of the algorithm is presented in Table 1.



(a) Situations where lanes are rejected (b) Situations where lanes are accepted

Fig. 3. Example frames of rejected (a) and accepted (b) from lane classification algorithm

Table 1: Pseudocode of the algorithm for (a) lane detection and (b) lane classification

(a) Pseudocode of the algorithm for lane detection
Initialise VideoPlayer and load Video Initialise camera Intrinsic parameters (such as focal length, principal point, image size, radial distortion, skew of the camera) for each frame: | perform Inverse Perspective Mapping | convert image to grayscale | fit function for each lane marking, | if left lane ->red | if right lane ->green

(b) Pseudocode of the algorithm for lane classification
Initialise video frames with lanes for each frame: | filter red and green Lines to single out left and right lane | count the number of pixels of green and red | fit a second order polynomial with detected pixels | obtain polynomial for left and right lane | find the horizontal displacement between green and red line | estimate lane width between red and green lines | using empirical thresholds left, right lanes are classified

4.2 Real-world experimental design to evaluate the impact of lane marking quality in a controlled facility

Real-world experiments were conducted utilising an instrumented vehicle at a controlled motorway facility. From the real-world experiment, the vehicle kinematics data are collected for repeated lane change manoeuvres with different physical appearance of lane markings. The data is used to test the ability of the MobilEye to provide LDW. When MobilEye detects a lane change, manual records are also created. Black duct tape was utilised to cover existing lane markers between lanes 1 and 2 to test algorithm detection rate. In the first experiment, the lanes were faded in a repeated pattern of fully covered lane markings followed by 75% covered lane markings. The resultant faded lane marking section has two fully faded (100%) and two 75% faded lane marking zones as shown in Fig. 4.

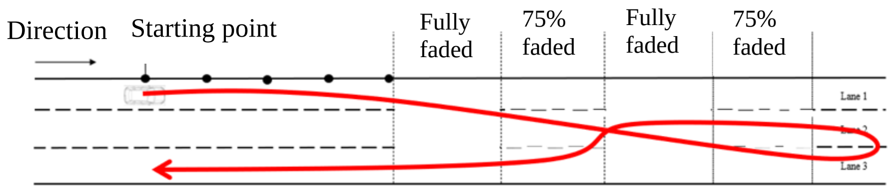


Fig. 4. Exp. 1(a) L1→L2→ L3; L2→L3

To carry out the experiment, the instrumented vehicle started moving in Lane 1 until it reached the first completely faded landmarking. A lane change from 1-to-2 was performed in the first fully faded zone and another lane change from 2-to-3 in the second 75% faded lane marking zone. At the end of the testbed, the vehicle moved from Lane 3-to-2 and made a lane change at the second 75% faded zone (Fig. 4).

Using the same setup, a different lane change manoeuvre pattern was performed. The instrumented vehicle started at Lane 1, a lane change was performed from 1-to-2 and then 2-to-3 in the second fully faded lane marking zone. At the end of the testbed, the vehicle moved from Lane 3-to-2 within the marking zone and back to lane 1 within the fully faded lane marking zone as represented in Fig. 5.

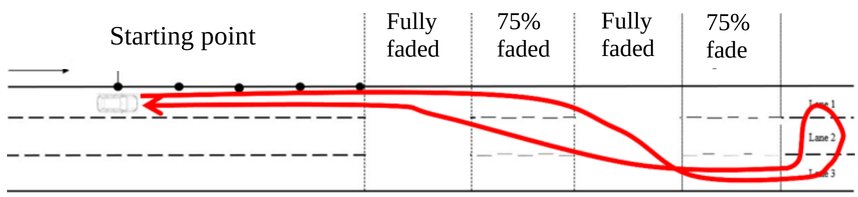


Fig. 5. Exp. 1(b) L1→L2 →L3; L3→L2→L1

In the second experiment, the lanes are faded in a repeated pattern of 50% covered lane marks followed by uncovered (original) lane marks (Fig. 6). The lane change manoeuvre pattern in this experiment included starting at Lane 2 and performing a lane change with 50% faded lane markings from lane 3-to-2 with 50% fadedness. The vehicle then moved to lane 3-to-2 in the 50% fadedness zone and ends in lane 3.

