Interactive Scenario Modelling for Hazard Perception in Driver Training

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Abstract

Vehicular traffic flow is a complex interaction between drivers, vehicles, and the road infrastructure. These interactions can be viewed as human-machine systems, describing the relationship between driver (human) and vehicle (machine) and the reciprocity of the driver-vehicle system with the environment. The driver component of the system is the most complex as they are generally characterised by higher-level processes. These processes include perceptual capabilities such as vision, hearing and sensation of forces on the body; cognitive functions, for example motivation and attitude; and control functions, such as limb coordination enabling steering and braking. Existing methodologies for representing these processes are limited in three fundamental ways: (1) the ‘lower level’ of detail in the modelling (2) the lack of behavioural intelligence within the modelled system and (3) the failure to integrate the three key elements of driver, vehicle and road infrastructure. The paper examines various driver behaviour models. It then focuses on the development of a framework for complex and interactive scenario modelling, particularly applied to hazard perception for driver training. A key element of this framework is the flexibility of qualitative visualisation, enabling a scenario to be seen from various viewpoints. The main aim of developing such a framework is to provide a modelling environment that can integrate theory, algorithms, software and experimental results generated by engineers and scientists in all of the traditionally disparate areas of driver-, vehicle-, traffic- and highway research. The framework has been validated using empirical data obtained from TRL’s driving (car) simulator, to assess driver perceptual and cognitive skills required in vehicle control to avoid collision with a parked car. In the context of hazard perception, the validation has demonstrated the potential of using the framework as a comprehensive modelling tool for engineers, scientists and decision-makers working in many commercial aspects of road transport.

Keywords: driver behaviour, interactive scenario modelling, hazard perception, driver training.
Introduction

Driver behaviour models

The three primary elements of a vehicular traffic system are the driver, the vehicle and the road environment. Drew (1968) suggests that the driver component of this system is the most complex as the human driver is generally characterised by higher-level processes, such as perceptual capabilities (e.g. vision, hearing and sensation of forces on the body); cognitive functions (e.g. learning, motivation and attitude) and control functions (e.g. steering and braking). For example, learning could concern the ability of the driver to improve their understanding of the driving task through repetition, with feedback allowing error adjustment to be made to improve situational responses. Control function on the other hand, could address the execution of actions, typically those involved with stabilising the vehicle’s path and speed e.g. steering, braking and acceleration.

Different types of driver behaviour models are critically summarised in (Michon, 1985). Some of these include; mechanistic models, adaptive control models (e.g. servo control and information flow control), motivational models and cognitive models. Michon’s categorisation of driver behaviour models is illustrated in Table 1.

Table 1: Categorisation of driver behaviour models (Michon, 1985)

<table>
<thead>
<tr>
<th>Input-Output (Behavioural)</th>
<th>Taxonomic</th>
<th>Functional</th>
</tr>
</thead>
<tbody>
<tr>
<td>Task analysis</td>
<td>Mechanistic models</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Adaptive control models</td>
<td></td>
</tr>
<tr>
<td></td>
<td>- servo-control</td>
<td></td>
</tr>
<tr>
<td></td>
<td>- Information flow control</td>
<td></td>
</tr>
<tr>
<td>Internal State (Psychological)</td>
<td>Trait models</td>
<td>Motivational models</td>
</tr>
<tr>
<td></td>
<td>Cognitive models</td>
<td></td>
</tr>
</tbody>
</table>

Task analysis – the seminal work by McKnight and Adams (1970a, 1970b; McKnight and Hundt, 1971) provides a comprehensive analysis of driver behaviour impacting the vehicular traffic system. They identified and categorised driving into over 1700 elementary tasks, e.g. accelerating, steering, speed control, lane usage, reacting to traffic, planning, car following, lane changing, and so on.

Trait models – attempt to capture individual personality characteristics e.g. aggressive or cautious driving, influence of stress, etc. These traits have an influence in certain types of driving behaviour, for example, many studies have demonstrated the effect of personality traits on the likelihood of accidents (Iversen and Rundmo, 2002; Lawton, 1998 and Ulleberg, 2002).

