

Using Neural Networks to Improve Behavioural Realism in Driving Simulation Scenarios

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Abstract

This paper describes the development of a neural network driver agent to improve the realism and perceived “intelligence” of autonomous vehicles in driving simulation scenarios. Driver agent refers to simulated entities which have an internal representation or knowledge of the traffic environment through their vision and can determine their own actions using their decision/cognitive capabilities. Driver agents can therefore mimic the basic elements of human drivers, for example planning, perception, learning and decision making, and therefore display behavioural intelligence. Neural networks are a modelling technique that can be used to improve the behavioural intelligence of driver agents.

Initial data was collected from human drivers in a TRL passenger car simulator to develop and train a feed-forward multi-layer neural network and enable the neural driver agent to learn how to produce lane changing behaviour. The behaviour of the neural driver agent and human drivers were then compared and it was found that the neural driver agent produced good results when estimating the change in direction and speed required for lane changing manoeuvres. The behavioural realism of the neural driver agent was assessed and it was found that participants could not correctly distinguish between human and neural driver agent driven vehicles, suggesting that the neural driver agent is capable of improving participants’ immersion in simulator scenarios.

Keywords

Neural Networks, Behavioural Realism, Simulation Scenario, Artificial Intelligence

Introduction

Improving the behavioural realism of autonomous vehicles in simulated environments would greatly enhance the realism with which driving scenarios in a simulator can be created since the autonomous vehicles will be capable of responding in a realistic manner to the participant’s behaviour. This will improve participants’ immersion in simulator scenarios, enabling them to drive in a more realistic manner and allowing greater confidence to be placed in resulting analysis.

Behavioural intelligence can be defined within the broader context of Artificial Intelligence, such that at the minimum level, the system can exhibit human-like properties for example, planning, perception, learning, knowledge, reasoning and decision making. The paper demonstrates the development and application of a novel technique for improving and verifying the realism of a neural driver agent modelling

technique which is able to show behavioural intelligence. The technique used a neural network to learn to control the behaviour of a vehicle in a simple lane changing task.

Firstly, a brief introduction to the TRL Car Simulator and neural networks is provided. The paper then describes the initial data collection from human drivers in a TRL passenger car simulator and the development and training of a feed-forward multi-layer neural network. The paper compares the performance of the neural driver agent and human drivers when estimating the change in direction and speed required for lane changing manoeuvres. The behavioural realism of the neural driver agent is then assessed, determining whether the vehicle control of the neural network based approach was an improvement over a more traditional rule-based algorithm approach. Finally a discussion of the results and future applications of the neural driver agent is included.

TRL Car Simulator

TRL's driving simulator (figure 1) uses a real Honda Civic family hatchback that has had its engine and major mechanical parts replaced by an electric motion system that drives rams attached to the axles underneath each wheel. These impart limited motion in three axes (heave, pitch, and roll) and provide the driver with an impression of the acceleration forces and vibrations that would be experienced when driving a real vehicle. All control interfaces have a realistic feel and the manual gearbox can be used in the normal manner. Surrounding the simulator vehicle are large display screens onto which are projected the images that represent the external environment to the driver. The level of environmental detail includes photo-realistic images of buildings, vehicles, signing, and markings, with terrain accurate to the camber and texture of the road surface. The driving environment is projected onto three forward screens to give the driver a 210° horizontal forward field of view whilst a rear screen provides a 60° rearward field of view, thus enabling normal use of all mirrors. Realistic engine, road, and traffic sounds complete the virtual setting.



Figure 1: TRL Car Simulator

Scenario specification for the behaviour of all autonomous traffic vehicles included in simulated scenarios is currently determined by applying specific programming commands via SCANer (Champion et al, 1999). Therefore the behaviour and actions of the autonomous vehicles are predetermined and cannot react to unexpected events. The use of neural driver agents to determine the behaviour of the autonomous vehicles would allow vehicles to react to the traffic environment and specifically the driven vehicle's actions. Neural networks can be used to learn the actions required to react in a realistic manner.

Neural Networks

Artificial neural networks are parallel computational processing systems which implement simplified models of biological neural networks. Artificial neural networks use a set of interconnected processing elements or nodes, loosely analogous to neurons in the brain, with signals propagating through the network. The network can then identify patterns in data as it is exposed to the data - in a way, the network *learns* from experience just as people do. This distinguishes neural networks from traditional computing programs that simply follow instructions in a fixed sequential order.

