Modelling Driver Interdependent Behaviour in Agent-Based Traffic Simulations for Disaster Management

David Handford and Alex Rogers

Abstract Accurate modelling of driver behaviour in evacuations is vitally important in creating realistic training environments for disaster management. However, few current models have satisfactorily incorporated the variety of factors that affect driver behaviour. In particular, the interdependence of driver behaviours is often seen in real-world evacuations, but is not represented in current state-of-the art traffic simulators. To address this shortcoming, we present an agent-based behaviour model based on the social forces model of crowds. Our model uses utility-based path trees to represent the forces which affect a driver's decisions. We demonstrate, by using a metric of route similarity, that our model is able to reproduce the real-life evacuation behaviour whereby drivers follow the routes taken by others. The model is compared to the two most commonly used route choice algorithms, that of quickest route and real-time re-routing, on three road networks: an artificial "ladder" network, and those of Lousiana, USA and Southampton, UK. When our route choice forces model is used our measure of route similarity increases by 21%-93%. Furthermore, a qualitative comparison demonstrates that the model can reproduce patterns of behaviour observed in the 2005 evacuation of the New Orleans area during Hurricane Katrina.

1 Introduction

Evacuation of large areas due to disasters requires effective management and realistic training environments are increasingly being used in order to teach operators how to manage traffic in the safety of a simulated environment. However for training to be effective, the simulated environment must have

David Handford · Alex Rogers
School of Electronics and Computer Science, University of Southampton, UK e-mail: {djh07r, acr}@ecs.soton.ac.uk

the flexibility to respond to the variety of actions operators can make, such as setting up road blocks or diversions, in addition to simulating situations with limited real-life data. To this end, the use of agent-based models of individual drivers has proven to be an effective way of modelling traffic systems [3], in which the aggregation of driver behaviours reproduces real-life patterns of overall traffic behaviour. During real-life evacuations, studies have shown patterns of traffic behaviour in which a perceived degree of physical danger causes drivers to choose routes similar those of others, so as to avoid being isolated [5, 12]. In the evacuation of the New Orleans area during Hurricane Katrina in 2005 this interdependence in driver behaviour led to situations in which, despite there being two possible escape routes, a disproportionate number of drivers used just one over the other.

However, route choice behaviour in current state-of-the-art evacuation simulations (such as MATSIM [9] or PARAMICS [3]) incorporate limited driver behaviours and thus it is difficult to reproduce real-life patterns of traffic behaviour. In PARAMICS, the behaviour of drivers who are "unfamiliar" with an area is to take the route that they believe to be quickest to the exit with a preference for using major roads over minor roads [11]. Both MATSIM and PARAMICS also offer route choice behaviour, known as dynamic route planning (used in PARAMICS for the behaviour of drivers "familiar" with an area). Here the drivers are able to re-plan their escape routes, factoring in real-time knowledge of the congestion on other roads. However, this causes a repulsive behaviour between drivers, the opposite of what is actually observed in real-life evacuations, where drivers desire to use routes which they believe others will be using [5]. Neither of the offered algorithms are able to replicate the observed patterns of behaviour in evacuations and thus their use for disaster management simulation is significantly impaired [4].

To address this shortcoming, in this paper we present a novel agent-based route choice forces model. Our approach is inspired by pedestrian behaviour models, where research into the interdependence between individual's decisions is more mature. As in the crowd social force model, a variety of factors or "forces" act on and influence an agent's decisions [6]. Within this model, forces become virtual signposts at junctions, the directions of which are determined from utility-based path trees. When an agent reaches a junction they probabilistically choose between the routes, based on the utility they believe they will gain from following each particular route, determined from the magnitude of the force. For evacuation simulation two forces are defined: the desire to take the quickest route to safety and a varying desire to be with others depending on the driver's particular level of panic. The utility-based path tree for the force representing the desire to be with others is created using a method inspired by floor field modelling in crowd behaviour [8]. Prior to running the evacuation simulation, drivers are simulated using their non-evacuation routes out of town, along which they leave a trail. These trails represent knowledge of routes used by others in the past. Within the path tree, the stronger the trail along a route, the more utility will be received for using it. The level of utility a driver believes they will gain varies with their particular desire to be with others.