Cognitive models – seek to decompose the complexity in driving behaviour into distinct hierarchical structure. Michon is one of the proponents of using cognitive models in modelling driver behaviour, proposing a hierarchical structure of driving behaviour divided into strategic (planning), tactical (manoeuvring) and operational (control). In this structure, planning and determination of goals is achieved at the strategic level, whilst selection of these goals is performed at the tactical level. At the operational level, actions are executed to achieve the planned goals and objectives. Tactical level decisions are critical for the support of operational goals execution. To understand these decisions, motivational models seek to capture the driver’s internal or mental state in terms of cognitive functions (e.g. emotions, intentions, beliefs). Cognitive modelling using Michon’s hierarchical structure is widely accepted to offer a sound basis for modelling driving tasks.

Whilst mechanistic models identify driving behaviour as physical systems for example, the fluid flow analogue of traffic, adaptive control models describe driver behaviour as either continuous or intermittent tasks i.e. servo-control models or flow charts/decision trees (information flow control models). The use of
servo-control models in describing driving is particularly useful in modelling the operational mechanisms of driver/vehicle interaction. The driver usually receives input signals from the vehicle and the external environment and then steers the vehicle in response to these signals. Although advances in computer simulation have brought about increasing application of adaptive control models, such models still lack intelligence and learning capabilities because of their data driven approach.

**Driving interaction and traffic flow methods**

Driver behaviour modelling is an important aspect of understanding the driver within the traffic system as well as analysing traffic flow. The interactions between the key components of vehicular traffic with respect to time and space can be viewed as a typical human-machine system i.e. driver (human), car (machine) and environment. Figure 1, illustrates some of the processes involved in driving.

![Figure 1 Basic components of driving (cited in Pursula 1999)](image)

The driver receives information from the environment (perception), makes decision based on the traffic information and then executes actions to respond accordingly. These interactive tasks are summarised in (Allen et al, 1996 p. 27-28), and include:

Control concerns psychomotor functions that stabilise vehicle path and speed against various aerodynamic and road disturbances. Guidance involves perceptual and psychomotor functions coordinated to follow delineated pathways, adhere to implied speed profiles, interact with traffic and avoid hazards. Navigation involves higher level cognitive functions applied to path and route selection and decisions regarding higher-level traffic interactions (e.g. avoiding congestion).

In fact, these tasks can be further simplified into three driving actions: perception-decision-control. This is often referred to as open and closed loop interaction. The open-loop operation is represented as a perception-decision-action sequence whilst closed-loop operation involves update to the driver/vehicle current state based on feedback from the environment.

Within the context of traffic flow, driver interactions can be explored in terms of vehicle following and lane changing using different approaches (i.e. micro-, meso- or macroscopic levels of behaviour details) Vehicle following is a fundamental driving tasks, and plays a very important role in understanding traffic flow (Rothery, 1997). Vehicle following is usually triggered when a driver cannot maintain their preferred speed and must adjust their speed to match the speed of the lead vehicle, whilst keeping a safe distance, referred to as either time- or distance headway. For a thorough review of this subject see Brackstone and McDonald, 2000. On the other hand, lane changing behaviour is a more complex task than Vehicle following, since consideration must be given to driving conditions in the target lane and the intentions (perceived behaviour) of other drivers in the target lane. An important part of lane changing behaviour is gap acceptance involving the assessment of the critical gap length of the target lane.

The level of detail required in a model is dependent on the intended application. Several methodologies can be adopted in representing the driving components i.e. vehicle, road network and driver. Macroscopic
models ‘describe the entities and their activities at a low level of detail’ (Lieberman and Rathi, 1997 p. 6) requiring less computational time. At the same time, these models are low fidelity and often based on the deterministic relationships between the traffic entities. Microscopic models on the other hand offer the most general method for realistically describing and analysing the nature of vehicular traffic. They are high fidelity models capable of representing the individual characteristics of the traffic elements such as driver, vehicle and road network in significant detail. Representation of such characteristics within microscopic simulations produces realistic interactions. In contrast, meso-scopic models are mixed fidelity - these models describe some elements of the traffic system at a higher level of detail but represent the interactions at a relatively lower level of detail than microscopic traffic simulation models.

Various other methods have been proposed in modelling driving interactions and traffic flow. These include rule-based systems, fuzzy logic, probabilistic models, hidden markov driver models and finite state machines. However, in his review, Michon noted in 1985 the lack of research in driver behaviour modelling. He observes that such lack of research in this area can be attributed to a number of issues, including, failure to improve on the driver behaviour models of the sixties (e.g. car following) and a lack of interesting research ideas on driver behaviour. Concerning the future direction of driver behaviour modelling, he suggests that ‘we are heading for an intelligent, knowledge and rule based model of the driver that will be capable of dealing with a wide variety of realistic, complex situations…’ Addressing these issues in the development of visual databases and scenarios for driving simulators would greatly improve behavioural responses of simulator participants.

