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An Agent-Based Traffic Simulation Framework To Model Intelligent Virtual Driver Behaviour

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Abstract

This paper presents an agent-based traffic simulation framework that supports intelligent virtual driver behaviour. The framework exploits concepts used in Artificial Life (ALife), Artificial Intelligence (AI) and Agent technology to model the inherent unpredictability and autonomous behaviour of drivers within traffic simulation models. Each driver agent in our system contains knowledge and a decision-making mechanism, both of which are based on heuristics. This approach replaces some of the prescriptive nature of driving simulation models by allowing behaviours to emerge as a result of individual driver agent interactions. The framework also contributes to accident analysis by improving current limitations in which accident investigation methods concentrate on the events themselves, rather than precrash influences. Within this context, the framework provides an opportunity to increase the understanding of accident causation factors, to examine alternative traffic scenarios (what if analyses) and methodology to obtain quantitative estimates of accident risk. Current implementation results show that driver agents within the integrated simulation are able to perceive other drivers' speeds and distances, avoid collisions, perform realistic vehicle following, and demonstrate emergent traffic flow. A major application area for this framework includes the evaluation of vehicle, highway and road user factors that precede a collision, or near misses.

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Un modèle de simulation de circulation capable de mettre en scène les comportements de conducteurs virtuellement intelligents

Résumé

Ce document présente un modèle de simulation de circulation capable de mettre en scène les comportements de conducteurs virtuellement intelligents. Afin de représenter le comportement autonome et l'imprévisibilité inhérente aux conducteurs, ce modèle de simulation exploite les concepts issus des recherches dans les domaines de la Vie Artificielle (Alife), de l'Intelligence Artificielle (AI) et de la Technologie d'Agent (Agent Technology). Dans notre système, chaque agent-conducteur possède une base de connaissance et un mécanisme de prise de décision basés sur des heuristiques. Cette approche repousse certaines limites des modèles de simulation de conduite actuels en permettant l'émergence de comportements résultant de l'interaction entre agents-conducteurs. Ce modèle contribue également à l'analyse d'accidents en repoussant les limites des modèles aujourd'hui basés sur l'étude des évènements en eux-mêmes plutôt que les influences de la période précédent l'accident. Dans ce contexte, notre modèle permet d'approfondir la compréhension des facteurs provoquant l'accident, d'examiner d'autres scénarios de circulation (« Que se passet-il si ...») et offre une méthodologie afin d'obtenir des estimations quantitatives de risque d'accident. Les résultats d'implémentation actuels montrent que les agents-conducteurs, dans la simulation intégrée, sont capables de percevoir les distances et vitesses des autres conducteurs, d'éviter les collisions, de suivre une file de véhicules et de montrer ainsi l'émergence d'un flux de circulation. Une des principales applications de ce modèle est l'évaluation des facteurs 'véhicule', 'autoroute' et 'automobiliste' dans le temps qui précède la collision ou son risque.

Introduction

The application of Artificial Intelligent (AI), Artificial Life (Alife) and Agent concepts offer the opportunity to simulate realistic behaviour through efficient model abstraction whilst minimising software complexity. The definition of AI covers a broad spectrum, however, in [1] the author suggests that at a minimum level, *intelligence requires the ability to sense the* environment, to make decisions and to control action. These elements provide a suitable context in which to describe intelligent behaviour. In ALife, the focus is on the synthesis of lifelike systems that exhibit behaviour characteristic of natural living systems [2]. The underlying principle of ALife is the simulation of simple interactions that produce complex emergent behaviours. Like AI, the definition of agent means different things to different people. However, within the context of software engineering in general, agent-based abstractions are often very similar to traditional object-oriented design methodologies [3]. An agent is simply an object or class entity with its own attributes and methods. As a result, agent-based frameworks can easily be represented for example, by the Unified Modelling Language (UML) notation albeit with modifications to standard UML representation. As noted in [4], 'an agent oriented semantic to UML provides a straightforward generalisation of its well-known object-oriented semantic'. Such a framework offers an effective approach to representing structure, behaviour and associated complexities in both real world and software systems.

