An integrated simulation framework to validate a traffic conflict prediction algorithm

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Abstract

With the ever-increasing advancements in technology and complexity of advanced driver assistant systems, one major issue arising is the safe and efficient operations of these driving functions in complex traffic scenarios. These emerging systems in the automotive industry have introduced safety-related challenges, in particular the need for a comprehensive way to identify traffic conflicts to avoid collisions. Although significant research efforts have been devoted to traffic conflict techniques applied for junctions, there is dearth of research on these methods for motorways. This paper presents the validation of a traffic conflict prediction algorithm applied to a motorway scenario in a simulated environment. An automatic video analysis system was developed to identify and extract lane change and rear-end conflicts as ground truth from a simulated motorway network. Using these conflicts, the prediction ability of the traffic conflict prediction algorithm was validated in an integrated simulation framework. This framework consisted of a submicroscopic simulator, which provided an appropriate testbed to develop a scenario to test the effectiveness of the algorithm, and a microscopic traffic simulation tool to simulate the surrounding traffic accurately based on real-time data. The datasets used include data from inductive loop detector data and via an instrumented vehicle equipped with multiple sensors driving on the M1 motorway in England. The validation results from this framework are significant, where 80% of rear-end conflicts and 73% of lane change conflicts were accurately predicted by algorithm for a 10% false alarm rate. Despite that the algorithm was not trained using the virtual data, the sensitivity is high. This highlights the transferability of the algorithm to similar road networks. This work is significant as it provides benchmarking for the identification of traffic conflict for virtual testing procedures and is a relevant step for developing safety management strategies for autonomous vehicles.

Keywords: Integrated simulation framework, traffic conflicts, sub-microscopic simulation, road safety, ADAS

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1. Introduction

With the rapid growth of artificial intelligence techniques such as machine learning and image recognition, the vehicle industry is currently undergoing dramatic changes. A vehicle is no longer considered to be a simple mechanical structure, but an entity which includes multiple advanced driver assistance systems (ADAS) aiming to improve both vehicle and driver safety. With these additional functions, vehicles are progressively becoming more intelligent, with the latest advancement being Autonomous Vehicles (AVs) and Connected and Autonomous Vehicles (CAVs). These emerging technologies in the automotive industry have introduced safety-related challenges and consequently, research has attempted to address these challenges by developing proactive and predictive safety management systems for these vehicles.

Traditionally, safety analysis has formed functional relationships between occurrences of safety incidents (e.g., accidents) and various kinematics or infrastructure related factors, using historical data (1). However, these approaches have been developed by static and aggregated data, and the effects of the sudden changes in traffic conditions which lead to collision risks are sometimes not captured (2). These limitations can be overcome by making use of real-time traffic data (3) and this approach is considered to be proactive rather than reactive (4). The underlying theory behind the approach of using non-accident data is based on that in accelerating vehicle-based proactive safety, traffic conflicts can be used a measure of accident nearness and a safety critical event as it has the potential to progress to a traffic collision. In fact, Tarko (5), establishes that traffic conflicts are probabilistically and statistically connected with traffic accidents. Traffic conflicts are characterised by a safety surrogate measure (SSM) which shows a spatio-temporal risk (two parties are in close proximity in either space or time) and an evasive manoeuvre (e.g., accelerating or braking (6) and/or steering (7)) that takes place so as to avoid a potential collision (8–10). Thus, a definition for a traffic conflict is an event including at least two moving vehicles moving spatio-temporally towards one another in a way that a traffic collision would take place unless one of the involved parties performs an evasive manoeuvre. In this way, traffic conflicts can be identified and assessed accurately and reliably.

Based on this concept, traffic conflict prediction algorithms have developed to assess and quantify the threat level surrounding an ego-vehicle. The technical reliability of adopting such systems for conflict prediction relies on the functionality of the multiple sensors that a vehicle is equipped with. These systems necessitate stringent safety tests to ensure robustness. To determine whether the algorithm can predict a traffic conflict adequately in a complex and organically changing real-world environment, testing and validation is the key for facilitating customer uptake. It is necessary that comprehensive testing, either on real-world test tracks and/or in virtual environments is performed. However, most of the testing methods are still carried out virtually rather than on public roads (11) since it is the only method that can safely and at a low-cost address unprecedented challenges that will arise from their implementation.