Visual Database and Scenarios for Driving Simulators

Driving simulators are used extensively to train drivers to develop new or improved skills. Examples of these include, TRL TruckSim and CarSim (TRL, UK), Iowa Driving Simulator (University of Iowa, USA), Leeds Driving Simulator (University of Leeds, UK.), COV Driving Simulator (University of Groningen, Netherlands), SIRCA simulator (University of Valencia, Spain), INRETS Sim2 / ARCHISIM (INRETS, France). A widely successful driver training simulator is that used by BSM, developed by FAROS (Wicky et al, 2001). Driving simulators provide safe, controlled and cost effective environments in which it is possible to analyse traffic flow, highway design and driver psychology using objective performance measures. In general, these simulators consist of a fixed or motion cabin, visual projection and sound systems, and a traffic generation module. The traffic generation module typically consists of visual database and driving scenarios.

It is important to make a subtle distinction between visual database and driving scenarios used in driving simulators. Visual databases are typically three-dimensional computer generated worlds developed using computer graphics tools such as Multi-Gen, 3D Studio Max or Open Inventor, although recently photorealistic imagery is been used to produce complex photorealistic scenery. The scenery can contain static and non-static objects, for example, buildings, sky, humans, vehicles. On the other hand, driving scenarios are those elements of the traffic generation module that support the specification and control of parameters for vehicle, driver, road network and task definition for any specific study. There is a growing debate on the realism of visual databases and scenarios. Parkes (2005) provides a very interesting discussion on improved realism and improved utility of driving simulators for the purpose of training. He contends that high fidelity of the simulator or realism in the visual database and scenario may not be necessary for the purpose of training. He underpins his argument with the concept of essential realism – developing reality essential for a particular training requirement rather than improved face validity. However, it can be equally argued that improved realism in visual database and driving scenarios is desirable for specific applications for example, perceptual or cognitive behaviour. Allen (2003 and 2004) argues that given a particular application (e.g. in research, driver training and assessment), scenarios and visual databases ‘need to be designed and chosen to match real-world conditions as much as possible to ensure proper transfer of training’.

Scenario specification or authoring can be achieved at three levels (Papelis, 1996). Examples of these levels include hand-tuned scenario authoring where direct access and modification of the source code is required to create various scenarios; parameterized scenario authoring allowing some flexibility through specification of initialised parameters such as preferred speed, preferred distance, preferred lane position etc. for the different scenarios. Finally, the authoring with dynamic coordinators level essentially assigns
simple instructions to modules (Behaviour Modification Options) responsible for high level behaviours instead of these high level tasks being scripted by the scenario creator. We demonstrate in this paper, the application and validation of scenario specification to assess driver perceptual and cognitive skills required in vehicle control e.g. lane changing to avoid collision with a parked car. The demonstration is achieved by using data obtained from one of the UK’s advanced full mission simulators located at TRL to configure a Synthetic Traffic SIMulation (ST-SIM) framework being developed at Loughborough University.

**Background**

**TRL Driving Simulator**

The Driving Simulator at TRL consists of a medium sized saloon car surrounded by projection screens onto which are projected the graphic images to create the virtual environment. The vehicle is mounted on hydraulic rams to supply motion, simulating the heave, pitch, and roll experienced under normal braking, accelerating and cornering. Realistic engine, road, and traffic sounds complete the virtual setting. Scenario specification for the behaviour of all autonomous traffic vehicles included in simulated scenarios is determined by applying specific programming commands via SCANeR (Champion et al, 1999). Beyond simple lane- and distance-keeping rules, the simulated vehicles have no in-built intelligence. The addition of software to provide artificially intelligent vehicles would greatly enhance the realism with which simulator trials could be created since the autonomous vehicles would be capable of responding in a realistic manner both to the behavioural responses of the participant and to any pre-programmed autonomous vehicle behaviour (e.g. a vehicle programmed to disobey a red traffic light). This would improve participants’ immersion into simulator scenarios increasing the likelihood that they will drive in a more realistic and representative manner with the consequence that greater confidence can be placed in resulting analyses. The current project is to validate some aspects of the current ST-SIM framework.