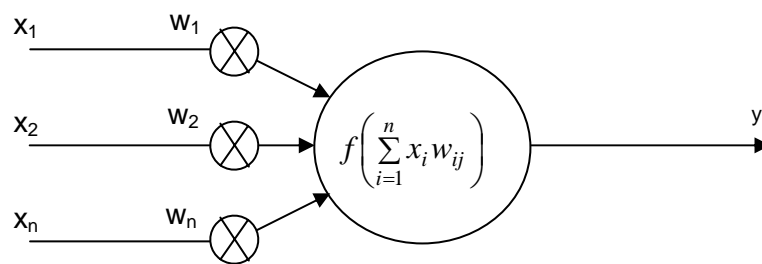


Figure 2: Artificial neuron, e.g. j^{th} neuron

Symbolically, the input to the neuron (Figure 2), i.e. the input vector, can be represented as, $x_1...x_2...x_n$. Also, each input is associated with a weight i.e. $w_1...w_2...w_n$. The output of the neuron is given by y . Mathematically the output of the j^{th} neuron is simply the sum of the inputs, x_i and weights for the j_{th} node, w_{ij} defined

$$\text{as: } y = f\left(\sum_{i=1}^n x_i w_{ij}\right)$$

The function f represents the threshold at which the neuron can fire and this threshold can be expressed in many forms, e.g. linear, step threshold, sigmoid, nonlinear and Gaussian. For further details see Gurney (1997). Feed-forward multi-layer neural networks consist of layers of neurons where the outputs of one layer of neurons feed-forward to form the inputs of the next layer, see Figure 3.

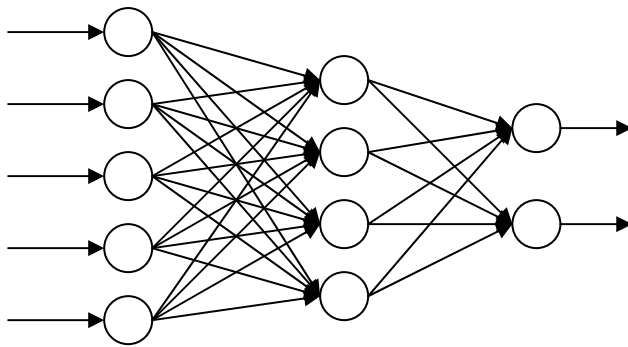


Figure 3: Structure of a feed-forward multi-layer neural network

There are many learning algorithms but the most commonly used with feed-forward multi-layer neural networks is the backpropagation algorithm. The network is presented with training data such that it can infer the nonlinear mapping implied in the data at a minimum average error between the network output and the pre-specified desired output in the training data. The backpropagation algorithm tries to minimise the error using an optimisation method known as *gradient descent* which essentially attempts to avoid the local minimum of a function by taking steps proportional to the negative of the gradient of the function at the current point. In other words, in training the network, the interconnecting weights are moved in a direction opposite to the direction of the gradient. Modifying the *learning rate* (the parameter controlling the step size) and *momentum* (parameter to avoid local minima and hence fast convergence of algorithm) can improve the performance of the training process.

Since neural networks are capable of learning from complex data and demonstrating generalisation by applying their learned behaviour in unseen situations, a number of neural network techniques have been applied in traffic. Abdennour and Al-Ghamdi (2006), for example, applied neural networks for the estimation of vehicle headways using data collected from different freeways in Riyadh, Saudi Arabia. Using the collected data they were able to model and train a neural network capable of estimating headways as a function of time (time series prediction) and headways as a general probability density function.

Hunt and Lyons (1994) developed neural networks to produce lane changing behaviour on a dual-carriageway using data collected from an interactive driving simulation on a computer monitor, which allowed subject drivers to control a vehicle by mouse. The data captured from subjects' drives consisted of time-scan traffic patterns which were used to train the network to replicate the subject driving style. Two approaches were implemented. Firstly, a predictive neural network with backpropagation training algorithm was used to predict the new lane and position of the vehicle. However, being unable to collect data outside the lane-change region affected performance of the neural network. To combat this problem, the authors used image processing techniques to improve data quality and to train a classification network to determine only the new lane for the vehicle. The new trained network produced significantly better results with classification of unseen data and the authors have gone on to improve their techniques with higher classification, for example, in Lyons (1995). However, this demonstrates the need to collect large scale training

samples and ensure the data is representative of the traffic interactions to prevent instability in performance. The impact of data quality on training neural networks was also observed by Pomerleau (1992) when training neural networks “on-the-fly” for road following. The difficulty in collecting training data outside of the normal driving range led to the problem of being unable to train the neural network to recover if going off track. Also the order in which training data was presented could lead to erratic driving, if the neural network was trained for a long period on a straight road, this led to it ‘forgetting’ how to perform on curved roads. This led to the author using image processing techniques and steering behaviour to ensure the training data sufficiently represented the driving task.