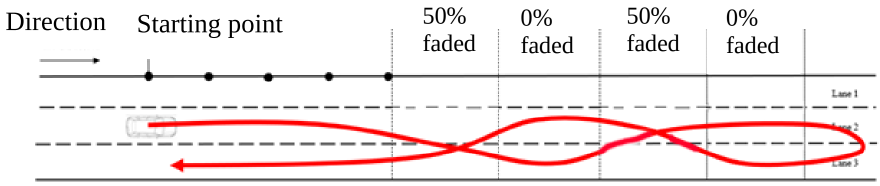


Fig. 6. Exp. 2 L2→L3→L2; L3→L2→L3

The system logged the time, whether the indication signal was on, and whether the sensor gave a warning for every lane change. In these experiments, the indication signal was not used to determine the algorithm's success rate. In this study, success rate is the percentage of lane change events where the system issues a valid warning. The controlled motorway environment made this possible. If the system doesn't alert during a lane change, it could be due to poor lane markers, a system fault, or bad weather. The findings from the experiments at the controlled motorway facility could only provide a snapshot of lane marking conditions to assess the quality of lane markings. Therefore, to validate the findings, the developed algorithm that takes video data from a camera as 'input' and continuously 'detects' lane markings was employed.

4.3 Simulation experimental design to evaluate the impact of lane marking quality

To understand the impact of safe and efficient navigation of AVs when the lane markings are impacted by poor weather, change in physical properties of lane markings, an integrated simulation framework was developed. The integrated simulation platform is composed of an AV, the road network, and human driven vehicles. This platform can simulate the functionalities of AVs through sub-microscopic simulation in a calibrated and validated mixed traffic microsimulation motorway environment. The integrated simulation platform development follows the framework developed by Formosa et al. (2022) where PreScan simulates intelligent mobility and its functions while VISSIM simulates the behaviour of individual vehicles within a predefined road network.

In this research, the baseline simulation scenario was constructed in PreScan by replicating the testbed at the controlled motorway facility and the instrumented vehicle's functional parameters (e.g., car model, sensor modelling). The data collected by the instrumented vehicle is pivotal for calibrating integrated simulation platform to model AV traffic flow in VISSIM. These two simulation systems are linked via Matlab Simulink to share data synchronously. To evaluate several scenarios, simulation parameters and control systems were changed. A more detailed explanation of each phase of the methodological framework is described in (Formosa et al., 2022) and Fig. 7 shows the connection framework.

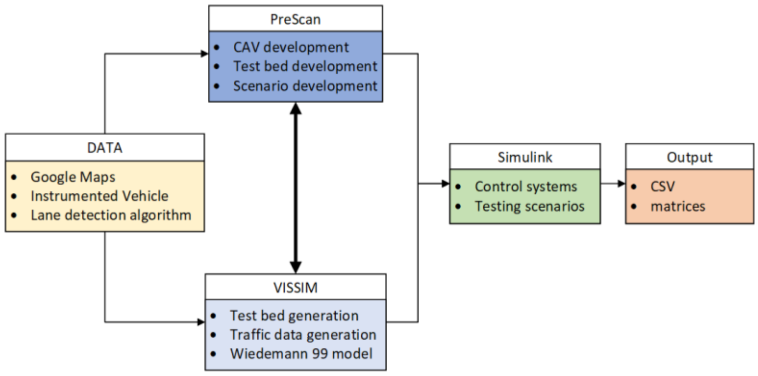


Fig. 7. Simulation experimental framework

4.3.1 Baseline Simulation Scenarios

Creating a baseline simulation scenario is required to compare simulations. The testbed simulation network was constructed in PreScan with dimensions matching the controlled testbed's topography. Real-world data for PreScan comes from an instrumented Ford Focus with AV-like sensors. PreScan keeps environmental sensor parameters (radar, laser, camera, GPS) consistent for comparison. Using the GUI, the sensor type and sensor attributes (e.g., range and field-of-view) were modified to match the sensors in the instrumented car. PreScan was linked to VISSIM through MATLAB/Simulink.

In VISSIM, the behaviour and the movement of each vehicle is ruled by the Wiedemann99 model which is suitable for a motorway scenario (Papadoulis, 2019). VISSIM divides lateral movements into mandatory and voluntary lane changes to replicate motorway lane changing. Driving behaviour requirements for this mandatory lane change include maximum permitted deceleration of the lane-changing vehicle and its follower in the target lane. Any lane change requires a safe space (> safety distance) in the vehicle's travel direction. The gap size depends on the lane-changing vehicle's speed and the following vehicle's speed.