Scenario modelling is a fundamental element in agent-based simulation. However, since the underlying objective of agent-based paradigms is to endow entities with life-like properties e.g. autonomy, reactivity, etc., it invariably poses many problems in creating realistic driving scenarios. For example, if agents are created to have their own agenda/mind how do we build scenarios that specify their behaviour and monitor their interaction? Papelis [5] identifies three possible levels of scenario authoring that attempt to address some of these issues. 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* allows some flexibility by allowing the specification of initialised parameters such as preferred speed, preferred distance, preferred lane position etc. for the different scenarios, each defined at the start of the simulation. Finally, the *authoring with dynamic coordinators* level essentially assigns simple instructions to modules (BMO, Behaviour Modification Options) responsible for high level behaviours instead of these high level tasks being scripted by the scenario creator.

In the context of these developments, the aim of this paper is two fold: firstly, to discuss the recent development of a framework that models inherent unpredictability and autonomous behaviour of drivers through scenario modelling. This has been achieved by using ALife, AI and Agent concepts and abstraction mechanisms to define intelligent behaviour for virtual driver agents operating in a microscopic or agent-based traffic simulation. As such, our virtual driver agents mimic the essential elements of human drivers, and are implemented within the simulation framework as objects or class interactions, using UML as a standard notation. These developments have been supported by a range of driving experiments involving the Police. The second aim of this paper is to discuss how these developments can contribute to the understanding of accident causation factors through evaluation of traffic scenarios,

analyses of pre-crash influences and quantitative estimation of accident risk. In addition, the work reported here is not too dissimilar to the traffic generation framework described in [6] where individual agent interaction is based on perception-decision-action mechanism. However, our work differs in the way our individual virtual driver agents combine vision and decision-making capabilities within an ALife concept.

Functional design of the agent-based traffic simulation framework

This section discusses the conceptual framework of our *Synthetic Driving Simulation (SD-SIM)* illustrated in figure 1. The framework consists of three main components: *Synthetic Traffic Environment (STE), Vehicle Dynamics Model (VDM)* and *Intelligent Virtual Driver (IVD)*. From a control system's point of view, the fundamental interactions within the framework can be described as either *open-loop* or *closed-loop*. The open-loop operation is represented as a perception-decision-action sequence whilst closed-loop operation involves update of the driver/vehicle current state based on feedback from the synthetic traffic environment. Such feedback mechanism allows virtual driver agents, for example, to perform mental evaluation of the traffic situation so that any deviations from the desired goals could trigger corrective actions such as steering to avoid collision. Within SD-SIM, the three main components are integrated in a well-structured and realistic manner.



Figure 1: An agent-based approach to microscopic traffic modelling and simulation

Intelligent Virtual Driver

The *IVD* module is the core to the agent based traffic simulation framework and consists of three main subsystems; *Visual Perception Model (VPM)*, *Decision Making Model (DMM)*, and *Execute Action Model (EAM)*. The concept of the IVD module is rooted in the areas of Artificial Life, Artificial Intelligence and Driver Psychology. Virtual drivers can be described as reactive (autonomous) agents because of their individual capability to perceive their

environment, make decisions based on what they 'see' and take appropriate actions. This autonomous and unpredictable driver behaviour leads to the emergence of traffic flow due to interactions between individual agents. Figure 2 demonstrates the logical sequence of processes performed by a virtual driver agent within SD-SIM. The agents' percepts are currently only associated with its vision capabilities but future implementations could include sound. To introduce further realism by removing the unrealistic availability of 'perfect knowledge' concerning the positions and velocities of vehicles in the simulation, a Scene Encapturing and Evaluation – SEE model was proposed as part of the VPM. The VPM is based on the abstraction of key visual processes into a logical vision model. SEE provides both image capture and visual information processing. Image capture uses ray tracing techniques to generate a binary image in each eye. Images at successive times are mapped into a 16-plane plane 'visual memory' for further processing.