Development of a Neural Driver Agent

The first stage in developing the neural driver agent was to determine the network parameters, the inputs and outputs to the neural network required to produce the desired driving behaviour and enable straightforward interfacing with the simulator module.

The neural driver agent was developed to produce the specific driving behaviour of lane changing. The inputs required were as follows:

- Current speed
- Current direction
- Distance from vehicle
- Current Lane
- Preferred speed

To execute the behaviour of lane changing the neural network needs to output the new speed and new direction required.

To enable the neural network to ‘learn’ how to change lanes to overtake another vehicle, training data was generated from human drivers in the TRL car simulator. Eight participants were recruited to complete a short drive on a simulated three lane motorway, as shown in figure 4. In this drive they were required to accelerate to a constant target speed, remaining in lane 1 of the motorway until they came across an autonomous vehicle travelling at a constant speed also in lane 1. Behaving as they would on a real UK motorway, the participant had to overtake this vehicle by moving to lane 2 and then return back to lane 1.

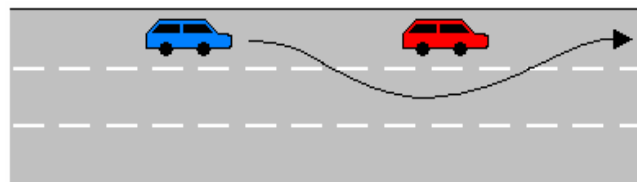


Figure 4: Scenario set-up to generate training data

The neural network was implemented and trained using the NeuroSolutions software package from NeuroDimension (www.nd.com). The training data was initially used to determine the structure of the feed-forward multi-layer neural network. Figure 5 shows the structure of the neural driver agent. It has two hidden layers of 60 and 30 processing units.

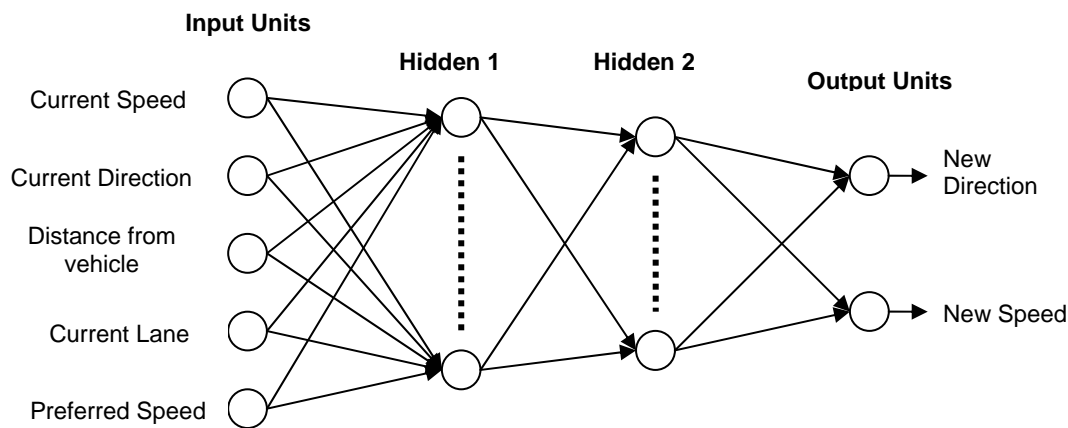


Figure 5: Structure of Neural Driver Agent

The neural driver agent was trained using the backpropagation training algorithm with momentum. 20% of the training data set was used for cross-validation and a further 20% kept aside for testing. NeuroSolutions automatically saves the network weights when the cross validation error is at a minimum to avoid over training where the network over-fits the training data and is unable to generalise to unseen situations.

Comparison of neural drivers and real drivers

Once the Neural Network is trained, the interconnecting weights are fixed and the Neural Driver Agent was implemented to interface with the TRL car simulator.