4.3.2 Simulation scenarios

Three simulation scenarios are created in PreScan to evaluate the impact of lane markings on AVs as discussed in Section 2.2. The objective of these scenarios is to (1) identify the road markings condition that can be reliably adopted for safe operations of AVs, (2) the effect of adverse weather and lighting conditions on road markings detection and (3) the importance of adopting lane-level digital maps for AVs.

- Physical appearance of roadworks

Prescan has several options to modify the physical appearance of roadworks for example, fading the marker paint of the lane markers, road markings and priority lines varying between 0 and 100% and by adding wear and tear to the lane lines. The visibility of lane markings is reduced in the nighttime. In this study, light was added to motorway signal posts to examine their effect. PreScan can adjust the luminous flux, light post spacing, and AV effect. At night, the AV can't read lane markers unless the highway is brightly illuminated. Hence, either increased street lighting or a lane-based digital map to guide drivers is required. The retro-reflectivity of lane markings was also modified in the simulation by allowing only 50% of the light to be reflected back to the vehicle and the sensors. This parameter is modified in the simulation as Matowicki et al., (2016) reported that retro-reflectivity is a crucial factor for correct lane recognition from real-world testing.

- Weather effects

Weather effects including precipitation, fog and snow were explored in this study. The baseline scenario developed to compare the weather effects is from a dry and sunny weather. In the case of precipitation, PreScan allows to change the parameter value. During adverse weather conditions, freshly marked road marking are hard to be identified, therefore, faded lane markings make it even harder for the AV to navigate. In terms of fog, PreScan allows to change the parameter value based on the range of visibility. It can be observed that while the most affected during fog is the visibility range, the AV will need to know of what’s ahead in the road network to be able to plan and navigate within the dynamic road dynamics. PreScan also allows snow to the simulation. During snow, the road situation became increasing difficult to navigate for AVs. This is due to the snowfall hitting the windscreen and the sensors, creating noises of the video input for the perception layer causing the quality of input for the sensors is hampered. The ability for sensors to pick up lane markings exacerbated under snow if the lane marking is already faded. Additionally, heavy snowfall covers the road and hence obscures the road markings.

4.3.4 Overall Simulation Design

In all tests, the instrumented vehicle follows a pre-defined path. In each test, the marker paint of the lane markings, road markings and priority lines were gradually faded (i.e., wearing and tearing of the lane markings) from 50% up to 90% faded. The faded lane markings were tested in clear weather, rain, snow, fog, and lower retro-reflectivity.

In every scenario tested, the instrumented vehicle gathers the surrounding dynamic information by its sensors and the minimum thresholds of lane marking conditions that can be identified by AVs in different weather and lighting environments. In some instances, the AV was not able to continue with its journey due to its inability to identify lane markings. In this study, only 50% and 90% physical appearance options are presented. This is because the results from 50% to 90% are similar. Results for more than 90% fading are significantly different. Further testing was carried out to see whether the lane-based digital road map can be employed to compensate faded lane markings.

To simulate the effectiveness of lane-based digital map, the vehicle's path planning algorithm from AVs receives information from lane-based digital map when the sensors are not able to do so. The lane-based map contains a digital map of the road layout consisting of lane-level centrelines as opposed to a road-centre lines based static map. In this way, the path planning algorithm can create new collision-free trajectories based on the fused data from the in-vehicle sensors and map. Multiple collision free trajectories are generated from a fourth-degree polynomial from PreScan taking the current location and the end point of the trajectory into account. Optimal trajectory is selected with the least cost for both longitudinal and lateral movements.

The path planning algorithm developed for the ego-vehicle initially generates a trajectory based on the location of the ego-vehicle received from PreScan. The trajectory generation function makes use of a fourth-degree polynomial:

$$x(t) = p_0 + p_1 t + p_2 t^2 + p_3 t^3 + p_4 t^4 \tag{1}$$

where $p_0 - p_4$ are the parameters which can be found based on the current location (t_0) and the end point of the trajectory (t_f). Multiple trajectories are generated from Equation 1 and the optimal one is found by minimising a cost function for the longitudinal and lateral movement as shown below:

$$C_{longitudinal} = k_j J_t(s) + k_t T + k_s(\dot{s_f} - \dot{s_t})^2 \tag{2}$$

$$C_{lateral} = k_j J_t(d) + k_t T + k_d d_f^2 \tag{3}$$

where $\mathrm{k_j}$, $\mathrm{k_t}$, $\mathrm{k_s}$ and $\mathrm{k_d}$ are adjustable weights, J is jerk, T is the time to execute the trajectory, s is longitudinal trajectory, $(\dot{s_\mathrm{f}} - \dot{s_\mathrm{t}})$ is the difference in the final velocity from current velocity, d is lateral movement, $\mathrm{d_f}$ is distance from desired lateral position. Trajectories that are not on a collision course are considered and the optimal trajectory is selected with the lowest cost calculated from the cost function. The control system enables data fusion where data from multiple sources was integrated to generate an optimal trajectory. To account for non-localisation issue, the control system makes use of additional information received from in-vehicle sensors and lane-based map to regenerate the trajectory based on the available paths if the ego-vehicle identifies a hazard. Trajectory of the ego-vehicle is hence determined by multiple criteria decision making and deterministic finite automata employed by Furda and Vlacic (Furda et al., 2011).

5. Results

5.1 Identification of causal factors from live motorway data

Using data collected from the live motorway, lane change events were manually recorded and cross-referenced with the events detected by the LDW algorithm. No discrepancies were found in terms of the total number of runs performed, lane changes made, number of lanes changing manoeuvres with and without lane departure warning through cross-referencing.

Amongst the total trips, a total of 32 ‘no warnings’ cases were recorded. This is equivalent to: 1.1% of the total cases indicating that the quality of lane markings on the SRN are excellent. A summary of the factors that contributed to the system issuing ‘no warning’ signal is presented in Fig. 8. These factors were determined by observing the video data collected by the instrumented vehicle at the timestamps where the warnings were not issued.

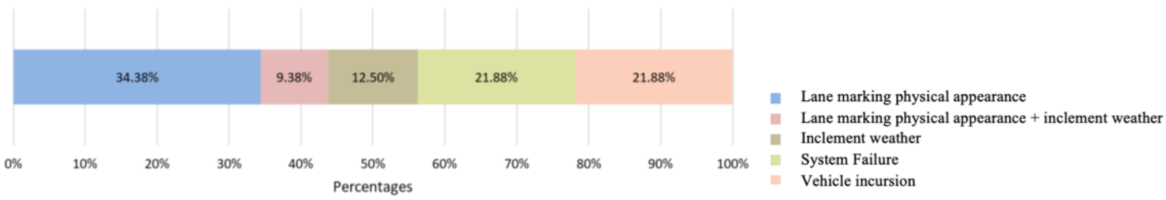


Fig. 8. Distributions of Root Causes for No Warnings cases from LDW system

From Fig. 8, one third of the missed detections were attributed to lane marking physical appearance. In fact, over 40% of the missed detection cases were related to lane marking physical appearance. Inclement weather also influenced a total of 30% of cases. Other root causes included system failures due to cold start of the Mobileye system and vehicle excursion which the instrumented vehicle drove in between the lane markings, causing the Mobileye failing to track the lane marks and perform accordingly. To evaluate the impact of these factors on the operations of AVs, experiments in the controlled facility and scenarios in a simulation setting were developed.

5.2 Validation of the lane detection and classification algorithm

To validate the experimental results, the developed computer vision algorithm was employed to evaluate the impact of lane marking quality on AV operations in the real-world. Live motorway data was used to test if developed lane detection and classification algorithm has a good performance. From the video data collected on a particular day (20th April, 2021), a total of 48,747 frames were derived. To evaluate the lane detection and classification algorithm, frames when the vehicle was stationary were removed, resulting in a total of 40,453 valid frames for the analysis. Out of 40,453 frames used to detect lane markings using the lane classification algorithm, two lines of a lane were correctly detected for more than 81% of the frames. For more than 13% of the frames, only one line was detected by the algorithm. This happened (i) when the vehicle made a lane change, (ii) the lines were not visible due to inclement weather conditions and (iii) the quality of lane markings falls below the threshold. The algorithm failed to detect any lane marking for about a 1.27% of the frames due to faded lane marking.