Thus in more detail, this paper extends the current state-of-the-art in driver route choice models in the following ways:

- We develop a probabilistic agent route choice mechanism known here as the route choice forces model, in which decisions are influenced by a set of forces representing the factors which influence a driver's behaviour. We incorporate real-life observed evacuation behaviours as a force representing a driver's desire to be with others.
- We define a metric to evaluate how effectively an algorithm can replicate a driver's desire to use the route of others during evacuations. We use this metric to benchmark our model against two existing route choice algorithms (shortest time and real-time re-routing) using three road networks: a simple ladder network and the cities of Lousiana, USA and Southampton, UK. We show that our model increases the metric by 21%-93% over using other algorithms, in addition to conforming to qualitative observations from evacuation during Hurricane Katrina in 2005.

The rest of the paper is arranged as follows: Section 2 describes the context within which the model is developed. Sections 3 presents the model itself. Section 4 describes the metric and empirically evaluates the model. Finally, Section 5 discusses the model's further development.

2 The Evacuation Setting

Our route choice force model forms a behavioural component within a disaster management and traffic operator training simulator in development at BAE SYSTEMS. This simulator is being developed to allow operators to manage traffic flows in the event of emergencies. Our model is being developed alongside the 3D visualiser component, which allows controllers to view the state of the roads through virtual CCTV cameras, and a driver behaviour component which models the tactical level behaviours such as car following and lane changing. An event-driven queue-based mesoscopic traffic simulation model, based on the agent-based MATSIM traffic simulator [2] and implemented in C++, is used to model the individual movement of the cars as they evacuate from a start zone to a predetermined safe zone. A region is represented by a road network defined by a set of roads with lengths and speed limit connecting a set of junctions. Within the queue model each road section has a corresponding queue, implemented as a FIFO queue with restrictions on entering and exiting. Drivers are represented by agents with the goal of reaching a safe destination by planning a route and then travelling through the road network. The only choice an agent must decide upon is which way to go once it reaches a junction, which is achieved using our route choice forces model.

3 The Route Choice Forces Model

Within our route choice forces model a variety of forces are defined which represents factors that act on and influence an agent's decisions. The model takes inspiration from the social forces model developed in crowd modelling, in that each force has a certain magnitude of appeal to a particular agent [6, 10]. Where agents need to make choices about their route at junctions, the forces become virtual signposts where they inform agents of a route to follow and the utility they gain from following that route. The agent then uses a mechanism to probabilistically decides which signpost to follow. The route represents a force's directions and the utility value represents its magnitude. These are determined using a utility-based path tree particular to a force. For evacuation simulation two forces are defined: a desire for the quickest exit route and a desire to be with others varying on their level of panic.

In order to create a force which represents a driver's desire to use routes they believe others will, a utility-based path tree is created in which the driver gains utility by using the route of others. To determine these utility values our model uses a concept similar to chemotaxis/stigmergy used in floor field modelling of pedestrian behaviour, in which agents lay down abstract trails as they move through the environment to which others are attracted [7, 8]. Here these trails represent the knowledge a driver will have prior to the evacuation of the usual routes used by others in the past. Prior to running the actual evacuation simulation, agents are simulated using their usual, non-evacuation, routes out of the evacuation area (using the quickest route algorithm). When each agent reaches their destination, each road they have used in their route is taken and the utility value for using their road in future is increased, making it more desirable. Dijkstra's algorithm is then used to create non-cycle highest utility routes through the network, creating the utility-based path tree.

The utility values are normalised by dividing by the total number of cars that have reached the destination. Thus utility value u_{ld} for route section l given the destination d, is given by this formula:

$$u_{ld} = \frac{|\{V : V \in R_d, l \in V\}|}{|R_d|} \tag{1}$$

where R_d is all routes that cars have taken to destination d.