Commercially available sub-microscopic simulators such as PreScan, CarMaker and CARLA provide a platform offering a variety of intelligent traffic modelling in order to investigate and validate various technologies and applications (12–17) such as testing the identification of traffic conflicts. This can be done by including a traffic conflict prediction model using deep learning within this simulator, so that complex and non-linear patterns are identified to classify and predict a traffic conflict (18). To boost the strength of sub-microscopic simulators, they can also be integrated with other available simulation tools such as PTV VISSIM (a microscopic simulator). However, the complexity of modelling all possible combinations of traffic situations and environmental conditions make this approach challenging. Hence, a number of 'benchmark' scenarios have to be developed allowing the investigation of driving behaviours and vehicle functionalities under different traffic conditions and scenarios.

Therefore, the purpose of this paper is to validate traffic conflict predictions that employ deep learning theory implemented within an integrated sub-microscopic simulation framework. To develop this simulation framework, data was collected via an instrumented vehicle and inductive loop detectors from a section of the M1 motorway in the UK. PreScan was the simulation tool adopted for this study, with the ability to integrate a number of variables including the ego-vehicle and the behaviour of the surrounding vehicles, the sensors used and the driving style of road users. These variables need to be modelled in a sub-microscopic simulation environment while a microscopic traffic simulator (PTV VISSIM) is used in conjunction to generate traffic dynamics. This simulation framework eases the modelling and simulation of critical scenarios, which leads to more efficient work flows when virtually testing automated driving. Such a process provides a platform for verification and evaluation. Due to its modular architecture, the framework can be adapted to the individual needs of future users and may be enhanced with customised models. It is important to note that rear-end and lane change traffic conflict scenarios are developed in the simulation framework in order to test the effectiveness of the prediction algorithm. The results provide recommendations to vehicle manufacturers so as to improve their collision-risk model allowing intelligent vehicles to operate safely and reliably.

2. Methodology

The methodology of this study consists of two key components: (1) traffic conflict identification to generate ground truth and (2) traffic conflict prediction algorithm validation. Developing a conflict detection model is challenging as data on traffic conflicts and their influencing factors are required. However, traffic conflict data is not readily available and therefore a method is developed to identify rear-end and lane changing conflicts using simulated data. The conflict identification process consists of detecting vehicles and lane geometry acquired through image processing techniques from a single front-facing camera. Based on these detections and defined criteria, an automated video analysis system is developed to identify traffic conflicts.

An empirical analysis is carried out on this data to identify traffic conflict defining patterns as well as the nature of performed evasive manoeuvres when a traffic conflict is identified. Based on this empirical analysis, derived scenarios are then transferred to an integrated simulation framework, to investigate safety performance. The simulation framework consists of a submicroscopic and a microscopic traffic simulation tool. The submicroscopic simulator aims to place the prediction model to predict the traffic conflicts while the traffic flow is calibrated and validated on the collected data microsimulation tool simulate the surrounding traffic accurately.

2.1 Generation of Traffic Conflicts Ground Truth from Simulated Data

The video analysis system was developed to identify traffic conflicts through the response to a evasive action and the temporal and/or spatial proximity (7). A set of defined conservative criteria derived from existing literature were used to include all traffic conflicts. Therefore, using these criteria an automatic extraction algorithm was developed to identify all the vehicles and time points where the thresholds were exceeded. The influential factors used to identify both lane change and rear-end conflicts are based on time, distance, speed, braking, acceleration and deceleration. The readers are referred to Formosa et al. (24) for a more thorough description of the traffic conflict extraction from the data. The flowchart for the lane change and rear-end conflict extraction algorithm is shown in Figure 1.