From the video data collected on the 21st May, 2021 there are 96,534 frames obtained. Out of 96,534 frames, 89,671 frames were used. Out of 89,671 frames used to detect lane markings using the lane classification algorithm, two lines of a lane were correctly detected 82% of the frames, (which is similar to 20th April performance). For more than 13% of the frames, only one line was detected by the algorithm. The algorithm failed to detect any lane marking for about a 1.27% of the frames due to faded lane marking. It was interesting to note that the distributions for both days are highly similar and it displayed the consistency of the lane detection and classification algorithm performance. Additionally, it can also proof that the lane marking quality are consistent across SRN network. The results are presented in Fig. 9.

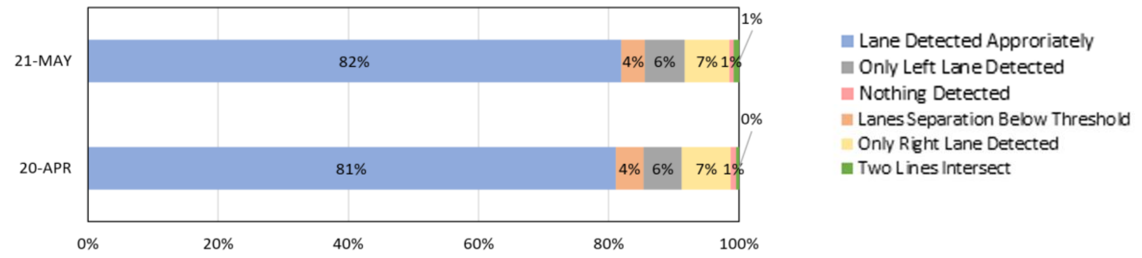


Fig. 9. Distributions of Lane Classified by algorithm - 20-APR and 21-MAY

According to the ground truth, 3 no warning lane changing cases were recorded for 20-APR. Using the lane detection and classification algorithm to apply for the lane change recorded in ground truth, there were 11 failed lane change detections. The difference is 8 out of 99 lane changes. Such proved that current algorithm is 90.9% sensitive and suitable for further application. Similar results were observed for 21-MAY data with 91% sensitive in lane detection and classification, representing a consistent performance from the algorithm.

5.3 Experiment results from controlled motorway facility

The lane change manoeuvres were used to test if factors implemented within the experiment affect the LDW systems' ability. All lane change events were also manually recorded and cross-referenced with the events detected by the LDW algorithm and no discrepancies were found.

For Experiment 1, 54 complete runs were carried out with 84 lane changes performed in the fully faded lane marking zone and 91 lane changes in the 75% faded lane marking zone. In the fully faded lane marking zone, the LDW algorithm achieved a successful lane detection and classification rate of 54.7% in the fully faded zone and 53.8% for 75% faded zone. For Experiment 2, a total of 29 runs were performed with a total of 114 lane changes made. The LDW can successfully detect 95.3% of lane changes.

Evaluating the LDW performance for Experiment 1, one observation is that these two levels of lane marking fadedness seem analogous. Additionally, the successful detection rate at the 75% faded zone is lower than that in the 100% faded zone. This may be due to the configurations of the test scenarios. To perform a lane change at the 75% faded zone, the vehicle needed to go past the fully faded zone. Such condition would affect the ability of the sensor to track the preceding lane markings. Hence, it failed to detect and issue an LDW. Conversely, in fully faded lane marking zone, the vehicle can track the limited available markings from the 75% faded zone, hence a slightly higher lane departure detection rate is recorded. In Experiment 2, the LDW algorithm in the MobilEye system performs well when performing lane changes at the 50% faded lane marking zone given the algorithm can track the partially obscured lane markings.

For Experiment 1 (i.e., 100% faded and 75% faded), two videos with a total of 29,401 frames were reviewed. Referring to Fig. 10, the algorithm can detect both lanes over half (51 to 57%) of the times. Almost 30% of the times, only one lane is detected. This could be due to more frequent lane change as well as situations in which the algorithm is confused for its incapability to fit the lines from the lane markings. For Experiment 2 (i.e., 50% faded and no faded), a total of 12,983 frames were evaluated. Between Experiment 1 and 2, the algorithm is more certain in Experiment 2 (57 %) than Experiment 1 (51%), indicating a better lane detection and classification performance. Moreover, only 2% of the frames in Experiment 2 failed lane marking detection compared to 4 % in Experiment 1.