The introduction of uncertainty is achieved through the driver's cognitive state, which holds their knowledge of the current traffic environment. Knowledge representation is achieved in terms of visual information processing heuristics for object detection and recognition, collision detection, estimation of apparent distance and speed, estimation of direction of motion and object tracking. These heuristics are simply AI algorithms based on binary image processing techniques e.g. segmentation and stereo analysis. In this regard, SEE not only acts as a filter for global visual information but also introduces an element of uncertainty within driver decision-making. For example, by comparing stereo images driver agents estimate the depth of objects. In addition, subtraction of images in successive visual memory planes, separated by a known time interval allows estimation of average velocities of objects. The expanding and contracting of image patterns due to looming and receding of objects also provide time to collision information. Thus, driver agents no longer rely on accurate position and velocity information, but instead generate their own subjective interpretation of the traffic situation. More detail of the vision model is given in [7, 8]. In terms of concept, the vision model is similar to the synthetic vision models proposed in [9, 10], however, unlike these and other previous models [11, 12], our vision model is adapted to support intelligent decision making in driving.

Decision making for each virtual driver agent is formulated as a rule-based approach employing a set of rules common to all drivers. A description of the DMM sub-system is given in [13]. Decisions are executed based on individual driver agents being able to determine the relevance of their rules using personal rule weightings, visual information received from the synthetic environment and other quantitative parameters (that collectively define individual driver preferences and personality). Driver agents also have a set of preferred parameters, which they strive to attain throughout the simulation. These parameters include speed, headway (distance to the vehicle in front), distance from the car behind, etc.

Finally, the *EAM* component is intended to be part of the biomechanical system of the driver agent and performs functions such as head gaze (e.g. scan within a wider field of view) and other driving related tasks. A complete 'man-model' derived from anthropometrics data is required to allow functionality of legs, hands and body of the driver agents. In other words, the EAM represents the operational level of Michon's driver cognitive hierarchy [14]. The execution of actions in terms of acceleration, braking and steering to effect vehicle control within the virtual environment is currently achieved by abstract processes.



Figure 2: An agent-based implementation structure

Vehicle Dynamics Model

The current *VDM* module exists as a simple deterministic rule-based entity, with vehicle responses resulting directly from driver actions. Whilst this is perhaps appropriate for a high level study on emergent behaviour within stable traffic flows, it excludes factors likely to be important to the understanding of accident causation, which may be as much physical as psychological. The intention is to incorporate a physically based vehicle model of the form commonly used in vehicle dynamics simulation [15]. Such a model places limitations on vehicle manoeuvrability due to factors such as vehicle inertia, limited engine power, limited friction between the tyre and road, dynamic changes in vertical tyre loads, etc. Limitations also arise from driver skills, which are sometimes crucial in accident causation; a skilled driver can recover from a skid or spin, regaining control of the vehicle, whilst a novice is more easily confused by unexpected vehicle behaviour.

Introducing more realistic vehicle behaviour immediately implies a need for a more sophisticated approach to the decision-action modelling within the Intelligent Virtual Driver. Currently the IVD operates at a high 'conscious' level based on the logical processing of traffic and driver intentions. Translating such desired actions into vehicle responses requires both open-loop and closed-loop activity at several levels. For example, once a decision has been made to attempt an overtaking manoeuvre, feedback from the traffic environment can countermand this decision, e.g. when new visual input indicates the danger of an accident. If the initial decision stands, the driver plans a new speed and path for the vehicle. An incredibly skilled driver could perform this 'with his eyes shut' (open-loop control) but in reality corrections (closed-loop control) are needed – extra throttle or slight changes in the steering for example. The more familiar the driver is with the car, the more smoothly he or she will drive, and the less feedback is required. At a lower level still, some control actions are very much sub-conscious; reactively, the driver will 'hit the brakes' if a child suddenly emerges from behind a parked car, or pro-actively a skilled driver will use opposite lock steering to correct incipient loss of control in spin. These actions are generally learned through driver training, and represent low level conditioned reflexes. These various levels of behaviour have

