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Abstract

This paper reviews and compares car-following and lane-changing logics embedded in some microscopic traffic simulation models, and comments are made on the existing techniques of traffic simulation. Future directions of traffic simulation are identified in three aspects: vehicle modeling, driver modeling, and vehicle movement modeling. To illustrate these ideas, a conceptual model, 2DSIM, is proposed, which consists of a dynamic vehicle sub-model and an intelligent driver sub-model. They are further integrated into a driver-vehicle-environment closed-loop system which constitutes the basic building block of road traffic.

1 Introduction

In general, simulation is the dynamic representation of part of the world by building a computer model of it and moving it through time. The ultimate goal of simulation is the representation of part of the real world as realistic as possible. Traffic simulation is such an example that has evolved from simple to complex, and can be illustrated by the following analogy. Suppose we are observing traffic on an airplane in the sky, traffic behaves like fluid whose states (speed, flow, and density, etc.) propagate like waves. Here is the arena of macroscopic approach. If we lower our plane, the sense of wave recedes and a feeling of particle looms. This is the scenario suited for mesoscopic approach. Now, let's get down even more, the scene is dominated by moving particles that interact with each other so as to maintain safe positions in the traffic stream. Here is the typical area where microscopic approach thrives.

Currently, there are hundreds of traffic models in the world, and some of them are very successful and have been widely used throughout the community. However, the world won't stop, so won't traffic simulation. Where will traffic simulation go in the future? This is the question that many researchers are trying to answer.

Since traffic simulation has gone from macroscopic to mesoscopic to microscopic, wouldn't it be natural to go

one step further? Let's continue our analogy. Now, what if we step down to the earth and join the traffic? The picture will be fundamentally different. There is neither wave nor particle, but a complicated nanoscopic system consisting of drivers, vehicles, and environment. They interact with each other, and the mechanism of which, if modeled, would provide insights into the mystery of traffic operation.

2 Review of Car-Following Models

At the core of almost every microscopic simulation model is a car-following and/or a lane-changing logics. Table 1 summarizes the inputs and outputs of the car-following logics of some basic models and some traffic simulation models. Limitations are found in three aspects: vehicle modeling, driver modeling, and vehicle movement modeling.

logics	input	output
1. GM [12,15,4]	Speed of leader, Speed of follower, Sensitivity factor, Pos of leader, Pos of follower	Acc
2. North-western [13]	GM inputs, Minimum following distance	Speed and Pos
3. UTCS-1 [11]	GM inputs, Length of leader, Critical headway	Acc
4. Aero-space [1,17]	GM inputs, Safe spacing limitation	Acc
5. PITT	Inputs of Northwestern and UTCS-1, Constant for high relative closing speed, Time lag	Speed and Pos
6. CAR-SIM [14]	GM inputs, Minimum separation constraint, Collision constraint, Buffer spaces	Acc

7. INTEL SIM [9]	GM inputs, Reaction time, Preferred time headway	Acc
8. ILLISI M [6]	GM inputs, Influence zone, Desired spacing	Acc
9. TEXA S [3,2]	Kinematic model GM inputs, driver characteristics, traffic-control device	Acc, Cosine-curved, LC
10. VISSI M [10]	GM inputs, Thresholds of four driving modes, Desired speed and safety distance, Characteristics of vehicle, Road regulations	Driving mode, Acc, LC
11. HUTSI M [7]	GM inputs, Normal deceleration Reaction time, Safety marginal, Driver attention, Driver aggressiveness, Destination, Desired speed, Surrounding vehicles and gaps	Acc, LC
12. PELOP S [5]	Kinematic model GM inputs, Desired speed and Acc, Reaction time, Level of perception, Level of attention, Need for safety, Traffic environment, Road and control devices, Surrounding traffic situation	Driving mode, Acc, LC
13. AASI M [16]	Kinematic model Knowledge base, Perception handler, Control queue, Lane congestion, Status of vehicles surrounding	Acc, LC

Note:

Acc - Acceleration; LC - Lane-changing; Pos - Position

Table 1: comparison of car-following logics

The above discussed models are summarized in Table 1, which reveals three possible directions for future traffic simulation: vehicle modeling, driver modeling, and vehicle movement modeling.