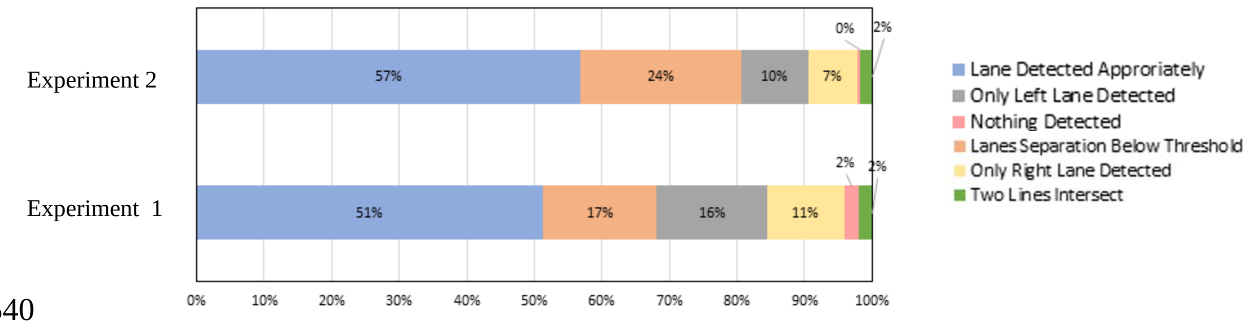


Fig. 10. Distributions of lane detection and classification Rate in Experiment 1 and 2

5.4 Simulation Experiments

Sensitivity analyses were conducted to evaluate the effect of adverse weather, reduced retro-reflectivity, and limited localisation performances on lane markings. In particular, the results from the integrated simulation platform were explored by degrading the lane marking physical appearance (such as including spills, potholes, lighting, and lane fadedness) and several parameters such as (i) clear conditions, (ii) rainy conditions, (iii) snowy conditions, (iv) foggy conditions and (v) lower retro-reflectivity. KPIs such as traffic conflicts and delays were used to evaluate the effects of deteriorating lane marking quality and the choice of maps. Three different scenarios were developed: 50% deterioration with a road-based digital map (blue bars in Fig 11), 90% deterioration with a road-based digital map (orange bars in Fig. 11) and 90% deterioration with lane-based digital map (yellow bars in Fig. 11). The KPIs from the scenarios were compared with the KPIs from baseline scenario (i.e., normal weather condition with freshly marked lane markings.

5.4.1 Traffic conflicts

A traffic conflict is a traffic event involving the interaction of two or more road users, where one or both road users takes evasive action, such as braking or swerving to avoid a collision (Formosa et al., 2022). Time-To-Collision (TTC) is the common measure of traffic conflict (Formosa et al., 2020). It is defined as the remaining time before an impact takes place between two road users unless an event to change their trajectories and speed occurs, such as braking or a change in steering angle (Equation 4).

$$\mathrm{TTC} = \frac{\mathrm{s}}{\mathrm{v_{ego-vehicle}} - \mathrm{v_p}} \qquad \forall\ \mathrm{v_{ego-vehicle}} > \mathrm{v_p} \tag{4}$$

where $\mathrm{v_{ego-vehicle}}$ is the speed of the AV, $\mathrm{v_p}$ is the preceding vehicle and s is the distance between preceding vehicle and AV. A critical value for TTC of 1.5 seconds is defined, following suit with the majority of studies (e.g., (Van der Horst, 1990)). The values of TTC surrounding the AV were captured at the 1.5 second threshold to determine the percentage increase in the number of traffic conflicts under different weather conditions and retro-reflectivity (Fig. 11).

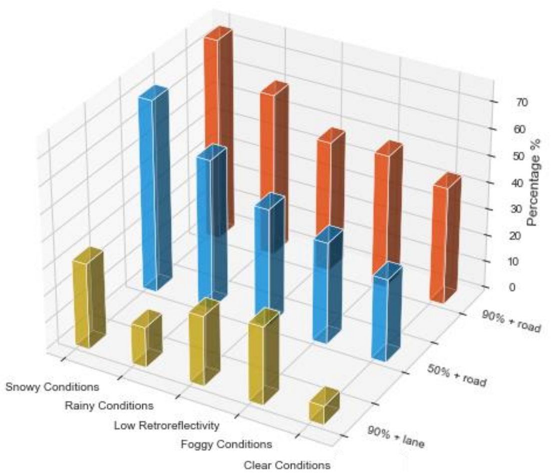


Fig. 11. Percentage change in traffic conflicts for different weather conditions and retro-reflectivity

From Fig. 11, any change in physical appearance of lane markings would result in more traffic conflicts relative to the baseline scenario (i.e., fresh lane markings). As expected, the 90% faded lane markings in snowy conditions provided the worst performance followed by rainy conditions. However, the impact of appearance change in lane markings was compensated when lane-based digital road map is employed. Despite lane-based digital map is used, low retro-reflectivity still caused a higher percentage of traffic conflicts. This could be due to the surrounding traffic not adopting a lane-based digital map.