been described in various papers (see for example [16] and a flexible and generic driver model that incorporates path planning and feedback control (at the conscious level) has been described in [17]). It should be clear from the above that the use of physically based modelling is a challenging development that is fundamental to the integration of an agent-based traffic model with real-life accident causation factors.

Scenario modelling within SD-SIM

The Synthetic Driving Simulation framework was designed in UML notation version 1.3 [18] and implemented in the C++ object orientated programming language. This approach is consistent with the principles of agent abstractions, based on traditional object-oriented design methodologies [3, 4]. The integrated simulation allows interactive creation and manipulation of scenarios. Scenario configuration in SD-SIM is based on a parameterised scenario authoring approach to define initialised parameters through the Scenario Modeller interface. The process of defining scenarios is performed in three main processes as illustrated in figure 3. The first process involves the specification by the user, of initial and state parameters as part of the scenario definition. Scenario definition includes (1) define people, vehicles and the road network (2) specification of road/traffic events (i.e. links between driver and vehicle, between vehicles and road network, and between pedestrians and road network) and (3) specification of simulation parameters (e.g. initial position, speed and acceleration of each driver). The internal data management of the scenarios is implemented in a hierarchical file structure containing vehicle properties, driver properties and road geometry descriptions. The final process, i.e. post-processing, is responsible for the visualisation of simulation runs as well as providing results and interaction to the user. As a compromise between reality and efficiency, the visualisation is currently achieved by a Virtual Reality Modelling Language (VRML) based tool [19], which is loosely integrated within a common Graphical User Interface (GUI). SD-SIM currently runs on a standard PC in a series of time steps.



Figure 3: The main processes of scenario definition

In a run of SD-SIM, every driver agent employs vision capabilities to compare their current image pattern with the previous image pattern stored in the 'visual memory plane' at each time step, to infer whether there is a looming or receding effect (i.e. expanding and contracting image patterns). If there is growing looming effect then the driver agent initiates corrective actions using decision-making mechanisms to identify those rules that are relevant to their situation, and to assess the importance of each relevant rule. Therefore, behaviours such as following, overtaking and other 'composite' behaviours emerge as a consequence of individual driver interactions. Figure 4 illustrates an emergent overtaking behaviour.



Figure 4: Visualisation of emergent overtaking behaviour

Evaluation of SD-SIM

As part of the evaluation of SD-SIM, experiments have been conducted with the assistance of Leicestershire Constabulary, Traffic Division to collect data in their instrumented vehicles whilst driving on a British motorway (M1 North) and on a racetrack. A more detailed description of the experiments and validation is given elsewhere [8]. In the experiments, video images of a lead car on the motorway were recorded from a following vehicle and its speed and distance measured using a laser gun. The video images were processed at a rate of 5 frames per second. Figure 5 shows the definition of some of these variables within the scenario modeller.



Figure 5: Specification of initialised parameters as part of scenario configuration within SD-SIM

The speed and distance estimated by the virtual driver agents were compared to the measured data as shown in Table 1. Figure 6 shows the errors in the estimates. These estimates depend on the virtual driver vision parameters, figure 5, for example, the visual acuity which is represented by the eye resolution parameters. Although the agent's estimates are close to the measured value, there is consistent underestimation and overestimation in both distance and speed. This is because distance calculations in SEE rely on comparing stereo images to obtain depth information, rather than exact distance value (i.e. z-buffer) along the ray at the point of intersection. These observations are plausible and consistent with experiments that have shown that human drivers tend to under- and overestimate distances and speeds respectively [20].





