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1 INTRODUCTION

PATH AVCSS researches have been traditionally oriented toward automatic vehicle design. Recently, the field of investigation has been extended from Automated Highway System (AHS) to assistance driving systems. One of the tools built at PATH for automatic system design and assessment is SmartAHS. SmartAHS is a micro-simulation tool dedicated to the simulation of automatic vehicles and has shown to be very useful for fully automatic system simulation. These simulations permit researchers to evaluate the impact of such system on throughput improvement. In order to apply the same method to the design of partially automated systems, it is necessary to develop a human driver component for this simulation tool. This component needs to allow the comparison of human driving characteristics versus automated vehicles in the long term, but first, it has to permit the production, for simulation purposes, of a realistic human driving behavior.

Modeling attempts of drivers behavior in the field of Human Factors have been conducted since the early 60's, in order to improve driving safety and driving learning. The first action taken was to describe driving behavior by organizing behavior in various tasks, themselves part of more macro categories. The principal limit of this approach was to be only descriptive and almost not predictive. Moreover, most of the taxonomies were different and the limits between the categories were sometime confusing. The limits of this first trend motivated another approach, in which the models were based upon risk management. These models discussed risk evaluation, acceptation, and perception. These models introduced the notions of driver's motivation, experience, and stressed the necessity to understand more about drivers' cognitive activity, as risk perception and evaluation are strongly associated with the way a driver understands a driving situation. So, in the continuity of these efforts of modeling the driver's behavior, a new generation of models has recently been developed, emphasizing the description of the driver process of thoughts. One advantage of these models is the potential to implement them, either by generating a simulation of the driver, or to integrate them to some already existing traffic simulation tools. Another application of this type of model is a direct integration either in the assistance system or in the design and development of the system.

Actually, these models can be classified in relation of the aim of their conception. A possible classification is: i) the investigation of human reactions and learning of driving (e.g., The Generic Driver System (GIDS) Wierda & Aasman (1992)); ii) the design of in-vehicle devices (e.g., Integrated Driver Model (IDM) by Levison (1993) Allen's model (1987); or iii) the improvement of the accuracy and realistic aspect of traffic simulation tools (e.g., ARCHISIM Espie & Saad (1995)).

The goal of the modeling effort presented here is twofold. On one hand, there is an objective to design and evaluate AVCSS at a driver level (respective of human processing constraints), which imply a consideration of the cognitive processes involved while driving. On the other hand, there is also a goal to integrate of the model to a micro-simulation tool, for evaluation of AVCSS at traffic level, and more specifically in terms of throughput evolution. This second goal implies the consideration of vehicle models

and control of the vehicle. SmartAHS mainly consists of automatically or semi-automatically controlled vehicles. This is why this component is called human driver model (as opposed to automated or semi-automated vehicles).

The method preferred for the realization of this model is a capitalization of these various approaches by the application of a driver cognitive model, COSMODRIVE (COgnitive Simulation MOdel of the DRIVEr) (Bellet, 1998). This model conceptual framework is a skeleton around which can be organized the relevant aspects of the different approaches for the purpose of driver modeling. The general architecture of this model will be presented first, with a detailed description of the modules content and exchanges. In Section 2, the implemented modules and procedure of implementation will be described. The third section will be the description of the simulation realized with the model, for both normal driving and emergency case. Finally, this report will conclude with the description of a calibration procedure for part of the model.

2 HUMAN DRIVER MODEL

The points that will be discussed in this section are related to the general architecture of COSMODRIVE, as well as an expansion of one of the modules, tactical, in order to show the different processes and structures involved at this level. Finally, the way this model inspired the human driver model and more specifically how we shifted from a design for an implementation with Artificial Intelligence object modeling technique to a hybrid and hierarchical structure will be discussed.

2.1 COSMODRIVE general architecture

COSMODRIVE[1] is the result of the capitalization of theories and methods in two fields, cognitive psychology and ergonomics applied to transportation studies for the theoretical framework, Artificial Intelligence for the implementation. The focus of this model is directed toward the driver, no vehicle constraints or dynamics have been integrated so far. The aim of the model is to reproduce driver behavior in any type of road environment (urban, rural highways, highways) and for any type of driver's experience and/or familiarity with the environment by simulating the processing of a driving scene by a driver.

The approach underlying its design had been to first define a functional structure describing the principal stocking structures and information processing. Second, a specification of the nature of the computational mechanisms (here the cognitive processes) had been realized. Third is the description of the data structures (knowledge and representation) on which operate these processes. Once these three steps have been followed, the choice for an implementation method has been done, in this case, it is object modeling oriented that had been chosen.