Figures 6, 7 and 8 show the changes in direction produced by the neural driver agent and real drivers when performing an overtaking manoeuvre at the three speeds 50mph, 60mph and 70mph. The direction scale is in degrees such that 0 is straight ahead, a negative value is steering to the right and a positive value is steering to the left. The graphs show how the drivers steer to the right to move into the middle lane, then steer to the left to move back into the inside lane. The graphs show how differently real drivers perform an overtaking manoeuvre and how individual drivers also produce different behaviour at different speeds. Despite the differences in driving behaviour produced by the real drivers, the graphs show that the neural driver agent has learnt the changes in direction required to perform an overtaking manoeuvre. The neural driver agent has produced a consistent driving style at all speeds. However, rather than capturing individual driving behaviour, the neural driver agent effectively produces an 'average' driving behaviour when overtaking.

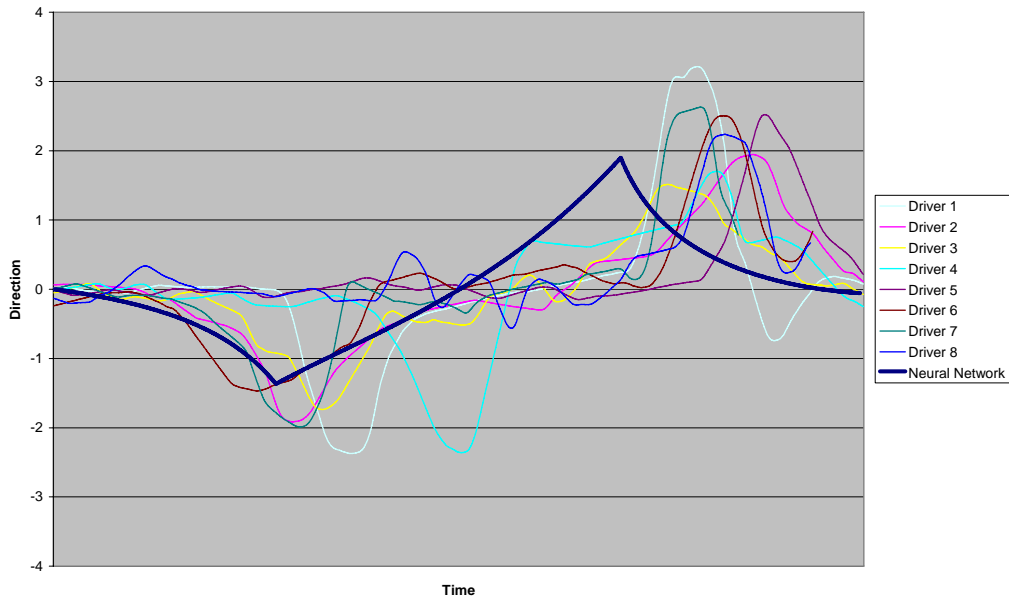


Figure 6: Drivers' change of direction when overtaking at a speed of 50mph

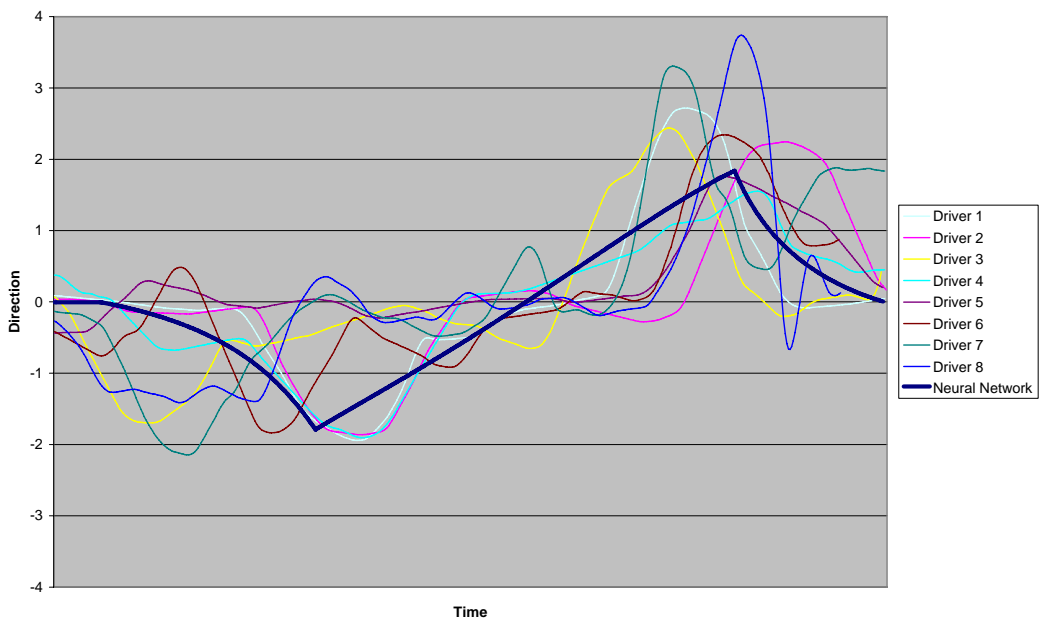


Figure 7: Drivers' change of direction when overtaking at a speed of 60mph

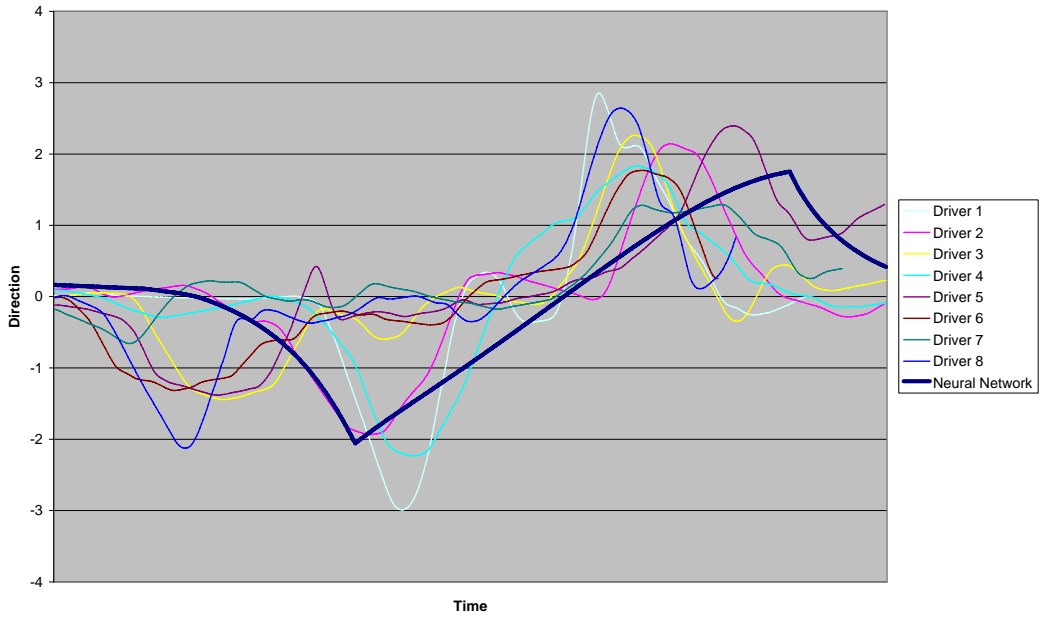


Figure 8: Drivers' change of direction when overtaking at a speed of 70mph

Figures 9, 10 and 11 show the real drivers and neural driver agent accelerating to and trying to maintain speeds of 50mph, 60mph and 70mph. These graphs also demonstrate the differences in the behaviours of the real drivers. When trying to achieve a speed of 50mph the neural driver agent accelerates too much but then decelerates to maintain a speed just under 50mph and when trying to maintain a speed of 60mph the neural driver agent maintains a slightly higher speed. However, overall the neural driver agent produces a smooth acceleration and can maintain a constant speed.