Now, we define the mechanism used by the agent to probabilistically decide which road to follow when at a junction. To this end, the two forces are weighted with coefficients representing how strongly they are acting upon an agent, k_a for the driver attraction force and k_s for the quickest route force, with k_a being used to represent an agent's level of panic. The direction of force $\mathbf{f}$ at a particular junction is given by its path tree and the magnitude, given that the path tree defined route is given by the set of roads R_f, is:

$$|\mathbf{f}| = k_f \sum_{l \in R_f} u_{ld} \tag{2}$$

where k_f is the agent's personal coefficient for force $\mathbf{f}$, for the two forces defined here these are k_a and k_s, and u_{ld} is the utility of using link l given destination d.

The score for road i at junction j given destination d is calculated by combining all forces in the direction of that road such that:

$$Score(i_{jd}) = \sum_{\mathbf{f} \in F} |\mathbf{f}| \tag{3}$$

where F is a set of all the forces which act upon the driver in the direction of road i.

Using the score, the drivers then use a probabilistic model to decide which road to take. In our model a normalisation function is used, however a range of possible functions could be used such as the softmax activation function [1]. The probability of a particular route i being selected by a driver with destination d at junction j is given by:

$$p_{ijd} = \frac{Score(i_{jd})}{\sum\limits_{a_d \in N_j} Score(a_d)} \tag{4}$$

where N_j is all the roads leading off junction j that it is possible for a driver to take.

4 Empirical Evaluation

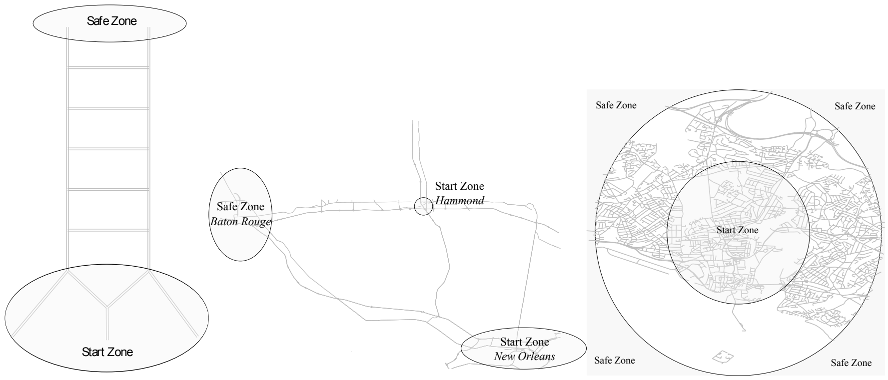
In order to investigate the occurrence of the route attraction pattern a metric is presented enabling the comparison of different types of route choice algorithms via a measurement of similarity between evacuating drivers' routes. For each evacuated driver a count is increased on each road which they have used, such that the count n_l represents the number of evacuation routes which have used road l and N is the set of all counts. If the routes are equally distributed across the road network then each road will have an equivalent level of usage. However, if the routes are concentrated on a few particular roads, then the road usage count will be more varied. The metric is therefore defined as $stdev(N)$. With road usage count n_l for road section l being given by:

$$n_l = \frac{|\{V : V \in R, l \in V\}|}{|R|} \tag{5}$$

where R is all set of routes which have been taken to an evacuation safe point.

Three road networks are now defined,

- A theoretical construct of a "ladder", as shown in Figure 1(a). In which drivers start at the bottom and escape at the top through one of the two exit points. The drivers have the choice of using one or other of the main



(a) Ladder (b) Lousiana, USA (c) Southampton, UK

Fig. 1: The three road networks on which the algorithms are evaluated.

roads to reach a safe point. The ladder is used to demonstrate occurrence of drivers desiring to be with others.