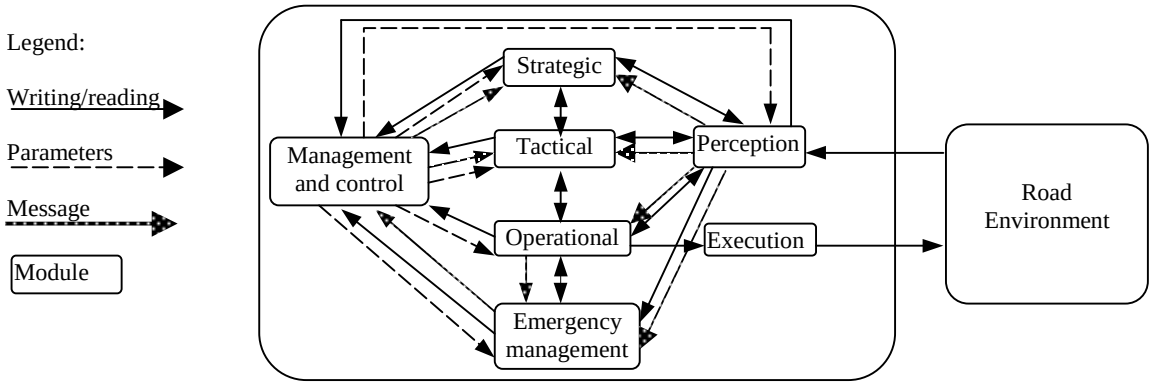


Figure 1: General Architecture of COSMODRIVE

[1] COSMODRIVE has been developed at the French Institute for Transportation Research and their Safety, INRETS, by T. Bellet and H. Tattegrain

Figure 1 displays the seven modules that compose COSMODRIVE. Each module is in charge of a specific activity. The strategic module is in charge of the navigational aspect (i.e., itinerary organization) and general objectives generation. The tactical module is an internal representation generator of the road environment. The main processes presented at this level are road environment categorization and recognition, decision-making and anticipation. Finally, the operational module is composed of a set of autonomous operational units specialized in the elementary driving tasks, such as lateral or longitudinal control. These three modules are the ones classically used for driving activity description. Four modules have been added to this classical architecture. The perception module allows the integration of human characteristics for driving scene processing. The emergency management module is activated when an emergency situation is perceived and proceeds to acquire the tactical and strategic module attention resources. This switch is made possible by the module of resources management and control. All of these modules function by the way of a limited amount of resources that they share.

Another important characteristic of this model is its modularity, which allows a step-by-step development, therefore permitting expansion of the focus from a specific scenario, with different levels of granularity.

2.2 Expansion of the tactical module

The modules presented above contain a set of processes. In this part, we will focus more specifically on the set of processes involved in the tactical module and the interactions it entertain with the other modules (cf. Figure 2)

This module interacts primarily with the perception module. This interaction is realized in two fashions based on the visual channel. There is an integration of events as well as a voluntary exploration of the environment. These two basic operations allow the simulation of both reaction (cognitive integration) and anticipation (exploration). The strategic module feeds the tactical module with “general” goals. Of great importance is also the module of management and control, as it regulates the resources available to the processes. The other module that exchange with the tactical module is operational. This interaction is related to the realization of action decided at the tactical level, concerning lateral and longitudinal control.

Within the module, three structures can be distinguished: i) cognitive processes, such as categorization, decision making, representation generation, ii) mental representation, split between a current state and anticipation state and finally iii) a knowledge base.