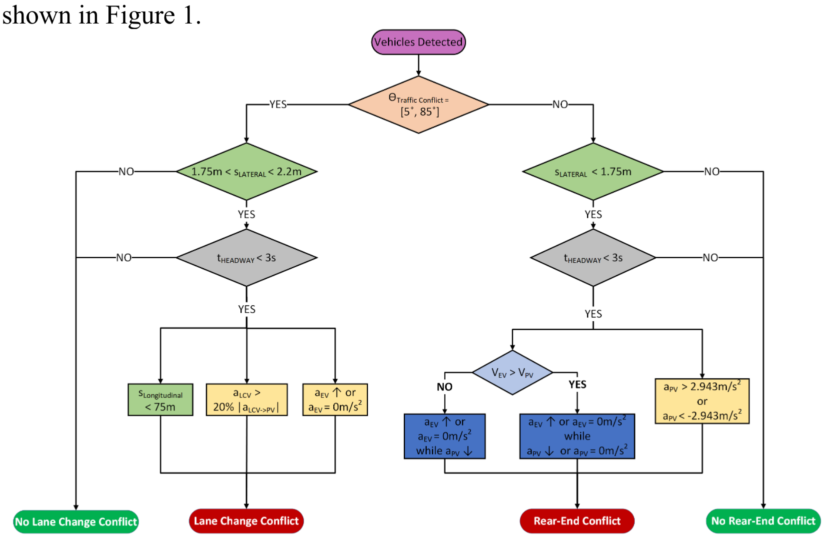

Figure 1: Automatic extraction algorithm for lane change and rear-end conflicts from video

2.2 Traffic Conflicts Algorithm Validation

Validating the results from the developed algorithm is key to prove their effectiveness. This process can be performed in a traffic simulation environment, providing a platform where the safety performance of the prediction algorithm can be evaluated and validated. This approach improves the cost-effectiveness of the development stage and was achieved by allowing the maximum number of scenarios to be tested against different factors. An advantage such as this would not be feasible in real-world tests given the inherent complexities in creating such scenarios (15).

2.2.1 Simulation Framework for Validating a Traffic Conflict Prediction Algorithm

Traffic simulation paves the way for intelligent technologies by allowing virtual testing and validation of emerging ADAS in a realistic traffic environment. This research implemented traffic simulations to test and validate the developed traffic conflicts prediction algorithm. Developing a simulation environment, which can simulate intelligent mobility and their functions is crucial, therefore, PreScan was used. However, to boost the strength of the PreScan software, it was advantageous to integrate with a traffic microsimulation software such as PTV VISSIM for creating surrounding traffic environments. When both are applied simultaneously, a comprehensive integrated platform is built which is powerful than the individual components. This allows for the investigation of driving behaviours and vehicle functionalities under different traffic conditions and scenarios.

The framework developed in this research consists of a sub-microscopic traffic simulation software (PreScan) which sends ego-vehicle information while the microscopic traffic simulation software (PTV VISSIM) sends the information about the locations and kinematics characteristics of surrounding traffic. These two simulators exchange data through the Transmission Control Protocol/Internet Protocol (TCP/IP) during every simulation step (20 Hz). The architecture of the integrated simulation platform is summarized in Figure 2.

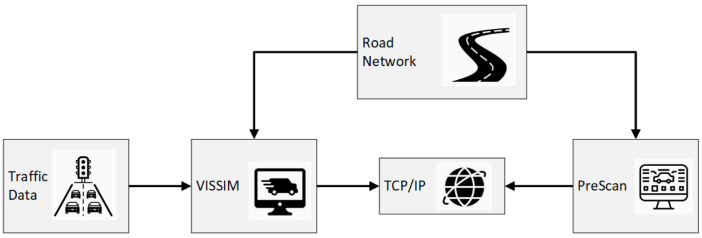

Figure 2: The architecture of the integrated simulation platform

2.2.2 Demonstration Experiments

A traffic conflict scenario depends on a number of factors, such as the ego-vehicle and the behaviour of the surrounding vehicles, and the sensors employed and the driving style of road users. These factors need to be modelled in a sub-microscopic simulation environment in the network. Based on these factors, benchmark scenarios were developed. These scenarios are able to be completely quantifiable, controllable and reproducible. Therefore, the prediction of lane change conflicts, rear-end conflicts and a mixture of both conflicts from the developed prediction algorithm can be evaluated and validated. Based on the criteria discussed for lane change conflicts and rear-end conflicts (see section 2.1) several scenarios were formulated.

Scenario development follows a four staged process as represented in Figure 3. Firstly, the network for the study area (a section of the M1 motorway between Junction 19-21 in the UK) is built using an aerial photograph. This includes building the derived scenario into the PreScan GUI, where Open Street Map and Google Earth images are used as underlays to create the road network. Besides the static road information, other parameters, such as the ego-vehicle model, do not vary between the scenarios. The environmental sensors of the ego-vehicle system are then modelled e.g., radar, laser, camera, infra-red, GPS within the submicroscopic simulator. The sensor design and benchmarking are made easier by modification of the sensor type and sensor characteristics from the PreScan GUI.