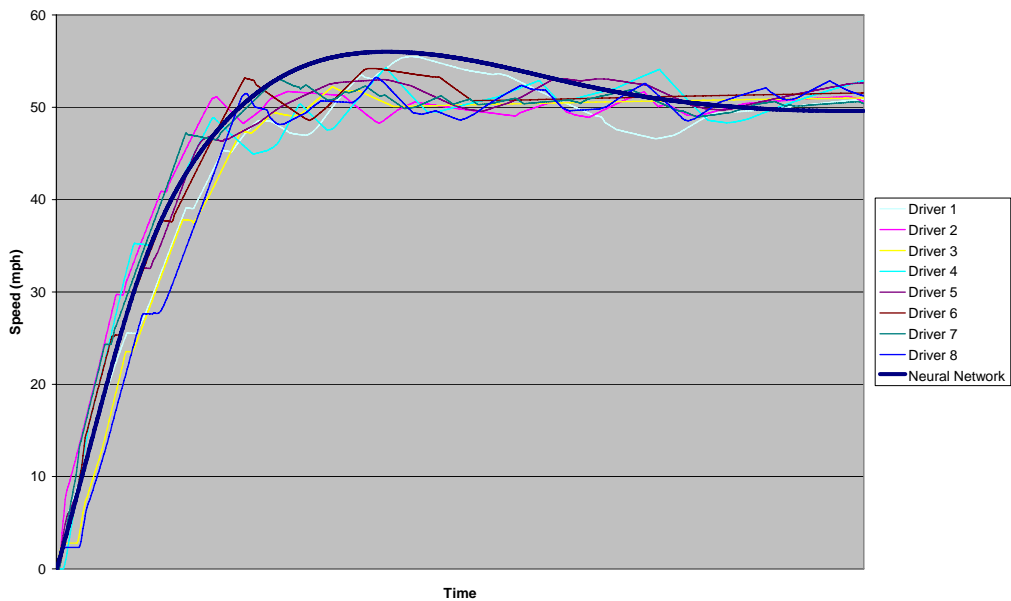


Figure 9: Drivers' speed when trying to maintain a speed of 50mph

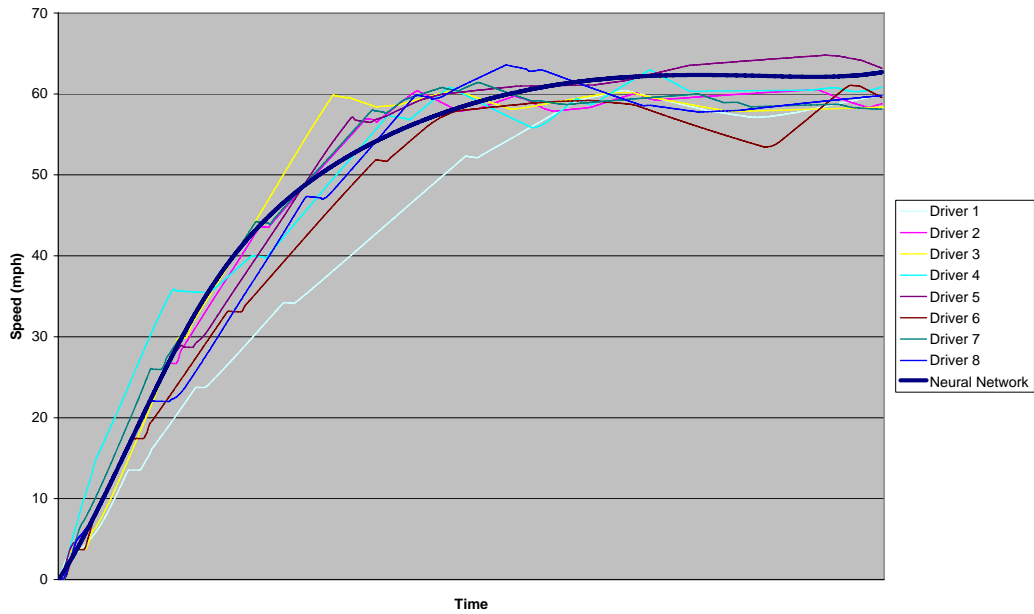


Figure 10: Drivers' speed when trying to maintain a speed of 60mph

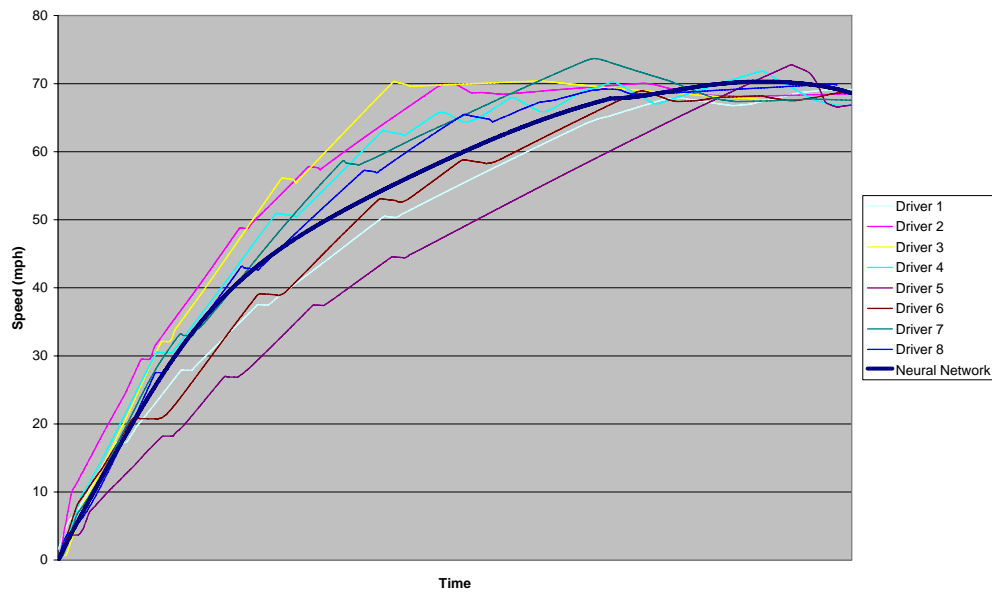


Figure 11: Drivers' speed when trying to maintain a speed of 70mph

Assessing the behavioural realism of the Neural Driver Agent

To assess the realism of the neural network model, its control of the driven vehicle was compared with a rule-based model, SD-SIM (from previous Loughborough University research, see Dumbuya and Wood (2003), Dumbuya et al. (2002)) performing the same task. Twelve participants were recruited to observe how each micro-simulation model controlled the driven vehicle and to rate the realism with which they thought the vehicle was being controlled. Participants each sat in the driver's seat of the simulator vehicle and were effectively 'driven' by the micro-

simulation models through the simulated scenario on which the neural network model had been trained. Participants also observed a pre-recording of how a human driver had completed the same manoeuvre. Participants were asked to rate how realistic they felt each model was on a ten-point scale from 1 to 10, where a rating of 1 indicated that they felt that the model was very unrealistic and a rating of 10 indicated that they felt that the model was very realistic. In rating the realism of the three computer models of driver behaviour, Figure 12 shows that on average, the human drive was the most realistic (average score of 7.83) and SD-SIM was the least realistic (average score of 2.92). It is important to note the realism of the neural driver agent in replicating the human drive (average score of 7.42). The results of the study demonstrated that participants thought that the neural network model was significantly more realistic in its control of the driven vehicle than the traditional rule-based model. Paired samples t-tests showed that the realism scores for SD-SIM differed significantly from those given for the neural driver agent ($t(11) = 7.24$; $p < 0.001$) and from those given for the Human ($t(11) = 11.3$; $p < 0.001$), whilst the comparison of the neural driver agent and the Human realism scores did not reach significance ($t(11) = 0.767$; $p = 0.46$).