**Synthetic Traffic SIMulation (ST-SIM) Framework**

Scenario modelling is a fundamental element in the framework illustrated in Figure 2. A previous version of ST-SIM has been reported in several papers (Wood and Arnold, 1997; Dumbuya and Wood, 2001; Dumbuya and Wood, 2002a, 2002b; Dumbuya and Wood, 2003; Wood et al, 2003). The framework has three main components – road network, vehicle and driver. The Road Network package includes Traffic Control Objects (e.g. traffic light, traffic signs, and direction signs, etc.) and a road geometry description modelling system. The vehicle exists as a physically based vehicle model of the form commonly used in vehicle dynamics simulation (Gordon et al, 2002), with vehicle responses resulting directly from driver actions. The driver model is based on principles of Artificial Intelligence and Cognitive models. Drivers can be described as intelligent and reactive (autonomous) agents because of their individual capability to perceive their environment, use their perceptions to make decisions and take decided actions. Perception currently involves vision of the local traffic environment, allowing estimation of other vehicles’ speeds and relative positions, together with the positions of fixed objects. Decision making within the driver model uses a small number of rules, each having a weight or importance factor. These weights, along with parameters in some of the rules, can be adjusted to characterise a wide spectrum of driver behaviour. The outcome of decision making is the intention to change vehicle speed and/or direction. The most novel feature of ST-SIM is that it is based on clear distinctions between drivers, vehicles and the road network, allowing the software to act as a ‘framework’ that can accommodate varying levels of detail to match the needs of different applications. At the same time, the framework explicitly integrates the three main components of the vehicle, driver and road network in an equitable and realistic manner. In this respect, ST-SIM makes a significant contribution to the current limitations of traffic simulation models.
For the analysis of simulation results, ST-SIM makes a distinction between qualitative and quantitative visualisation. In qualitative visualisation, a scenario can be seen from various viewpoints such as Figure 3a. In contrast, Figure 3b is a quantitative (or binary image of the driver’s perception) representation of Figure 3a, revealing the discrete nature of the current driver vision model. Each driver’s viewpoint is rendered as a pixel map or binary image of the scene. In Figure 3b, the presence of the road and other objects (cars) in the scene can be inferred from the pixel map. Quantitative visualisation of ST-SIM also allows detailed investigation of vehicle motion and its relationship to driver decisions and actions. The performance of ST-SIM is measured here in terms of its capability to replicate a driving simulator study previously conducted at TRL.

**Empirical Validation of Situational Awareness**

*Data Collection: Driving Simulator Study*

The aim of this study was to obtain data on driver lane changing behaviour, via simulation. For the simulator study, sixty participants between the ages of eighteen and sixty-eight were recruited from TRL’s participant database of over 1200 members of the public. As shown in Tables 2(a) and (b), participants were grouped by both age and experience.
Table 2(a) Demographics of participants, grouped by driving experience

<table>
<thead>
<tr>
<th>Experience grouping</th>
<th>N</th>
<th>Years</th>
<th>Age</th>
<th>Mean</th>
<th>SD</th>
<th>Since licence acquisition</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Novice (0-5 years)</td>
<td>9</td>
<td></td>
<td></td>
<td>20.89</td>
<td>2.09</td>
<td>3.00</td>
<td>1.73</td>
<td></td>
</tr>
<tr>
<td>Experienced (6-25 years)</td>
<td>24</td>
<td></td>
<td></td>
<td>34.75</td>
<td>6.47</td>
<td>15.79</td>
<td>5.60</td>
<td></td>
</tr>
<tr>
<td>Veteran (&gt;25 years)</td>
<td>27</td>
<td></td>
<td></td>
<td>56.00</td>
<td>7.15</td>
<td>36.11</td>
<td>6.64</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>60</td>
<td></td>
<td></td>
<td>42.23</td>
<td>14.78</td>
<td>23.02</td>
<td>13.89</td>
<td></td>
</tr>
</tbody>
</table>