Subsequently, PTV VISSIM is used to represent the network section to generate the surrounding traffic flow based on the real data. The network development involves defining model parameters, vehicle composition, the number of lanes, the required input traffic data and driving behaviour characteristics. Nevertheless, for the simulation model to replicate real-world road traffic conditions, the calibration of the road network and simulation parameters are required. This is carried out to minimize the deviation between observed field data and simulated data to prevent any misleading conclusions.

Typical parameters requiring calibration include simulation period, resolution, random seed number and simulation runs (29). These parameters are initiated with the default parameters set by VISSIM and real-world traffic counts of flow, speed and headway used as inputs. Multiple simulation runs are then performed to obtain simulation outputs comparable to the real-world values. If the error is within the acceptable range, this indicates that the simulation model has been properly validated. Should the traffic model not be properly validated, the calibration and confirmation procedures are repeated until the differences between simulated and observed values are within an acceptable range. To quantify the model calibration performances, GEH statistic is used. GEH is defined as:

$$\mathrm{GEH} = \sqrt{\frac{2(M-C)^2}{M+C}} \tag{1}$$

where M is the simulated values and C is real-world values. Based on the guidelines by Federal Highway Administration (FHWA) (30), a GEH lower than 5 for more than 85% of the observed pairs is acceptable to use traffic flow and travel times as inputs.

Thirdly, the microsimulation model is linked to PreScan (GUI) over a Component Object Model server (Matlab) where the surrounding traffic is simulated at the same time with the conflict vehicles – 'actors'. Every change in the PreScan GUI is associated with a change in the Matlab/Simulink software. This Matlab/Simulink interface allows the user to design, add, implement or validate the developed traffic conflicts prediction algorithm within the ego-vehicle through a compilation sheet. The compilation sheet is composed of the infrastructure, vehicle tracking information, display ports and the sensors in the scenario developed in PreScan.

With every run, the output files are stored in a database for post-processing. A 3D visualization viewer allows the user to analyse the results of the experiment by providing multiple viewpoints, pictures, and video generation capabilities. A summary of these stages is presented in Figure 3. The evaluation of the traffic conflict algorithm was carried out by analysing the output of the developed algorithms. An AUC value for each simulation run was obtained by comparing the traffic conflicts predictions from the developed algorithm to the traffic conflicts ground truth data. The traffic conflicts ground truth data was obtained by applying the criteria developed in section 2.1 on the simulated data.

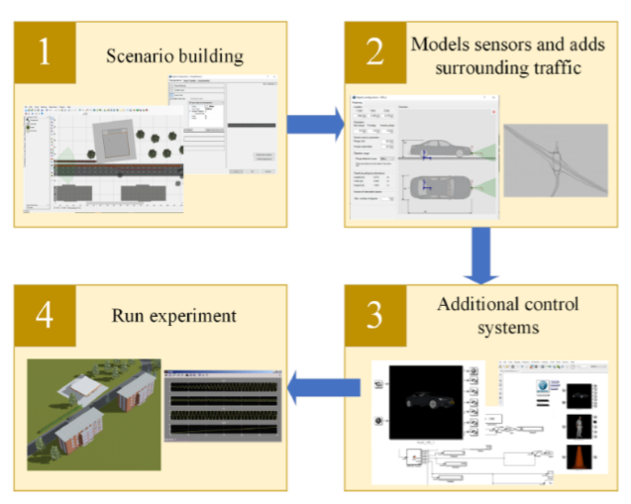

Figure 3: Developing stages of integrated simulation platform

3. Analysis and Results

To prove the effectiveness of the traffic conflict predictor, testing and validation is key. This was demonstrated in a virtual simulation environment. It is important to note that the algorithm was not trained on the virtual simulation data but on the real-time data collected from the instrumented vehicle. PreScan (the sub-microscopic traffic simulator) provided an appropriate testbed to validate and test the traffic conflict predictions from the developed algorithm. PTV VISSIM was utilised to generate dynamic traffic surrounding the ego-vehicle. By implementing the prediction algorithm to the ego-vehicle in the Simulink interface, the algorithm was able to use the simulated data as input and predict traffic conflicts or safe traffic dynamics surrounding the ego-vehicle in a virtual environment. However, the complexity of modelling all possible combinations of traffic situations and environmental conditions make this approach challenging. Hence, a number of ‘benchmark' scenarios had to be developed. These included (i) a rear-end conflict, (ii) a lane change conflict and (iii) a combinational scenario.