2.1 Vehicle modeling

An obvious trend of car-following is the divorce of the vehicle model from the driver model. For example, some models represent driver and vehicle as a single entity (as in model 1-8, 10, and 11). There is no interaction between them, and the “vehicle” can always execute whatever the “driver” wants exactly and timely. Model 9, 12, and 13 have separate vehicle models and driver models such that the driver model receives stimuli and makes decisions which are then passed to vehicle model, who responds accordingly. However, in a general sense, these vehicle models deal only with vehicle kinematic properties. In fact, a vehicle is a dynamic system that interacts with driver and road. The driver applies the gas or brake to control longitudinal movement and the steering wheel to control lateral movement. The vehicle executes these instructions but not always responds exactly and timely as desired due

to its mass. The differences are fed back and constitute part of the input of future decision. In this case, the vehicle and the driver form a dynamic closed-loop system.

2.2 Driver modeling

Driver models have evolved from deterministic to random to intelligent. Early models are essentially some equations that govern vehicle movement according to stimuli. For example, models 1 through 5 are deterministic in that the association between stimuli and response repeats from run to run. To better approximate the real world, randomness is introduced (such as model 9) to represent the inherent uncertainty of human behavior. However, mere randomness is not sufficient to describe human behavior. Some models (such as models 11 and 13) introduce fuzziness – a kind of artificial intelligence (AI) – to mimic a human’s ability to reason. In addition to this, humans are capable of self-learning and self-adjusting. For example, a lesson from yesterday can shape one’s future behavior. Modeling this feature would approximate the real world even more.

2.3 Vehicle movement modeling

Vehicle movement modeling has gone from one-dimension (1D) to two-dimension (2D). For example, models 1 through 8 are one-dimensional because they describe only longitudinal movement. Models 10 through 13 are pseudo-2D models because they describe not only longitudinal but also lateral movement. However, they are not true 2D models because their lateral movement (lane-changing) is discretized. More specifically, vehicles in these models essentially move along some parallel strings, and they “jump” when changing lanes. Model 9 is nearly a 2D model in that the lateral movement is smoothened by a cosine curve. In fact, real world lateral movement is not necessarily cosine curves. It can be curves of any shape and has much to do with road geometry. A true 2D model would describe vehicle movement on a 2D planar surface, and enables vehicles to move along any curve as long as vehicle dynamics permits. The key to this approach is to introduce a steer angle (combining with vehicle dynamic model) to control lateral movement.

To demonstrate the above modeling philosophy, a new simulation model is proposed in the next section, which is dynamic, intelligent, and two-dimensional in nature.

3 2DSIM – The Proposed Model

The proposed model consists of an intelligent driver sub-model and a dynamic vehicle sub-model. The driver sub-model receives and processes stimuli, and outputs driving instructions. The vehicle sub-model executes the instructions and responds accordingly. Status of vehicle movement is fed back to the driver sub-model, contributing to driving strategies of future steps.

3.1 Dynamic vehicle sub-model

Vehicle dynamics is one of the core areas of Automobile Engineering. Many models are available to describe vehicle response (transient or steady) to handling maneuvers, depending on the level of detail one wishes to model. Typically, components of a vehicle are modeled as rigid bodies, and the number of degree of freedom (DoF) is a measure of level of detail. As a healthy trial, a 3DoF model [8,18] suffices for our purpose because it elegantly describes some important features of vehicle movement with reasonable complexity. Briefly, the model can be represented as:

lateral speed = $f(\text{longitudinal speed, steer angle, vehicle mass, other vehicle parameters})$

Given longitudinal speed, steer angle, vehicle mass and other related vehicle parameters, the corresponding lateral speed is found by solving a set of dynamic equations. Longitudinal movement can be described by Newton's second law of motion:

longitudinal acceleration = $f(\text{gas, brake, engine characteristic, vehicle mass, other vehicle parameters})$

Controlled by lateral speed and longitudinal speed (computed from acceleration), the vehicle can now move freely on a planar surface.