Table 2(b) Demographics of participants, grouped by age

<table>
<thead>
<tr>
<th>Age grouping</th>
<th>N</th>
<th>Years</th>
<th>Age</th>
<th>Mean</th>
<th>SD</th>
<th>Since licence acquisition</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Younger (18-42)</td>
<td>31</td>
<td></td>
<td></td>
<td>29.94</td>
<td>7.47</td>
<td>11.77</td>
<td>7.37</td>
<td></td>
</tr>
<tr>
<td>Older (43-68)</td>
<td>29</td>
<td></td>
<td></td>
<td>55.38</td>
<td>7.35</td>
<td>35.03</td>
<td>7.65</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>60</td>
<td></td>
<td></td>
<td>42.23</td>
<td>14.78</td>
<td>23.02</td>
<td>13.89</td>
<td></td>
</tr>
</tbody>
</table>

The scenario was setup for motorway driving. In the task, participants were instructed to drive along the motorway as they normally would in light ambient traffic conditions. At 20.580km (20,580m) into the trial, there was an obstruction vehicle parked in the fend-in position in lane one of the motorway. At a distance of approximately one mile (1609.344m) before the obstruction vehicle, the ambient traffic was removed from the driving environment so that participants were not impeded when making the avoidance manoeuvre. Participants had to move from lane one into lane two or lane three of the motorway to avoid the obstruction vehicle.

Data was recorded at 20Hz over the course of the trial. Parameters recorded were time, current lane, distance through the trial, lateral distance, steering wheel angle, accelerator and brake pedal depression, and the speed of the driven vehicle.

Scenario Configuration within ST-SIM

ST-SIM currently runs on a standard PC in a series of time steps. In this comparison, scenario configuration in ST-SIM was based on the experimental data obtained from the TRL driving simulator. A sample of twenty-five data sets were selected from the sixty drivers and organised into the same groups of Novice (four Male and five Female Samples), Experienced (five Male and five Female samples), and Veteran (three Male and three Female samples). The driver’s lane changing manoeuvre was simulated along with lane changing behaviour, taking into account the need to prevent collision with an obstruction vehicle parked in the fend-in position in lane one. The setup of parameters in ST-SIM is shown below:

- **TS**: Simulation Time Step (0.06s)
- **TL**: Simulation Time Length (4.5s)
- **STS**: Sample Time Steps from experimental data (selection based on the experimental scenario and data)
- **X**: Initial Abscissa (0m for driven vehicle, 80m for obstruction vehicle)
- **Y**: Initial Lateral Distance to road centre (m)
- **Spd Dir**: Initial Speed Direction (deg)
- **SEL**: Speed Error Limitation under which the driver takes no action, defined as the percentage of current preferred speed (percent)
- **APL**: Angle Percept Limitation below which driver will not execute manoeuvre, defined as the percentage of current horizontal vision angle (deg).
- **FR**: Foreseen Range (i.e. the foreseen distance for driver's steering angle decision)
**HL**: Headway Limit, the driver's safe distance to the front driver, defined by the percentage of pixels occupied by the front vehicle in the driver vision model pixel map

**SYL**: Safe Yaw Limitation, the yaw velocity below which driver will feel safe (deg/s)

**PreSpeed**: Preferred Speed (mph)

The SEL, APL, FR, and HL are setup based on the driver’s decision rule weights in the decision model as shown in Table 3

**Table 3 – Driver rule weights used to configure the decision model**

<table>
<thead>
<tr>
<th>Driver Group</th>
<th>Rule1</th>
<th>Rule2</th>
<th>Rule3</th>
<th>Rule4</th>
<th>Rule5</th>
<th>SEL</th>
<th>APL</th>
<th>FR</th>
<th>HL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Novice</td>
<td>0.3</td>
<td>0.8</td>
<td>0.8</td>
<td>0.3</td>
<td>0.6</td>
<td>5</td>
<td>0.1</td>
<td>0.8</td>
<td>0.02</td>
</tr>
<tr>
<td>Experienced</td>
<td>0.6</td>
<td>0.7</td>
<td>0.5</td>
<td>0.5</td>
<td>0.7</td>
<td>2</td>
<td>0.05</td>
<td>0.85</td>
<td>0.01</td>
</tr>
<tr>
<td>Veteran</td>
<td>0.7</td>
<td>0.6</td>
<td>0.3</td>
<td>0.6</td>
<td>0.8</td>
<td>0.5</td>
<td>0.01</td>
<td>0.9</td>
<td>0.01</td>
</tr>
</tbody>
</table>

Rule no. Description
1 Slow down
2 Speed up
3 Maintain Preferred speed
4 Maintain Preferred lane
5 Maintain Preferred forward distance