5.4.2 Delays

Delays caused by poor quality lane markings occur due to increased driver workload. Under challenging driving conditions such as night-time and/or inclement weather, delays are further exacerbated. Similarly, vehicles with lane marking sensors and/or AVs would struggle in situations where lane markings are hard to detect. Delay, formalised as the difference between the actual travel time and the free-flow travel time, was measured to determine whether journey times are affected by the deteriorated lane markings. This KPI is explored and presented in Fig. 12.

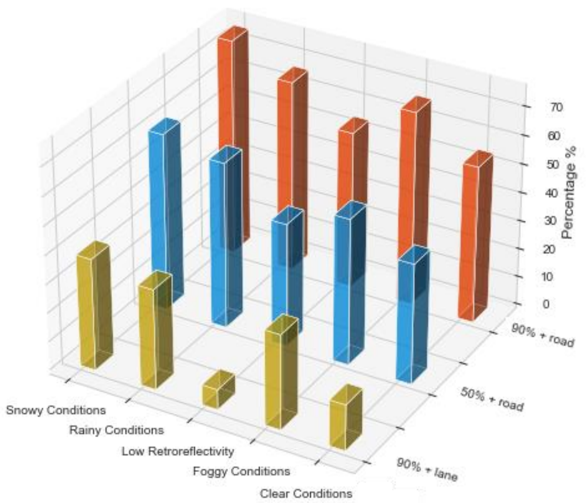


Fig. 12. Percent change in delays for different weather conditions and retro-reflectivity

From Fig. 12, it is observed that deteriorated lane markings under inclement weather and lower retro-reflectivity would cause delays. The 90% obscured lane markings provided the worst performance irrespective of any prevailing condition. This was most evident in snowy conditions, which is expected. The delays also show that the impact of changes in physical appearance of lane markings was generally reduced when lane-based digital road map is used.

6. DISCUSSION

Current road infrastructure designs are intended to maximise comfort and safety for human driving. With the advancement in vehicular technology, various ADASs are being developed and embedded in

AVs. These systems replace the need of human involvement in driving with increasing level of automation. However, current road infrastructure is not designed with AVs and ADAS considerations. This situation raises the prospect of incompatibility between road infrastructure and ADAS, with this likely worsened under adverse weather and complex manoeuvring as commonly shown in the findings from field tests. To overcome such limitations from ADAS, the investigation of the failure mechanisms of different ADASs is essential. More specifically, the causes of failure at adverse weather or complex manoeuvring need to be understood (Yoneda et al., 2019). Therefore, the perception, planning and control system of autonomous vehicles can be adjusted accordingly. Such shaped the aim of this paper to assess the impact on AVs under changing weather and physical conditions of roads.

Both real-world experimentation and simulation analysis were carried out in this study. In terms of real-world experimentation, the MobilEye LDW system was employed to evaluate the impact of poor lane markings. Repeated lane change manoeuvres are performed in a controlled testing facility with the lane markings obscured by black duct tape. Results show that the LDW system is accurate in over 54% and 95% lane change events when lanes are obscured by 75% and 50% respectively.

In the simulation studies, the impact of inclement weather and impaired retro- reflectivity of lane markings are evaluated. The KPIs such as delay, and time-to-collision are used to assess the performance of AV in terms of localisation and navigation. Comparison of the localisation ability is also made between the use of road-based map and lane-based digital map. Considering the KPIs of the AVs, a decrease throughout all KPIs was observed when a road-based map was provided to the vehicle to navigate in the network. This shows that lane markings deterioration has a significant negative impact on the safe and efficient operation of AVs. Furthermore, a combination of lane markings changes in physical appearance, adverse weather, and large or fast-moving vehicles generating spray reduces visibility creating a dangerous scenario of AV disengagement. However, it is also worth noting that even excellent quality lane markings in inclement weather conditions such as snow and heavy rainfall may also pose a threat.