3.2 Intelligent driver sub-model

Like any other control system, the proposed intelligent driver sub-model receives information, processes information, and outputs control strategies. Input information of the driver sub-model comes from three sources: environment stimuli, vehicle feedback, and driver characteristics. The outputs are gas, brake, and steer angle. This is exactly the way that the real world works. At the core of the driver sub-model is a processor built on neural network and wrapped by a fuzzy adapter. The fuzzy adapter mimics the vagueness of human perception and decision-making. The neural network simulates the way humans learn and apply knowledge.

3.2.1 Inputs of driver sub-model

Inputs of the driver sub-model come from three sources: environment stimuli, vehicle feedback, and driver characteristics.

A. Environment stimuli

In this paper, the term environment refers to the small context in which a particular vehicle is running, such as neighboring vehicles, signals, and signs, etc. Environment stimuli include: road type, road curvature, signals, signs, markings, and other control facilities. In addition, a driver receives information from his/her surrounding vehicles. The relationship between a vehicle and its surrounding is sketched in Figure 1.

Figure 1: vehicle 0 and its surrounding

In this figure, vehicle 0 interacts with 8 immediate surrounding vehicles (they may or may not actually exist). Meanwhile, it keeps track of multiple vehicles running ahead (e.g., vehicle 9, 10, and 11), if necessary. The interaction between vehicle 0 and its surrounding vehicles are summarized in Table 2. Based on this, it is desirable to incorporate the following stimuli: surrounding vehicle types, surrounding vehicle actions, relative speeds of surrounding vehicles, and relative distances of surrounding vehicles.

Vehicle	Interaction
1	This is the major entity with which vehicle 0 performs car-following. This relation has been well documented in past literature.
2	The effect of vehicle 2 on vehicle 0 has long been neglected in past literature. In most cases, vehicle 2 doesn't affect vehicle 0. However, when vehicle 2 becomes so aggressive that it follows vehicle 0 too closely, vehicle 0 usually tries to keep away from the follower by accelerating or changing lane, a phenomenon which becomes more evident at high speed and/or when the follower is a heavy truck.
3, 4	The effect of these two vehicles has also been neglected in past literature. Generally, a driver tends to shy-off its side vehicles, i.e. avoids running parallel with them, a phenomenon which becomes more evident at high speed and/or when the side vehicle is a heavy truck.
5, 6	These two vehicles take effect when vehicle 0 wants to change lane, i.e. vehicle 5 affects changing to the left lane and vehicle 6 affects changing to the right lane. This relation has also been well documented in past literature.
7, 8	The same as vehicle 5 and 6. The purpose is to check whether a gap is long enough to make the intended lane change.
9, 10, 11, ...	They represent multiple vehicles running ahead. This multi-anticipation is desirable to maintain stable traffic, and has also been documented in past literature.

Table 2: interactions between vehicle 0 and its surrounding

B. Vehicle feedback

Suggested by daily experience and supported by Ergonomics, feedback that a driver perceives include:

longitudinal velocity, longitudinal acceleration, yaw velocity (one of the outputs of dynamic vehicle sub-model), and deviation from lane center. Longitudinal velocity can be read from speedometer and perceived from relative movement between the vehicle and its environment. This variable tells a driver how fast he/she is running and thus how to adjust gas or brake in the future. Longitudinal acceleration can be perceived by the human body. It tells the driver how comfortable this rate of speed change is and gives the driver an intuitive feeling whether an emergent braking can avoid an imminent collision. Similar to acceleration, yaw velocity is also a variable that can be perceived by the human body. It tells the driver how stable the vehicle is and suggests how to steer next. Deviation from lane center is a variable that the driver should check from time to time to make sure that the vehicle is running on the right lane. Usually the driver watches the road and traffic condition some distance ahead, depending on his/her current speed. This distance is called "preview distance," which also helps the driver to adjust steering wheel, gas, and brake.