**Results and Discussion**

Figure 4 presents selected examples drawn from ST-SIM simulation runs and TRL simulator results. The results compare the behaviour of real drivers and simulated drivers for the three categories of driving experience – novice, experienced and veteran. As a simple demonstration, we provide the results for two novices, two experienced and two veterans. The driving profiles show the lateral positions of the drivers as they travelled in the northbound direction of the motorway. Both the real and simulated drivers were able to make an avoidance manoeuvre by moving from lane one, lane two and lane three to avoid the obstruction vehicle. For comparison of actual and simulated veteran drivers agreement is good, with slightly greater variation between simulated and actual driving for one of the experienced drivers. However, there is a noticeable difference in simulated and actual behaviour of the novice drivers. This is contributed to by three factors: The actual novice driving is relatively erratic; Fine tuning of driver character in ST-SIM is currently a demanding task; The current vehicle model in ST-SIM lacks some of the detailed inertial and frictional effects found in the steering and suspension of real vehicles so, creating a driver character in ST-SIM to match real vehicle behaviour implicitly involves some compensation for this. However, it is important to note that ST-SIM provides a framework in which the realism of the component models can be developed in the future.
Figure 4 – Comparison of driving profiles for real and simulated drivers

Figure 5 (a) provides qualitative visualisation of one instant in the scenario, as seen from the driver’s viewpoint, when the real driver’s car has moved to lane two to avoid the parked car on the left (lane one). Figure 5 (b) shows the pixel map generated in the driver vision model within ST-SIM at the same instant.

Figure 5 – Qualitative and quantitative visualisation of the driving scenario
Interactive scenario modelling for hazard perception

The study reported in this paper has demonstrated an aspect of Hazard Perception (HP) involving avoidance action. Hazardous situations can be dynamic involving other road users such as vehicles, pedestrians, or may simply include static or environmental features. Various studies have shown the need for evaluation of hazard perception. For example, research studies have shown correlation of hazard perception skills and potential for crashes, especially for inexperienced drivers (Grayson and Sexton, 2002; Quimby and Watts, 1981 and Maycock et al, 1991). Other studies have also demonstrated that hazard perception skills can be improved through training (McKenna and Crick, 1994) and this research evidence has led to the hazard perception test administered by the UK Driving Standard Agency (DSA).

The DSA paper (Wedge, 2002), list some of the competencies linked to HP as: effective scanning to enable early clues to be recognised, anticipation and planning, safe separation distance and correct use of speed. Hazard perception training typically involves the use of video recording (clips) of either planned (staged events) or unplanned (opportunistic) hazardous driving scenarios. The subject responds by pressing a button within a set time period after they have identified the hazard.

Responding to the DSA’s Hazard Perception Test, BSM have exploited computer game technology to produce a commercial tool for improving hazard perception skills. The training package called MAP – Mind Alertness Programme (McCormack, 2003) is targeted at learner drivers to help improve cognitive skills such as reaction time, visual scanning, risk avoiding, hand-eye coordination, etc.

The results presented here show that ST-SIM is capable of performing some aspects of hazard perception e.g. simulated driver agents are able to identify parked car as a hazard and consequently decide and apply preventative driving action e.g. lane changing behaviour to avoid collision with the parked vehicle. In the context of hazard perception, the paper has demonstrated the potential of using ST-SIM as a comprehensive modelling tool for practitioners, engineers, scientists, and decision makers working in many commercial aspects of transport.

Current limitations

ST-SIM is still under development and as such has current limitations which are briefly commented upon here:

- Driver steering behaviour is based on the analysis of pixel map output from the vision model. However, the driver’s brake/accelerate behaviour is not fully implemented, currently relying only on output from the driver decision making model, with linear interpolation between driver’s anticipated speed and manoeuvre time. One solution to this is to use non-linear interpolation functions for the brake/accelerate behaviour using.
- The Vehicle Control System is currently not fully developed; the vehicle’s braking, steering, and acceleration models should simulate the vehicle dynamics response to the driver’s control behaviour in more realistic level (e.g. time delay between driver’s steering behaviour and vehicle’s yaw response and lateral speed change, or the delay between brake/accelerate behaviour and vehicle’s speed change, etc.)
- Driver perception of vehicle forces has not yet been implemented

Acknowledgment

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References