- A road network crafted from the roads in Lousiana, USA, shown in Figure 1(b). The map is generated from OpenStreetMap data for Lousiana, but only including the major evacuation routes. Drivers evacuate from New Orleans and Hammond, through the city of Baton Rouge, similar to the actual routes taken by residents during the 2005 Hurricane Katrina.
- A network that represents the full road network of the Southampton, UK area, shown in Figure 1(c), generated from OpenStreetMap data. Using this road network the performance of the algorithm over a large-scale area can be observed.

Using these road networks, the evaluation compares three different algorithms,

- **Route choice forces model.** A number of runs of our route choice forces model with different coefficient weightings for the forces. Two forces act upon the agent: shortest route time and driver attraction.
- **Shortest time.** A behaviour algorithm which has the simplistic behaviour of finding a quickest path tree to the exit points, with a preference of using major roads. This algorithm is the same as the one used in PARAMICS for “unfamiliar” drivers [11].
- **Real-time rerouting.** A dynamically re-routing algorithm which at regular intervals re-calculates the quickest path trees to take into account the delays caused by congestion. This algorithm is the same as the one used in PARAMICS for “familiar” drivers [11].

We first consider the results on the ladder road network. Figure 2 shows the road network usages and Figure 3 plots the metric of similarity for evacuating routes, both after 200 seconds of simulation time for the three different

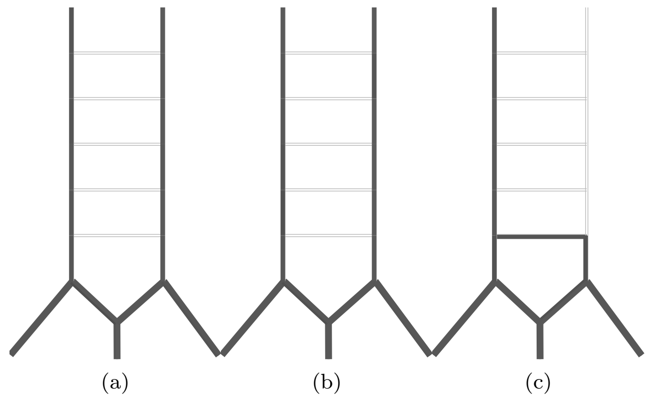


Fig. 2: Road network usage for the ladder road network after 200 seconds when using (a) shortest time, (b) real-time rerouting and (c) route choice forces model. Road usage is represented by the thickness of the line.

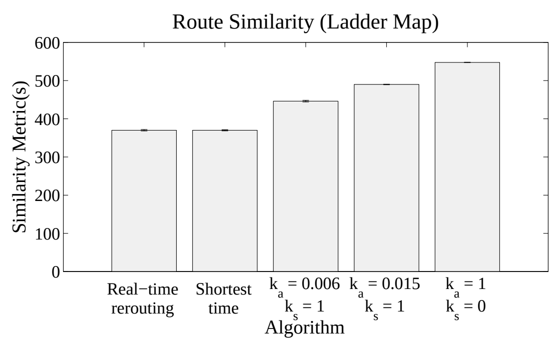


Fig. 3: Similarity in routes when using different route choice algorithms.

algorithms. The route choice forces model is used with coefficient values of $k_s = 0$ for the shortest time force and $k_a = 1$ for the driver attraction force. As show in Figure 2, when using the shortest time or real-time re-routing algorithms drivers symmetrically use both legs of the ladder. However, when using our model traffic asymmetrically uses only one of the legs of the road network to escape, demonstrating the occurrence of driver desires to be with others. Figure 3 shows our algorithm with three different coefficients being used, as well as the two algorithms we are benchmarking against. When comparing our model to the shortest time algorithm, the metric shows that driver routes have become more similar by up to 49%. Varying the coefficients is shown to give a degree of control over the driver's level of panic causing the attraction behaviour, from usual to evacuation situations.

