Cognitive and Hybrid Model of Human Driver

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Abstract

The purpose of this model is to allow simultaneous simulation of vehicles controlled by drivers and semi-automated systems for comparisons between automated vehicles and human drivers. The method discussed here fused a cognitive model with the existing simulation tool, SmartAHS\(^1\). The contribution of the cognitive approach relies on the formation of a driver’s knowledge database and the modeling of the cognitive processes underlying the driving activity. At the current state of development, a perception module provides information on range and range-rate with a leading vehicle. This information allows the simulated driver to choose a behavior among a set of possible behaviors, such as following or overtaking. The thresholds for choice behavior were initially chosen through a literature review and then tuned with microscopic driving data. The feasibility of the model is also discussed, as well as the application of the model to other simulations.

1. Introduction

An important initial step prior to deployment of fully automated vehicles is the partial automation of vehicle control. This partial automation is realized with systems such as ACC or RECAS. The development and deployment impact of such systems has to be estimated in terms of cost and safety as well as performance. One of the best options for performing this estimation is to provide a tool that allows simulation of either human or semi-automated control of a vehicle.

The method described here for building such a simulation tool relies on the fusion of a cognitive model of the driver with a California PATH simulation tool, SmartAHS. COSMODRIVE [1] was chosen as the framework for the cognitive model as it integrates the classical description of driving behavior in three levels: Strategic, Tactical, and Operational. It utilizes the addition of four more modules, Perception, Attention and Resources Management, Execution, and Emergency Management.

In this paper, we will focus on the already implemented parts of a PATH version of the model. Then, we will provide a description of the perception and tactical modules, elicited by two cases. Thereafter, these scenarios simulated by SmartAHS based on SHIFT\(^2\), the simulation language, are shown. Finally, we will present a validation example of the model, which relies on real driving data provided by University of Michigan, Transportation Research Institute (UMTRI).

2. Perception Module

The perception module allows a driver to receive the current road and vehicle environment information and update the representation of the driving situation. Scanning information as well as velocity and lateral position will be considered and described.

According to Hoffmann’s experiment [2], the justnoticeable increments of \(\delta R/R\) and angular velocity are 0.12 and 0.003 (rad/sec) respectively where \(R\) is the range and \(\delta R\) is the increment of the range. Furthermore, the geometric approximation, \(R \theta = d\) where \(d\) is the width of a preceding vehicle and \(\theta\) is the visual angle, can be used to derive the mathematical relationship between the range and range-rate. A similar car-following model based on the above range-rate perception model is also suggested by Fancher et al [3]. The range-rate perception model will also be used in the proposed regional behavior decision map.

Two more pieces of information, time gap and Time-To-Collision (TTC) will be included in the regional decision maps in the tactical module. The driver’s feelings, such as

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\(^1\) See http://www.path.berkeley.edu/SMART-AHS/

\(^2\) See http://www.path.berkeley.edu/SHIFT/
being in comfortable or dangerous following situations, has been investigated by Ohta, with respect to mean time gap [4]. Time gap is defined as follows:

\[ T_g = \frac{R}{V} \]  

(1)

where \( V \) is the velocity of the following vehicle. TTC is based on kinematics and the assumption that decelerations of both the leading and the following vehicle are equal as follows:

\[ TTC = -\frac{R}{a} \]  

(2)

Currently, the perception module has been coded in SHIFT and incorporated into the SmartAHS library for modeling human perception [5].

3. Tactical Module

The current tactical module is composed of several elements: categorization, decision, anticipation; mental representation, and a driving knowledge database. The units of this database are described as schema. We will provide a description of the database structure and the categorization process. We will then describe in more detail two cases, longitudinal following and overtaking.

3.1 Driving Behaviour Database

Retrieval of knowledge associated with a driving situation needs to be a fast process. One method to achieve quick retrieval is to organize the knowledge into categories. The categorization of human knowledge has been demonstrated at many levels. Driving knowledge can be organized in different fashions, depending on the categorization criteria. The knowledge hierarchy is structured based on the driving environment and the traffic level [6]. Elements, or schemas, in the categories are the tasks to be performed. The first application of the simulation shown here is highway driving. Figure 1 represents the driver’s knowledge database for highway driving.