3.1 Results of the Safety Performance Evaluation

This section presents the performances of the traffic conflicts prediction algorithm. The virtual data produced was used to validate and test the predictions generated by the algorithm. The first three sections provided an example of a particular simulation instance predicted as a (1) rear-end conflict, (2) lane change conflict and (3) safe traffic dynamics scenario, by the algorithm. Each section describes the parameters of the ego-vehicle and the opponent vehicle during this instance. The parameters include the time headway, velocity, acceleration, and distance parameters. This was undertaken in order to determine whether these parameters satisfy the criteria established in Section 2.1. Finally, the overall results in terms of AUC value, sensitivity and accuracy of the developed algorithm are presented.

(i) Example of a Rear-End Conflict

This section presents an example of a predicted rear-end conflict during one simulation run. It demonstrates an example of how the parameters changed during which a rear-end conflict was predicted. This scenario is presented in Figure 4.

Figure 4: Rear-end conflict in the simulation environment from (a) top-view and (b) from a driver's view.

In this example, the PV performs a harsh deceleration in front of the ego-vehicle. During the predicted conflict, the time headway of the ego-vehicle is below 3 seconds at certain instances and the velocity and acceleration of both the ego-vehicle and the PV were examined. In this instance the ego-vehicle satisfied a criterion established in section 2.1 for a rear-end conflict. For this example, $v_{EV} > v_{PV}$, and the preceding vehicle exerts a large deceleration force when $t_{HEADWAY} < 3$ s. These parameters are depicted in Figure 5.

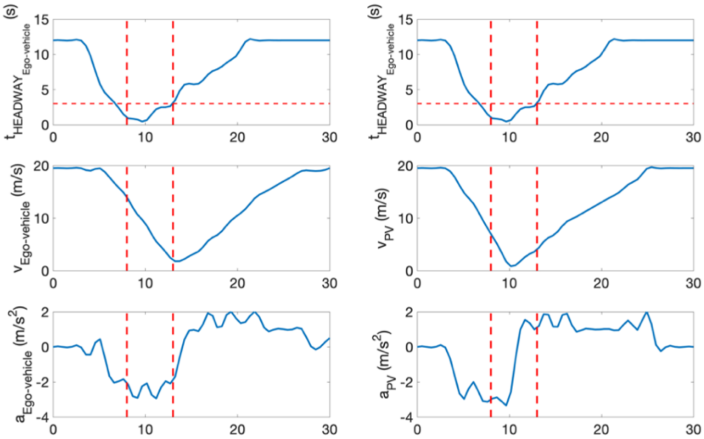

Figure 5: Time Headway of ego-vehicle, velocity and acceleration of ego-vehicle and opponent vehicle

(ii) Example Evaluation of a Lane Change Conflict

This section presents an example of a predicted lane change conflict. It demonstrates an example of how the parameters changed during a lane change conflict prediction. This scenario is presented in Figure 6.

Figure 6: Lane change conflict in the simulation environment from (a) top-view and from (b) driver's view.

In this example, the LCV performs changes lane abruptly in front of the ego-vehicle. Similarly, during the predicted conflict, the time headway of the ego-vehicle is also below 3 seconds at certain instances. The velocity and acceleration of both the ego-vehicle and the PV were examined. Following the criteria in section 2.1, these criteria were also met. For this example, $a_{EV} > v_{PV}, a_{EV} \uparrow$, when $t_{HEADWAY} < 3$ s. Some of the parameters were depicted in Figure 7. It is also important to note that the criterion of $s_{LONGITUDINAL} < 75$ m metres was met throughout this whole example.

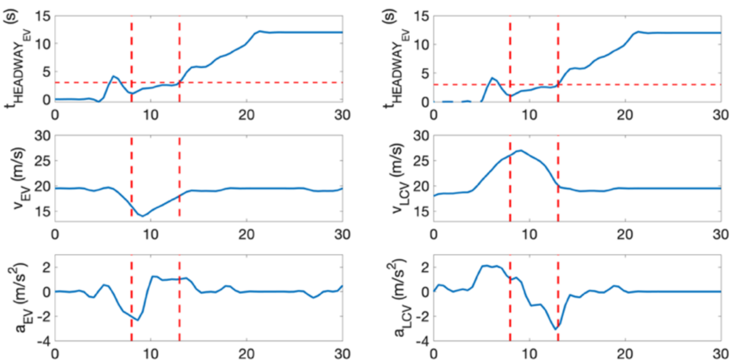

Figure 7: Time headway of ego-vehicle, velocity and acceleration of ego-vehicle and opponent vehicle

(iii) Example Evaluation of a Safe Traffic Dynamic Scenario

In this example, the simulation instance was chosen from a situation predicted as safe. This scenario is presented in Figure 8.