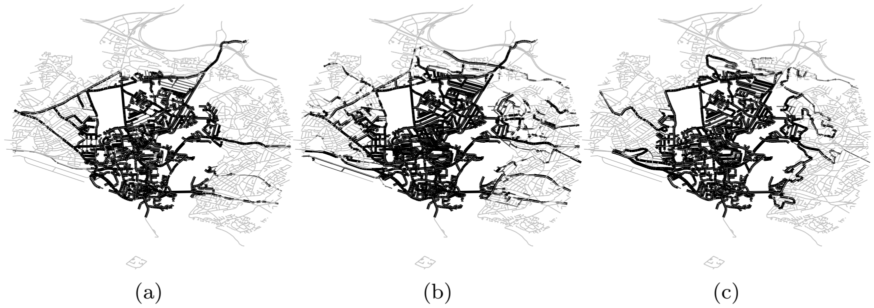


Fig. 4: Road network usage for the Southampton, UK network after 300 seconds when using (a) shortest time, (b) real-time rerouting and (c) route choice forces model. Road usage is represented by the thickness of the line.

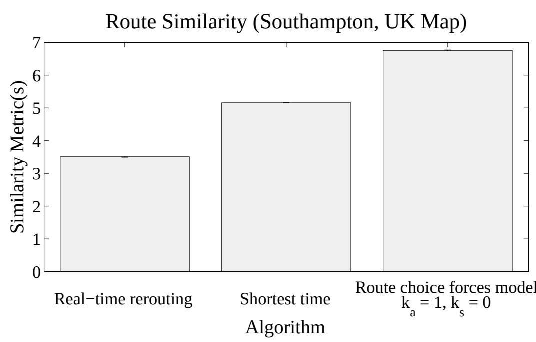


Fig. 5: Similarity in routes when using different route choice algorithms.

The road network usage maps for Southampton and Lousiana are shown in Figure 4 and Figure 6 respectively. These graphs show the road usage after 300 seconds and 1000 seconds respectively, the same point at which the metric is calculated using the routes of the escaped drivers. Figure 4 shows the differences in behaviour when using the different algorithms can be seen directly. When agents are using the shortest time algorithm traffic takes 6 routes out of the town. When using a real-time re-routing algorithm this number increases to around 13 and routes are more distributed around the road network. When our model is used, the number of routes to the exit drops to 3. As Figure 5 shows, the use of our model over the shortest time model gives an increase in the metric of 31% and over the real-time re-routing model of 93%. Considering the Lousiana road network, Figure 7 shows that, using our model, the metric of route similarity is increased by 21% over the shortest time algorithm and 28% over using real-time rerouting. From Figure

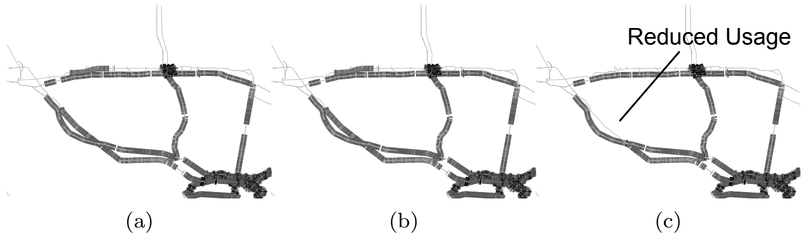


Fig. 6: Road network usage for the Louisiana, USA road network after 1000 seconds when using, (a) shortest time, (b) real-time rerouting and (c) route choice forces model. Road usage is represented by the thickness of the line.

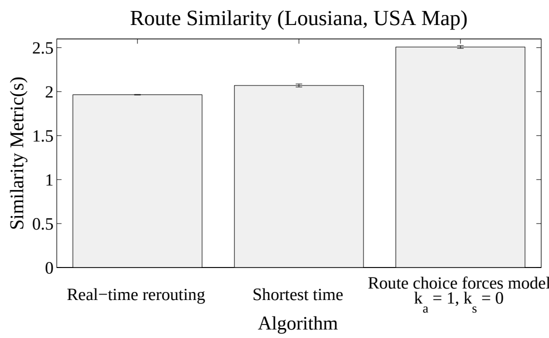


Fig. 7: Similarity in routes when using different route choice algorithms.