For presentation simplicity, the schemas here are associated with a level of traffic. In fact, each set of schemas is "dynamically constituted" based on the current level of traffic. This means that the pursuit schema present in low traffic and medium traffic in fact refers to the same procedure, while the value of some parameters (time gap for example) might be traffic and driver dependent. Each schema is a procedure associated to a driving situation. It is composed of a goal, driver’s preferences (desired speed, time gap, etc), the actions to be performed for reaching this goal and the expectancies associated with this situation. Another aspect of the dynamic constitution of a subset related to traffic conditions is that using a schema present in the same subset is faster than using a schema in a different subset. For example, a pursuit schema in a low traffic condition i.e. reaching a slower vehicle, the driver will expect to change to a following or overtaking mode, but not a stop and go mode. In the latter case, the appropriate procedure, braking, would take longer to initiate than if the driver was in a following schema for heavy traffic conditions.

![Figure 1. Driver's knowledge database](image)

3.2 Categorization

The categorization process, from a cognitive perspective, consists of matching the current driving situation with the appropriate driving schema. This matching is realized through an activation principle.

![Figure 2. Schematic Diagram of Categorization](image)
A finite state machine is proposed to implement the categorization in the simulation (Figure 2). Since the simulation scenarios are on a straight highway with two lanes, overtaking is also considered as drivers may overtake rather than brake for a slower leading vehicle. Two flags and two channels are used to communicate with a driving schema: Command (CMD), Flag, Request (REQ), and Response (RES). The channel has only binary information, such as response/no response or request (r)/no request (nr).

### 3.3 Case Study

#### 3.3.1 Car-Following Case

The local control goal for car-following is to maintain a comfortable time gap with the preceding vehicle. The comfortable time gap will be described in more detail in the following regional decision map.

**Computational Driving Schema**

Time-gap and range-rate control are proposed to achieve the above local control goal for the longitudinal following. They communicate with a regulation layer in the operational module in order to initiate and control the vehicle. Furthermore, safety for car-following is checked based on the regional decision map (Figure 3). As before, a finite state machine is used.

![Figure 3. Schematic Diagram of Schema for following](image)

**Regional Decision Map**

The decision map results from the fusion of range-rate perception and car-following comfort zones [7]. The proposed decision is made on a regional decision map, which explains driver behavior with the goal of remaining in the comfortable zone. Through the information from the perception module, the regional decision map is updated to indicate degree of safety and comfort and used for the categorization process.

Figure 4 presents the regional decision map when the current velocity is 60mph (26.5m/s). Dangerous, critical, and comfortable zones are respectively defined as zones IV, III, and II based on the time-gap. Moreover, zones V and VI are approaching zones and zone VII is a separating zone. A driver can track range-rate in these region as mentioned in the perception module description. The zones V and VI are based on TTC which is used to choose either braking or overtaking. The driver, therefore, will reduce speed or check for safe overtaking when in zones V and VI.

![Figure 4. Regional Decision Map for Following](image)

#### 3.3.2 Overtaking Case

It is assumed that overtaking can happen in zones IV, V, and VI (Figure 4) because the driver may feel in an uncomfortable and dangerous situation when following too close to a car. We will also consider both the computational overtaking schema and regional decision map with respect to an adjacent lane.

**Computational Driving Schema**

Figure 5 presents the finite state machine of the overtaking schema that is in the knowledge base. The lane-change control state is linked with the regulation layer in the operational module in order to execute the lane change maneuver. Two safety check logic based on two regional decision maps are proposed. Safety 1 is performed by use of the same decision map for car following with respect to a leading vehicle in the adjacent lane. The other decision map will be described as follows.
Regional Decision Map for Overtaking

Jula et al calculated the minimum longitudinal safety distance (MSD) for lane changing/merging scenario [8]. The MSD is used to check safety for a lane change maneuver, which takes place in the Safety 2 state of the overtaking schema (Figure 5). Furthermore, TTC is proposed to define a comfortable zone for lane changes.

Figure 6 contains two regional decision maps, which perform Safety 1 and Safety 2 in the schema. First, zone I is obtained by calculating the MSD, which is an uncomfortable zone where a collision could happen during lane change maneuvers. Zone II is a marginally safe zone where human perception error and personal preference are considered. They are defined by TTC, which is a design parameter and tuned based on characteristics of each driver. The other zones are grouped in a comfort zone for lane changes. This region can be divided in the same way as the following regional decision map with respect to a preceding car in next lane. Similarly, zones IV, V, and VI will be the comfortable critical, and dangerous zones respectively. Therefore, the velocity will be adjusted during transition to lane change so that the driver maintains the comfortable time gap after completing the lane change.

When there is a rear vehicle in the adjacent lane, a similar decision map can be used to check the safety for lane change. Also, it is assumed that road environmental data are acquired based on attention and resources manager. In this case, visual attention allocation is distributed among the proposed maps.