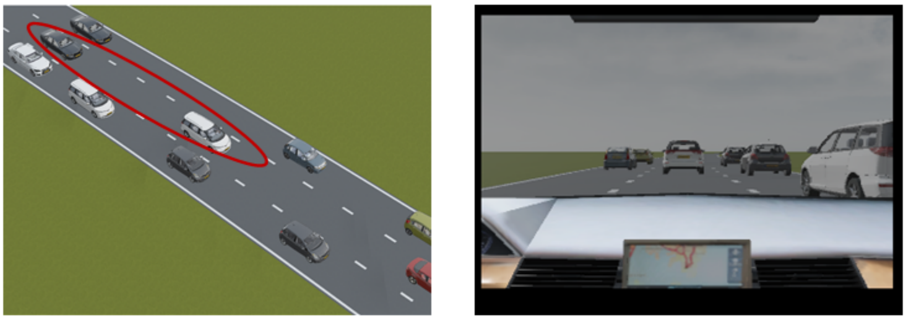

Figure 8: Safe Traffic Dynamic Scenario in the simulation environment from (a) top-view and from (b) driver's view.

Neither conflict criteria threshold was exceeded. In this experiment, although the opponent vehicle starts a smooth deceleration because of slight congestion ahead, the ego-vehicle had enough time headway to react to the smooth deceleration from PV. The algorithm did not predict this as a conflict. These parameters are depicted in Figure 9.

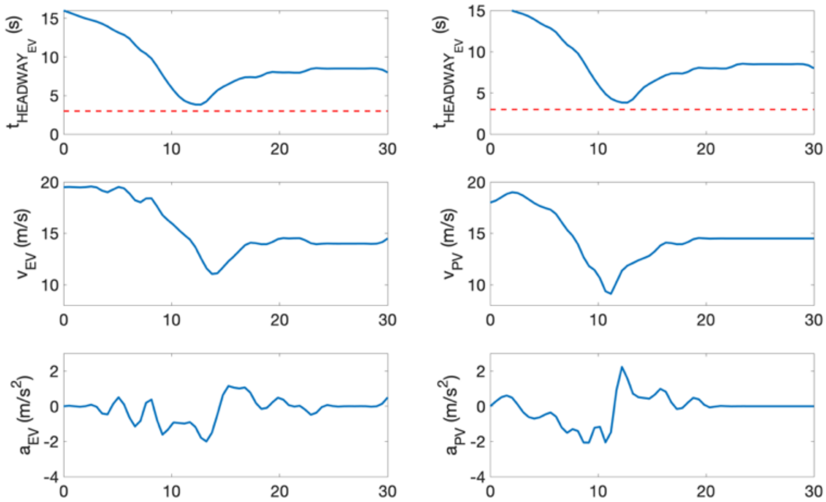

Figure 9: Time Headway of ego-vehicle, velocity and acceleration of ego-vehicle and opponent vehicle.

The algorithm predicted this instance as safe. In fact, neither vehicle exceeded the conflict criteria. The PV smoothly decelerated because of congestion ahead and the ego-vehicle followed suit. However, there is no critical event.

3.2 Overall Results

The optimal traffic conflicts prediction algorithm was implemented within the ego-vehicle in the Simulink interface. Approximately 25 conflicts were manually developed in PreScan for each simulation run. However, other conflicts also arise from the randomly generated surrounding traffic dynamics. Each scenario was simulated 100 times by utilising 100 different random seeds. The ground truth data was generated by applying the criteria in Simulink blocks. This was required to compare with the actual predictions from the developed algorithm. By utilising the evaluation script, the output of the algorithm predictions were compared to the ground truth data and the overall performance metrics of the algorithm in each scenario (1) PV performing harsh braking preceding the EV, (2) LCV cuts in front of the ego-vehicle and (3) combination of both scenarios, are presented in Table 1.