C. Driver characteristics

In this category, we consider the following variables: lane preference, speed preference, aggressiveness, and driver type. Lane preference reflects a driver's habit. For example, some drivers like to drive in the fast lane and some prefer the middle lane. This variable may also be affected by the origin and destination of a particular trip. Speed preference reflects the free flow speed that a driver desires to reach whenever possible. As suggested in early literature, aggressiveness affects gap acceptance and following distance. The last variable assumes four levels, depending on a driver's decision-making and action-taking: a nimble driver (quick in both thought and action), a steady driver (quick in thought but slow in action), a rash driver (slow in thought but quick in action), and a sluggish driver (slow in both thought and action).

3.2.2 Outputs of driver sub-model

The control strategies of the driver sub-model include: gas, brake, and steer angle. Gas and brake control longitudinal movement and steer angle controls lateral movement. To help get an overview of the picture, the inputs and outputs of the driver sub-model and their possible values are summarized in Table 3.

Inputs	Possible Values
<i>Environment stimuli</i>	
Surrounding vehicle types	Heavy truck, light truck, bus and RV, passenger car
Surrounding vehicle actions	Moving straight, changing lane L/R, turning L/R
Relative speed	NL, NM, NS, ZO, PS, PM, PL
Relative distance	NL, NM, NS, ZO, PS, PM, PL
Road type	Highway, surface street
Road curvature	NL, NM, NS, ZO, PS, PM, PL
Signal	Future

Sign	Future
Markings	Future
Other controls	Future
<i>Vehicle Feedback</i>	
Longitudinal speed	ZO, VS, S, M, F, VF
Longitudinal accel.	NL, NM, NS, ZO, PS, PM, PL
Yaw velocity	NL, NM, NS, ZO, PS, PM, PL
Deviation	NL, NM, NS, ZO, PS, PM, PL
<i>Driver character</i>	
Lane preference	Left lane, current lane, right lane
Speed preference	No need to fuzzify
Aggressiveness	Very timid, timid, normal, aggressive, very aggressive
Driver type	Nimble, steady, rash, sluggish
Outputs	Possible Values
<i>Control Strategies</i>	
Gas*	ZO, PS, PM, PL
Brake*	ZO, PS, PM, PL
Steer angle	NL, NM, NS, ZO, PS, PM, PL

Note:

RV: recreational vehicle, NL: negative large, NM: negative median,

NS: negative small, ZO: zero, PS: positive small, PM: positive median, PL: positive large.

VS: very slow, S: slow, M: median, F: fast, VF: very fast; L/R: left/right

Future: this variable is considered but not yet modeled.

* Gas and brake are mutually exclusive. They are not allowed simultaneously.

Table 3: summary of I/O of driver sub-model

3.2.3 The intelligent driver sub-model

Figure 2 shows the structure of the proposed intelligent driver sub-model. At the center of the driver sub-model is a processor built on neural network and wrapped by a fuzzy adapter. The fuzzy adapter mimics the vagueness of human perception and decision-making. The neural network simulates the way humans learn and apply knowledge. The driver sub-model works in the following way: first, information from the three sources is collected and fuzzified. Then, the fuzzy information is fed into the processor built on neural network. After trained, the neural network is capable of associating input patterns with corresponding output patterns. The output pattern is defuzzified and used to control vehicle movement.