Between lane-based digital map and road-based map, the findings from the simulation highlight the superiority of lane-based digital map. Not only would a lane-based digital support the safe localisation of AVs, but it would also have a significant positive impact on areas where the lane markings have deteriorated no matter the prevailing conditions. However, to be of value, any lane-based digital map must be allied with accurate road positioning capability within the vehicle itself. At present most vehicle sensors are accurate to around 1m. This is not accurate enough to ensure safe in-lane driving when the pavement markings are obscured.

In terms of practical implication, this study recommends that developers of AVs (OEMs) develop more sophisticated sensors which can integrate with lane-centrelines based on digital maps (for example, digital twins) to compensate for difficulties with lane marking visibility, whether that is caused by the quality of the marking themselves or other factors such as weather. Additionally, the AVs can also take advantages of the communication abilities such as V2V and V2I to alert approaching vehicles in changing weather conditions.

However, this study does not come without limitations. In the real-world experiment, no lane change manoeuvre was conducted in the acceleration zone and the time for each lane change was not recorded. Additionally, the exact location zone of lane change cannot be determined easily when reviewing the video frames, by adding data from other sensors such as GPS and gyroscope to extract precise coordinates and heading. Moreover, the original lane marking quality in the controlled facility was rather poor such that the physical appearance of the lane markings was not 100% flawless which further impaired the performance of the lane detection and classification algorithm. Some limitations in the simulation study include that biased result might exist due to the underlying assumptions of the software. When considering the sub-microscopic simulation environment, one major limitation is that the scenarios developed relate to motorway operations and are based on human-related situations. For example, the scenarios developed might not reflect the new critical situations faced by AVs. Moreover, changing many parameters involve high computational requirements; hence only the essential parameters such as weather and lane marking conditions were varied.

Future studies should assess a variety of lane marking types to develop a more robust understanding of the effect of varying marking properties and the resulting contrast between the marking and darker or lighter pavements. This study was conducted on a closed-course facility. To gain a better understanding of how various marking characteristics affect the performance of machine vision products, real-world investigations on open roadways should be considered. Test conditions could include areas with conflicting signals that may make it more difficult to detect the markings, such as roadways with conflicting messages from previously removed markings, blackout markings, crack seal, varying road surfaces, rutting, and shadows. Testing should include markings with varying levels of wear that may impact how well defined the edge of the marking is. The impact of different overhead lighting systems on nighttime detection of markings on different pavement surfaces in different weather conditions needs to be investigated further.

7. Conclusions

Lane marking is one of the most important infrastructure elements on the existing roadway systems for safe operations of AVs. The differences in their physical properties can limit the effective deployment of AVs. This is because the sensing systems in AVs requires accurate detection of lane markings to avoid disengagements. However, the lane markings appearance and retro-reflectivity deteriorate over time, causing localisation issues for AVs. To examine the effect of lane marking on AVs, this work conducted experiments at a controlled facility to assess the LDW performance of Mobileye sensor when lanes were 50%, 75% and 100% obscured. About 50% and 60% of lane change manoeuvres can be identified at all three levels of obscuration. To holistically evaluate the impact of safety and traffic efficiency for AVs under deteriorated physical appearance of lane markings, an integrated simulation platform was developed to model lane marking scenarios influenced by external factors such as: (i) lower retro-reflectivity, (ii) foggy conditions, (iii) snowy conditions, (iv) rainy conditions and (v) clear conditions. The data from our analyses showed that both inclement weather and retro-reflectivity affect the AV lane marking detection, especially when lane marking quality is severely deteriorated. However, results showed that by adopting a lane-based digital map rather than the road-based digital map, the impairment of lane detection and classification ability due to limited visibility arising from the physical appearance change in lane markings and light conditions was reduced. This highlights the importance of lane-based digital map. Not only would a digital roadmap support the safe localisation of AVs, but it would have a significant positive impact on areas where the lane markings have deteriorated no matter the prevailing conditions.

The implication of this study is significant to provide guidance for AV developers and infrastructure providers in understanding the importance of lane markings for the safe deployment of

AVs. This research highlights the importance of real-world trials and simulation experiments to assess the impact of lane markings as an appraisal for AV deployment. Findings from this study proved that other than vehicular technology, road infrastructure plays an important part in AV localisation and safety. Such finding provides extra insights to that a safe AV implementation needs a complete revamp on all the components of transportation network and a long transition period is needed for automation and the coexistence of conventional and AVs on the same network.

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9. Data Availability statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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