Following veh. (5s)

Leading veh. (5s)

Frame rate [s]	Measured data		Estimated data	
	Relative	Relative	Relative	Relative
	distance [m]	speed [m/s]	distance [m]	speed [m/s]
5	33.80	0.00	33.79	0.00
10	38.62	0.45	38.62	0.45
15	32.19	-0.45	32.19	-0.45
20	32.19	0.45	32.18	0.44
25	28.97	0.00	28.97	0.00
30	32.19	-0.89	32.19	-0.89
35	27.36	0.45	27.36	0.45
40	41.84	0.89	41.85	0.90
45	41.84	1.34	41.84	1.34
50	53.11	2.24	53.11	2.24
55	62.76	1.79	62.77	1.79
60	67.59	1.34	67.59	1.34
65	74.03	0.00	74.03	0.00
70	67.59	0.00	67.59	0.00

Table 1: Comparison of relative distance and speed



Figure 6: Perception errors by virtual driver agents

Potential applications in modelling road accident data

An understanding of crash causation is necessary to develop countermeasures to reduce crashes and traditionally a "chain of events" approach is adopted. This assumes that a crash occurs when several factors occur together but if one factor is removed the crash would be prevented. These factors are identified by in-depth crash investigations [21], and have resulted in strategies for improved crashworthiness, drink/drive enforcement, speed control and improved highway design for example. Current in-depth studies of traffic causation frequently develop models to support an understanding of the crash events, reconstruction models quantify the pre-crash vehicle kinematics while rigid body or finite element models are used to simulate the crash phase. There are no models currently available that simulate the precrash decision making of the crash participants in a quantified manner and the availability of an agent based simulation framework opens the possibility for a variety of new understanding. A pre-crash simulation procedure, implemented via SD-SIM for example will enable crash researchers to recreate specific crashes and examine the perceptions and decision making of each crash participant. Parametric modifications to driver, vehicle or highway characteristics can be made within the simulation to assess the relative probability of modified crash outcomes. The use of multiple driver agents, corresponding to the spread of specific driver characteristics in the normal driving population, will permit crash involvement risk to be assessed quantitatively. In modelling road accident data, it is generally the case that parameterised-rather than hand tuned scenario authoring is more appropriate since it removes the need for accident investigators to have programming skills. This is consistent with the use of a GUI. Therefore, by providing an interface, with the internal logic hidden away, there is flexibility and ease for the investigator to simply define accident parameters within the GUI and observer the implication of the data.

Conclusions

The traffic simulation framework introduced in this paper draws inspiration from three key concepts – Artificial Intelligent (AI), Artificial Life (Alife) and Agent technology to model intelligent behaviour within virtual driver agents. In so doing it explicitly integrates the three main interacting components of traffic – driver, vehicle and the environment in a well-structured and realistic manner. In particular, it represents virtual drivers as autonomous agents with inherent unpredictability by allowing individual driver agents to perceive their environment, make decisions based on what they see and take appropriate driving related actions. This provides an effective approach to representing structure, behaviour and associated complexities in the context of scenario modelling for traffic simulation models. Finally, this approach also has implications in the understanding of accident causation factors through evaluation of traffic and accident scenarios.

References

[1] Albus, J. S., 1991, Outline for a Theory of Intelligence. *IEEE Transactions on Systems, Man and Cybernetics*, **21** (3): 473–509.

[2] Langton, C. G., 1989, Artificial Life. In C. G. Langton, (ed) Artificial Life VI, SFI Studies in the Sciences of Complexity, (Redwood City, CA: Addison-Wesley), pp. 1-47.

[3] Shoham, Y., 1993, Agent-oriented programming, Artificial Intelligence, 60 (1): pp. 51-92.

[4] Bergenti, F., and Poggi, A., 2000, Exploiting UML in the Design of Multi-Agent Systems, In A. Omicidi, R. Tolksdorf, F. Zambonelli (eds) *Engineering Societies in Agents World: Lecture Notes on Artificial Intelligence* (Berlin: Springer-Verlag), pp. 106-113.