Figure 2: intelligent driver sub-model

3.2.4 The neural network processor

The processor is a typical multi-layer error back-propagation (BP) network, the topological structure of which is shown in Figure 3. The processor contains an

input layer, zero to multiple hidden layers, and an output layer. A BP network must be trained before use. Training is the process by which a neural network “learns” knowledge. Input patterns and output patterns are imposed on the input layer and output layer respectively, so the inner of the network is forced to adjust itself such that, when error occurs, it is viewed as the fault of all nodes and the error is back propagated from output layer to input layer. Working is the process by which a neural network “applies” knowledge. After training, if an input pattern is put on the input layer, the network searches its memory and recommends the closest output it has ever learned. There are two modes of working: working and working while training, with the latter extending training process into working.

Figure 3: the topological structure of BP network

3.3 Integrated driver-vehicle-environment system

Based on the dynamic vehicle sub-model and intelligent driver sub-model, a driver-vehicle-environment closed-loop system is setup as shown in Figure 4. It is the basic building block of road traffic. The system works as follows: the intelligent driver sub-model collects information related to its driving task. The information comes from three sources: environment stimuli, vehicle feedback, and driver characteristics. Some of the information may need to be fuzzified. These inputs are then fed to a trained neural network processor. The neural network is intelligent in that it is capable of associating input patterns with their corresponding output patterns, just as a human has the ability to deal with an unknown situation based on his/her knowledge and past experience. According to the information fed in, the neural network suggests the corresponding control strategies, i.e., gas, brake, and steer angle. They are defuzzified and fed into the dynamic vehicle sub-model, which advances vehicle by longitudinal and lateral movement. Part of the outputs, such as longitudinal velocity, acceleration, yaw velocity, and deviation from lane center, are fed back to the intelligent driver sub-model for decision-making in the future. Traffic operation is then the integration of the above process over time and vehicles.

Figure 4: integrated driver-vehicle-environment system.

4 Summary and End Notes

Next generation traffic simulation is a hot field in the transportation community and this paper tries to contribute some ideas. Based on review of some typical car-following (and lane-changing) models, future directions of traffic simulation are suggested on vehicle modeling, driver modeling, and vehicle movement modeling. To demonstrate these ideas, a new model is proposed based on a driver-vehicle-environment closed-loop system. It is dynamic because its vehicle sub-model is capable of describing vehicle dynamic properties. It is intelligent because its driver sub-model is capable of learning and applying knowledge. It is two-dimensional because it allows vehicle movement on a planar surface. Finally, since it simulates traffic in a great level of detail, it is a nanoscopic model.

The question that immediately arises is “does the cost justify such a level of modeling detail?” It is difficult to answer this question. First, it is true that it would be very cumbersome for contemporary computers to model such a level of detail, especially considering the huge volume of entities in the system. However, computer technology is developing so fast that who knows how powerful future computers will be. Shouldn’t we be prepared when that day comes? Second, the eternal goal of simulation is to represent part of the world as realistically as possible. This goal has been driving the evolution of traffic simulation, which is still far from realistic. Third, different simulation techniques have their own suited applications. For example, some applications (such as planning and design) emphasize the collective rather than individual behavior of the traffic. However, there are some applications (for example, accident reconstruction) that do require great level of detail, and nanoscopic models are highly appropriate in these areas. Better yet, the proposed model is fully compatible with Automated Highway System (AHS) in which a highway lane is specially equipped and vehicles’ longitudinal (speed and headway) and lateral (steering) elements are automatically controlled.

As an interesting point, collision has long been eliminated from almost all traffic simulation models. Considering that traffic accident occurs every day and the impact of which is not negligible in some cases, what's the point of excluding collision in the first place? This philosophy has also been reflected in the proposed model, which tries its best (through pattern association by a neural network) to prevent collision, though sometimes it may not be able to.

Finally, the model is proposed as a conceptual model without implementation due to its complexity. However, the major goal of this paper is to explore and illustrate future directions of next-generation traffic simulation, and, more importantly, invite more thinking about this topic.

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