4. Two-layered Operational Module

The operational module is activated by receiving a message from the tactical module and generates the corresponding control input to the vehicle. In order to deal with various kinds of driving maneuvers, a two-layered operational module is proposed: regulation and lower-level layer. Consequently, a four-layer hierarchical structure is built into the tactical and operational modules as presented in Figure 7.

4.1 Regulation Layer

Four different controllers are proposed for performing three driving maneuvers: following, driving alone, and overtaking. As already introduced in the driving schema, the time-gap and the range-rate controls are used by a driver for staying in the comfortable zone. Feedback errors of the time-gap and the range-rate controllers are defined with respect to a desired time-gap and perceived range-rate respectively. Furthermore, the trajectory control is designed to keep the driver's desired speed. The lane-change control is proposed for overtaking as
described before. Their errors are based on the desired speed for driving-alone and both a yaw angle and a lateral position for lane change.

4.2 Lower-level Layer

It is assumed that the driver is skilled at manipulating the vehicle controls to obtain the desired speed and time-gap. Under this assumption, control inputs to a vehicle are calculated in the lower-level layer: a throttle angle, a brake pressure, and a steering angle. A sliding control approach has been used in the operational module in order to perform these objectives. Four different sliding surfaces can be defined in the controllers of the above regulation layer and one of them will be chosen. Then, the surface error, which is the feedback error, is transferred to the lower-level layer. Finally, the desired control input can be calculated with the surface error based on the simplified vehicle model. A more detailed description of the proposed operational module can be found in [5].

5. Simulation

The model was used in both macro- and micro-level simulations. At the macro level, our simulations involved hundreds of vehicles. For simulation efficiency, we used a simple kinematic vehicle model. Large-scale simulations are quite sensitive to variations in the parameters of the model: time-gap thresholds, gain constants, etc. This highlights the importance of tuning these parameters using real-world data. In the micro-simulation, a powertrain vehicle model, including engine, transmission and tire components, was used in order to describe driver throttle and brake control in more detail.

One application of this work is an ongoing project at California PATH to simulate highways with a mixture of human drivers and various adaptive cruise control systems. The goal is to understand the costs and benefits of various deployment sequences of automated vehicle technologies.

5.1 Car-following Case

It is assumed that the following car is going at 26.5 m/sec initially and is 5 m/sec faster than the leading vehicle. The initial range is 70 m. Figure 8 presents the regional decision map for checking Safety 1 in the longitudinal following schema and range versus range-rate trajectory of the following vehicle. When the range of the vehicle approaches 40 m, the driver considers overtaking to avoid reducing speed. At that time, the regional decision map for overtaking is used to confirm safety for lane change. For the given example, the range is assumed to be less than MSD. That is, the driver is in an uncomfortable or a dangerous zone. Thus, the speed is reduced to stay in the initial lane and to maintain a comfortable time gap.

5.2 Lane-change Case

Figure 9 presents the regional decision map for overtaking and the trajectory with respect to a leading vehicle in the next lane. The given initial conditions here are the same as in the previous scenario, plus range with the leading vehicle in the next lane. When the safety check for overtaking is done, the driver is already in the comfortable zone for following as well as in the safe zone for overtaking. Therefore, a lane change occurs and following of the new leading vehicle within the comfortable zone commences (Figure 8).
6. Calibration

Model calibration was realized through data obtained from the ICC-FOT performed by UMTRI [9]. We used a subset of data composed of manual driving for following events at velocities above 55 mph. Figure 10 shows a real, 40 second, longitudinal following event for one driver overlaid with our model boundaries. The driver approached the comfortable zone and remained there while the leading vehicle kept a constant speed. At the end, the leading vehicle slowed down. Consequently, the following vehicle moved into the critical zone. Although the next event is not shown here, the driver returned to the comfortable zone by reducing speed.

![Figure 10. Experimental example of a driver for the longitudinal following](image)

7. Conclusions

A hybrid and hierarchical structure as a modeling paradigm has been shown to be useful for descriptions of automated systems. Here we extended their field of application to human modeling by the adaptation of a driver cognitive model. The proposed model is composed of a four-layer structure. These layers communicate with each other and within each layer is a hybrid structure.

The continuation of this model relies in the development of modules not developed here, such as the attention management or emergency management, as well as some of the sub-processes within the tactical module (e.g., anticipation). It is also necessary to expand the driver’s knowledge database to other driving environments and scenarios. Further improvements will benefit from the collection of naturalistic driving data corresponding more precisely to model parameters.

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References