Table 1: Validation from PreScan of traffic conflicts prediction algorithm in a virtual environment

(i) Scenario 1 – Preceding Vehicle performs harsh deceleration			
Average Sensitivity	FAR	Average Accuracy	Average AUC value
0.622	5.0%	0.903	0.916
0.797	10.0%	0.844	
0.843	20.0%	0.783	
0.925	30.0%	0.682	
(ii) Scenario 2 – LCV cuts in before Ego-vehicle			
Average Sensitivity	FAR	Average Accuracy	Average AUC value
0.573	5.0%	0.853	0.883
0.730	10.0%	0.819	
0.785	20.0%	0.764	
0.834	30.0%	0.673	
(iii) **Scenario 3 – Combination of both scenarios**			
Average Sensitivity	FAR	Average Accuracy	Average AUC value
0.607	5.0%	0.875	0.901
0.774	10.0%	0.839	
0.812	20.0%	0.782	
0.867	30.0%	0.653	

Table 1 shows that the AUC values from each traffic scenario in the simulation framework to evaluate and validate the traffic conflict algorithm based on key conditions related to motorway operations. The safety performance evaluation showed that the algorithm obtained a high AUC value of 0.916, 0.883 and 0.902 for rear-end, lane-change and a combination of both conflicts respectively. These values are relatively high, showing that the model is capable of eliciting complex and non-linear patterns to classify and predict traffic conflicts based on a novel data set, from which the model was not trained on. This is optimal for real-time implementation as part of a system for CVs. The threshold value was maintained constant as when the algorithm was developed (i.e., 0.389). The sensitivity values for this threshold value are lower than when applied to the data the algorithm was trained on, as expected. However, the algorithm had the ability relatively sensitive results especially in Scenario 1. For Scenario 1 for a FAR of 5 - 10% the algorithm is able to predict 62.2 - 79.7% of traffic conflicts. When comparing Scenario 1 to Scenario 2, the algorithm is more sensitive in predicting rear-end conflicts. Scenario 2 was able to predict 73 - 79% of lane change conflicts for a 5 - 10% false alarm rate. Scenario 3 is also more sensitive to Scenario 2. This is attributed to less lane change conflicts on which the algorithm trained on. Sensitivity is arguably more important as missing a conflict identification could be more severe. Overall, even though the algorithm was applied to a novel data, high sensitivity values were obtained for a FAR acceptable by industry (19).

4. Discussion

A plethora of literature has stated the importance of emerging vehicle technology for safety on roads. However, most of the claims are not quantitatively supported (20). Virtual vehicle testing and validation is key to address this gap in the research. Simulation framework can be developed with different scenarios simulated under various combinations of parameters. Exploration of this area would not be cost effective in real-world test, as it imposed huge cost in the development cycle (11).

Several projects have assessed the safety performance of vehicle technologies in a virtual environment (21–24). However, testing measures have not been standardised to date. It is challenging to assess different vehicle technologies as numerous scenarios need to be developed. In this research, the developed traffic conflict prediction algorithm was tested and validated based on the identification of relevant existing risky situations linked to rear-end and lane change conflicts. The scenario considered static attributes such as road design, and dynamic content such as surrounding vehicles, their trajectories, and behaviours. The results derived from the framework can be used as pre-stage or parallel activity to field operational tests on public roads. To the author's knowledge, no research has been published which uses an integrated framework to allow the assessment of the vehicle-based traffic conflicts algorithms on a motorway scenario.

Traffic scenarios were developed in the simulation framework to evaluate and validate the traffic conflict algorithm based on key conditions related to motorway operations. The safety performance evaluation showed that the algorithm obtained a high AUC value of 0.916, 0.883 and 0.902 for rear-end, lane-change and a combination of both conflicts respectively. The validation results of the algorithm were also significant due to high sensitivity and a low FAR, from which 80-84% and 73-79% of the rear-end and lane change traffic conflict were predictable for 10-20% FAR respectively. This demonstrated that the model was capable of eliciting complex and nonlinear patterns to classify and predict traffic conflicts based on a novel data set, from which the algorithm was not trained on. The sensitivity values were also high demonstrating the significant prediction ability of traffic conflicts from the vehicle-based algorithm. Moreover, it is worth noting that the algorithm is more sensitive to rear-end conflicts which could be due to the higher number of these events during training the algorithm.