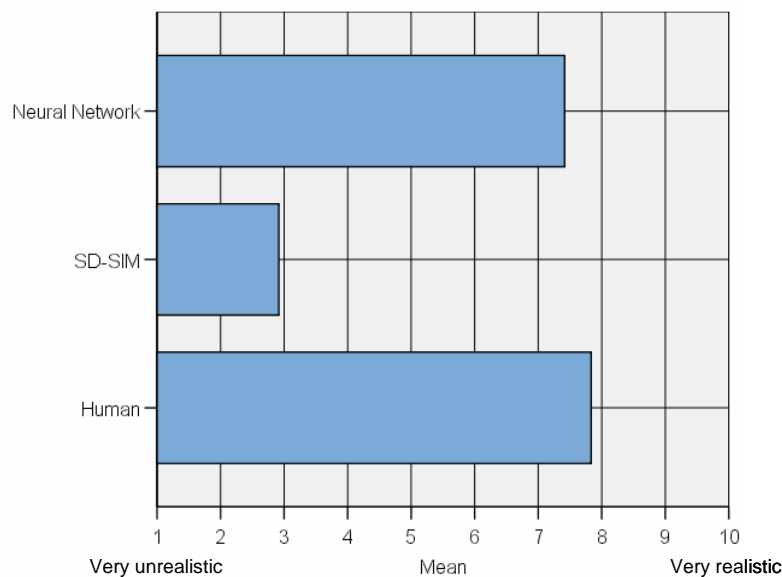


Figure 12: Mean realism ratings of each of the models presented to participants

To further explore the realism of the three models, participants were asked to rate how likely it was that each of the three drives presented to them was actually completed by a human driver. Again, a ten-point scale from 1 to 10 was used, where a rating of 1 indicated that they felt that it was very unlikely that the drive was completed by a human driver and a rating of 10 indicated that they felt that it was very likely that the drive was completed by a human driver. The aim was to see if participants could correctly distinguish the human drive from the SD-SIM and neural driver agent-based drives. Figure 13 illustrates the participants' performance in classifying the models. Participants were unable to discriminate between the human and the neural network in their control of the driven vehicle.

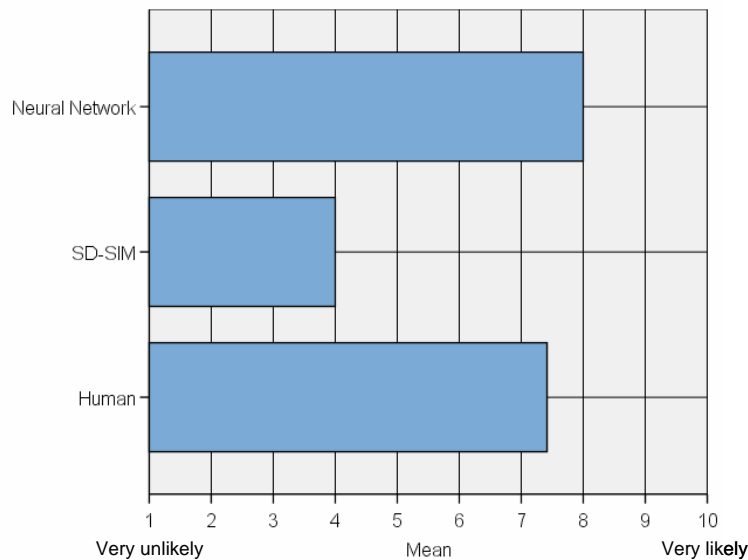


Figure 13: Mean ratings of how likely it was that each drive was completed by a human driver

Discussion and Conclusions

The neural driver agent successfully learnt the changes in speed and direction required to produce lane changing behaviour and achieved an average realism rating of 7.42, which was not significantly different to that received by the human drive, showing that the neural network had learnt to replicate human behaviour. This suggests that a neural driver agent could be used to improve the behavioural realism of autonomous vehicles in driving simulations. Participants also thought that the neural driver agent was significantly more realistic than the traditional rule-based model. However, the full functionality of SD-SIM (e.g. the vision model capability to allow driver agents to predict other drivers' speeds, distances, etc.) was not implemented, as the study focused on developing the neural network model that could potentially enhance or replace the rule based mechanisms in SD-SIM.

Participants could not correctly distinguish between the human and neural driver agent driven vehicles, suggesting that the neural driver agent developed is capable of improving participants' immersion in simulator scenarios. Neural driver agents could potentially be developed to participate fully in driving scenarios, responding realistically in both situations to which they have been trained and novel situations. This would enable participants to drive in a more realistic manner rather than adjusting their behaviour due to the predictable nature of prescribed autonomous traffic. This would lead to improvements in simulator trials with the consequence that greater confidence can be placed in resulting analyses. Allen (2003 and 2004) suggests that driving scenarios 'need to be designed and chosen to match real-world conditions as much as possible to ensure proper transfer of training'. Therefore, this level of immersion may also allow the subsequent transfer of driving knowledge to the real world improving a driving simulator's performance as a driver training tool.

Parkes (2005) suggests that high realism in the driving scenario may not be necessary for the purpose of training. However, he underpins his argument with the concept of *essential realism* – developing reality essential for a particular training requirement rather than improved face validity. Therefore, the ability to create realistic scenarios for a greater range of driving situations would increase the range of areas where research and training using a driving simulator will be applicable.

Training the neural driver agent using data obtained from drivers with specific characteristics, such as aggression or caution, would enable the representation of the range of behaviours displayed by real drivers in driving scenarios. By adjusting the structure and/or connection weights of the neural network, it may also be possible to create simulated impaired drivers, such as alcohol-impaired, fatigued or elderly drivers. This would enable new driving scenarios to be created where the autonomous vehicles can react to the participants' behaviour in a realistic manner and to display a range of driving styles.

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