6(c) it can be observed that using our model usage of the roads into the north-west corner has decreased from two to one, so that only the southern road is used. This pattern of road usage is the same as was observed during the evacuation of Lousiana, USA during Hurricane Katrina [12].

5 Conclusion

We have presented a route choice model which represents influences on a driver's behaviour as a variety of forces or factors. Within the evacuation context, two factors have been defined: desire to take the quickest route and desire to be with others. We have shown that this model can be used to replicate independent driver behaviours seen in evacuation situations, including those seen in the 2005 evacuation of Lousiana, USA during Hurricane Katrina. Empirical evaluations using a metric of route similarity and the road networks of an abstract "ladder", Lousiana, USA and Southampton, UK, showed that the route choice forces model gives a 21%-49% increase in route similarity over the shortest path algorithm and 28%-93% increase over the real-time rerouting algorithm.

Within the context of the BAE SYSTEMS simulator, future work includes the expansion of the model to include forces relevant to other scenarios, including driver responses to directly observing the routes of others, route planning within unfamiliar environments, variable driver knowledge of routes and driver compliance behaviour to real-time information.

6 Acknowledgements

This work is jointly funded by BAE SYSTEMS and the EPSRC.

References

1. C. Bishop. *Neural networks for pattern recognition.* Oxford University Press, USA, 1995.
2. N. Cetin and K. Nagel. A large-scale agent-based traffic microsimulation based on queue model. In *Proceedings of Swiss Transport Research Conference*, Monte Verita, CH, 2003.
3. X. Chen and F. Zhan. Agent-based modelling and simulation of urban evacuation: Relative effectiveness of simultaneous and staged evacuation strategies. *Journal of the Operational Research Society*, 59(1):25–33, 2006.
4. R. Church and R. Sexton. Modeling small area evacuation: Can existing transportation infrastructure impede public safety? Technical report, California Department of Transportation, 2002.
5. K. Dow and S. Cutter. Emerging hurricane evacuation issues: Hurricane Floyd and South Carolina. *Natural Hazards Review*, 3(1):12–18, 2002.
6. D. Helbing, I. Farkas, and T. Vicsek. Simulating dynamical features of escape panic. *Nature*, 407(6803):487–490, 2000.
7. C. Henein and T. White. Agent-based modelling of forces in crowds. In P. Davidsson, B. Logan, and K. Takadama, editors, *Multi-agent and multi-agent-based simulation*, Lecture Notes in Computer Science, vol. 3415, pages 173–184. Springer, 2005.
8. A. Kirchner and A. Schadschneider. Simulation of evacuation processes using a bionics-inspired cellular automaton model for pedestrian dynamics. *Physica A: Statistical Mechanics and its Applications*, 312(1-2):260–276, 2002.
9. G. Lämmel, M. Rieser, and K. Nagel. Large scale microscopic evacuation simulation. In *Pedestrian and Evacuation Dynamics, Proceedings of the 4th International Conference*, Wuppertal, Berlin, 2008. Springer.
10. Q. Lin, Q. Ji, and S. Gong. A crowd evacuation system in emergency situation based on dynamics model. In H. Zha, Z. Pan, H. Thwaites, A. Addison, and F. Maurizio, editors, *Interactive Technologies and Sociotechnical Systems, 12th International Conference, VSMM 2006*, Lecture Notes in Computer Science, vol. 4270, pages 269–280. Springer, 2006.
11. Quadstone Limited. *Quadstone Paramics V5.0 Technical Notes*, Oct. 2004.
12. B. Wolshon. Empirical characterization of mass evacuation traffic flow. *Transportation Research Record: Journal of the Transportation Research Board*, 2041:38–48, 2008.