There is an ongoing effort in the automotive industry to develop robust and reliable algorithms to estimate the threat assessment surrounding the ego-vehicle. These algorithms are key to ensure safety and efficient operations for future intelligent mobility. The virtual experiments conducted within this research quantified the safety performance and prediction capabilities of the developed traffic conflicts algorithm. Three scenarios were tested to represent (1) lane change conflicts, (2) rear-end conflicts and (3) a combination of both. Each simulation run was defined by different random seeds which generated different traffic dynamics surrounding the ego-vehicle. Parameters such as road design, driving manoeuvres and behaviour of the ego-vehicle were kept constant. The variable parameters included the lateral and longitudinal position of the opponent vehicle and the velocity of the ego-vehicle. Changing parameters involve high computational requirements, hence only three essential parameters were varied. These simulation runs took approximately 4 minutes to be completed and the evaluation script to be computed on average 30 seconds. In total 100 simulations were conducted for each scenario, resulting in a total of 300 simulations to complete all the calculations. Though this process was time consuming, improving the computational time was not the focus. These set of parameters was sufficient to assess the performance of the vehicle-based traffic conflicts algorithms.

To evaluate the prediction ability of traffic conflicts algorithm in the integrated framework, the mean of the AUC values obtained from each simulation run was calculated. However, to acquire these AUC values, traffic conflicts 'ground truth' data from the simulation was required. This 'ground truth' data was obtained by the same criteria which were adopted in section 2.1. It is important to note that the traffic conflicts in the simulation scenario were easier to extract compared to real-time data since the vehicles' trajectories and velocities were all known and did not require a tracker. In addition, the sensors to detect objects in the simulation have an 100% accuracy rate. This implies an ideal system, which is not the case in a real-world scenario because of errors associated with the sensor. Therefore, to accurately reproduce real-world behaviour and the limitations of the sensors, some of the data applied to the developed prediction algorithm was carried out using high-fidelity sensors.

The integrated simulation framework developed in this research was based on a real-world motorway configuration in the UK. Although this is harder to implement, it has more benefits than adopting an artificial, virtual motorway. This is because static information for the scenario development such as lane widths, hard shoulders and gradients can be taken from on-site observations. Dynamic information provided by the PreScan's GUI such as brakes, tyres and suspension system are well-recognised reference models. These reference models were all validated and represented in blocks. Each block can be enhanced, transferred, or even replaced by other modules as long as they can provide the same output quantities. Other blocks can also be developed based on the aim of the simulation experiment. For example, the criteria used to extract the traffic conflict ground truth data was also developed in a self-contained block. These blocks have future implications for intelligent mobility as they are transferable and can be readily applied by other studies.

While the traffic simulation model within VISSIM was intensively calibrated and validated using real-world data, some results can still be biased due to the underlying assumptions of this software. When considering the sub-microscopic simulation environment, one main limitation is that the scenarios developed relate to motorway operations and are based on human related accident situations. For example, the scenarios developed might not reflect the new critical situations faced by intelligent vehicles. It is also important to mention the safety risks due to mixed traffic, i.e., both intelligent and driver-operated vehicles are still subject to research. For example, intelligent vehicles make use of onboard sensors to determine their environment, but still face a number of limitations in an urban environment, inclement weather conditions or in a situation with an unexpected behaviour of traffic participants. These challenges are not explored in this study.

5. Conclusions

Testing and validating the developed traffic conflict prediction algorithms is key to prove their effectiveness. However, the complexity of modelling all possible combinations of traffic situations and environmental conditions make this approach challenging. To validate the safety performance and prediction accuracy, the traffic conflicts prediction algorithm was placed within the ego-vehicle in an integrated simulation framework. The framework consists of a submicroscopic simulator, which provides an appropriate test bed to develop a scenario in order to test and validate the algorithm, and a microscopic traffic simulation tool to simulate the surrounding traffic accurately based on real-time data. Rear-end and lane change traffic conflict scenarios are developed in the simulation framework to test and validate the effectiveness of the algorithm. The validation results from the integrated simulation framework are significant due to high sensitivity and a low FAR obtained for each scenario.

As a result, this algorithm has the potential to be used in ADAS systems to develop proactive safety management strategies for improving traffic safety, presenting a viable solution for implementation within CAVs.

Though this framework provided several advantages for testing and validation, the developed scenarios need regular updating with new knowledge and data. This is because the generated scenarios might change over time as road user behaviour may alter with the increase in market penetration rate of intelligent vehicles. It is unclear whether new critical situations may arise as a result such as data inaccurately interpreted in a mixed traffic situation or in complex urban environments. Additionally, some situations are not yet fully known (20).

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