[5] Papelis, Y., 1996, Graphical Authoring of Complex Scenarios Using High Level Coordinators, In *Workshop on Scenario and Traffic Generation in Driving Simulation*, Orlando, USA, pp. 3-10.

[6] Tran, J. M., 1995, Pedagogical Environment for driving simulators: traffic generation and intelligent aids to scenario control, In *Proceedings, Driving Simulator Conference,* Sophia-Antipolis, France, pp 246-259.

[7] Dumbuya, A.D., and Wood, R.L., 2001, Visual Perception Modelling for Virtual Driver Agents in a Synthetic Driving Simulator, In A.G. Gale et al. (eds.), *Vision in Vehicles IX* (Amsterdam Netherlands: Elsevier Science Publisher B.V.). In press.

[8] Dumbuya, A.D., and Wood, R.L., 2002, Visual Perception Modelling for Intelligent Virtual Driver Agents in Synthetic Driving Simulation, *Accepted for publication in the Journal of Experimental and Theoretical Artificial Intelligence (JETAI)*.

[9] Thalmann D., 1995, Virtual Sensors: A Key Tool for the Artificial Life of Virtual Actors, In Sung Yong Shin, Tosiyasu, L. Kun (eds), *Computer Graphics and Applications* (New Jersey: River Edge World Scientific), pp. 22–40.

[10] Noser, H., Renault, O., Thalmann, D., Thalmann, N. M., 1995, Navigation for Digital Actors Based on Synthetic Vision, Memory and Learning. *Computers and Graphics*, **19** (1): 7–19.

[11] Reynolds, C. W., 1987, Flocks, herds and schools: A distributed behavioral model. *Computer Graphics*, **21** (4): 25–34.

[12] Yaeger L., 1994, Computational genetics, physiology, metabolism, neural systems, learning, vision, and behaviour or PolyWorld: Life in a New Context. In C. Langton (ed), *Artificial Life III, SFI Studies in the Sciences of Complexity*, (Reading: Addison-Wesley), pp. 263-297.

[13] Wood, R. L., and Arnold, J. E., 1997, An automata based simulation of co-operative decision making, In R. A. Adey, G. Rzevski and R. Teti (eds) *Application of AI in Engineering*, (Southampton UK: Wit Press), pp. 105-109.

[14] Michon, J. A., 1985, A critical view of driver behaviour models: what do we know, what should we do? In L. Evans and R. Schwing (eds) *Human Behavior and Traffic Safety* (London: Plenum Press), pp. 485-524.

[15] Sayers, M.W., 1998, Vehicle Models for RTS Applications, In *Proceeding, of the International Symposium on Advanced Vehicle Control, AVEC'98*, Nagoya, Japan.

[16] Weir, D. H., and McRuer, D. T., 1970, Dynamics of driver vehicle steering control, *Automatica*, 1970, **6**, 87-98.

[17] Gordon, T.J., Best, M.C., and Dixon, P.J, 2002. An automated driver based on convergent vector fields, In *Proceedings, of the Institution of Mechanical Engineers: Part D, Automobile Engineering.* **216**, D4, 329-347.

[18] Object Management Group: <u>http://www.omg.org/</u>

[19] ParallelGraphics: <u>http://www.parallelgraphics.com/</u>

[20] Groeger, J. A., Carsten, O. M., J., Blana, E., and Jamson, H., 1999, Speed and Distance Estimation under Simulated Conditions, In A.G. Gale et al. (eds.), *Vision in Vehicles VII* (Amsterdam Netherlands: Elsevier Science Publisher B.V.). pp. 291–299.

[21] Hill, J., Byard, N., and Thomas, P., 2001, On the Spot Accident Research In the UK: A New Approach To In-Depth Investigations, In *Proceedings, Traffic Safety on Three Continents Part 3*, Moscow, pp. 96 - 107.