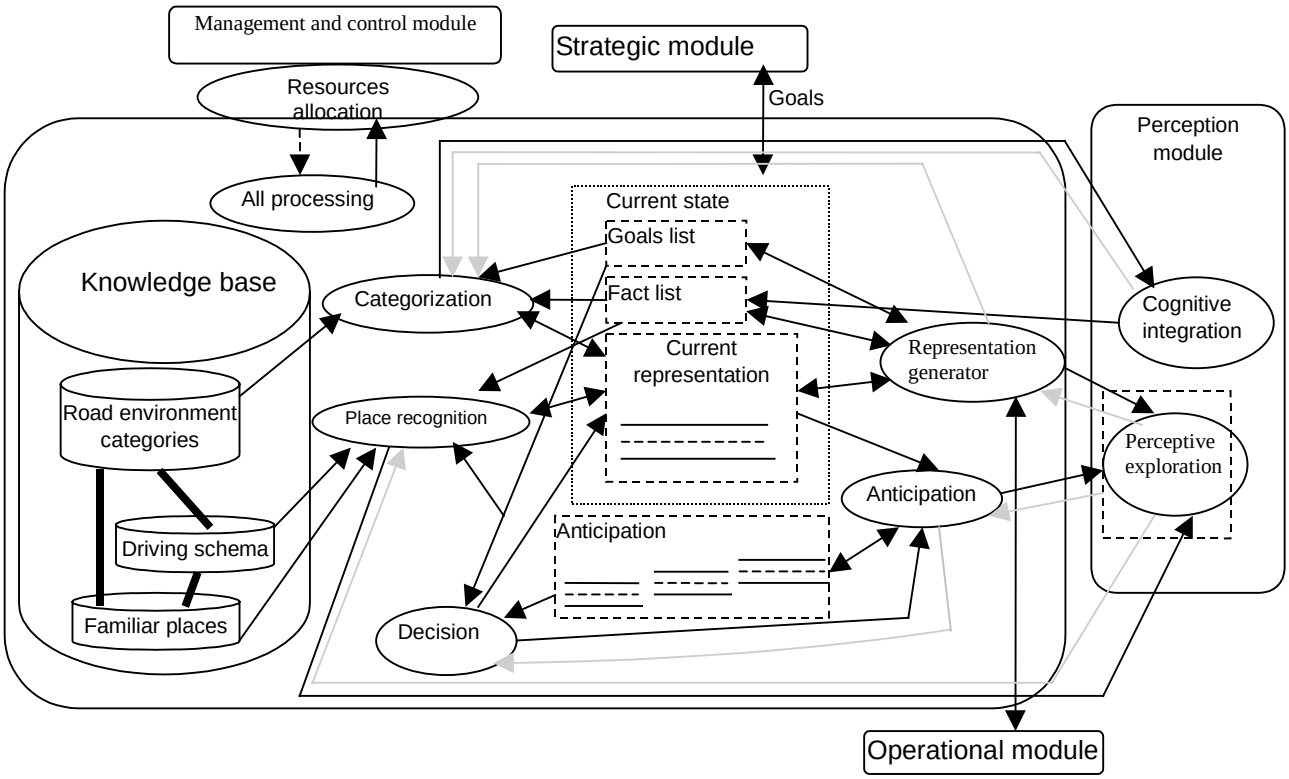


Figure 2: Schematic Diagram of Perception and Tactical Module

The role of the processes is to "interface" the data "sampled" in the road environment with the knowledge that a driver has and to manipulate these two sources of information for controlling and adapting his/her behavior. The different actions executed by these processes are: i) generate and update a current representation of the driving scene, ii) mobilize the appropriate knowledge to process the situation, either via a categorization process or a place recognition process, iii) make decisions about the behavior to adapt, iv) anticipate the future behavior.

The driver knowledge database is organized in two sets. One set is made of a general knowledge about driving. This knowledge is organized on a hierarchy based on driving environment, mainly urban, rural and highway. Each of these categories are themselves divided in more sub-categories depending on other environment features (such as the number of lane for a highway for example). The other set is knowledge a driver dispose of about a specific place. The smaller units of this hierarchy are called driving schema. For example, in the highway category of the general knowledge set, there is a schema for exiting a highway. Part of the schema is the procedure to do so, like moving into the right lane at a certain distance from the exit. The driver may also know a specific exit which is on the left of the highway and then the schema he has for this exit is made of rules for this specific exit, integrating some marks from this specific environment (to be on the left lane at a certain point).

The mental representation of the current driving situation is a transitory stocking structure. The selected schema is instantiated in the current representation and then

provides the guide to manage behavior by specifying the information to be considered, the one necessary prior to undertake an action. This instantiation also integrates the information persent in the environment and leads to the construction of an internal model of the situation. Most decisions are based on the status of the information present in the mental representation. Only a certain amount of information can be considered at a time and the status of the information, in terms of validity, decays with time.

Because COSMODRIVE is still currently under implementation, the models describing the action of the processes described in Figure 2 are not yet available. This led to the adaptation of this model by the use of models interfacing appropriately SmartAHS, which will now be discussed.

2.3 Human Driver model design for an implementation via hybrid and hierarchical structure

COSMODRIVE is a very detailed model and its implementation is a long-time commitment. In order to interface this model with SmartAHS structure, it was simplified in many ways. First, the implementation focused mainly on four modules: perception, tactical, operational, execution. Two different types of vehicle models (Kinematic and two-dimensional) were also integrated. Within these modules, and more specifically the tactical module, the stocking structure and processes have also been simplified. Furthermore, the perception module is principally providing information about the traffic in front of the vehicle (presence or not of a leading vehicle, range and range-rate). The tactical module is composed of a categorization process, which matched the current driving situation with the knowledge the driver has about this situation. This knowledge is represented via the formalism of schemas, which are procedures describing the behavior to adopt by the means of a goal, actions to undertake and expectancies (i.e., a specialized subroutine for a specific driving scenario). Once a schema is activated through the decision logic, it is transmitted to the operational module where the "control laws" associated with the schema are instantiated as well as the regulation of the situation. The execution of the action is realized and results in an input to the vehicle model. These simplifications are presented in Figure 3.

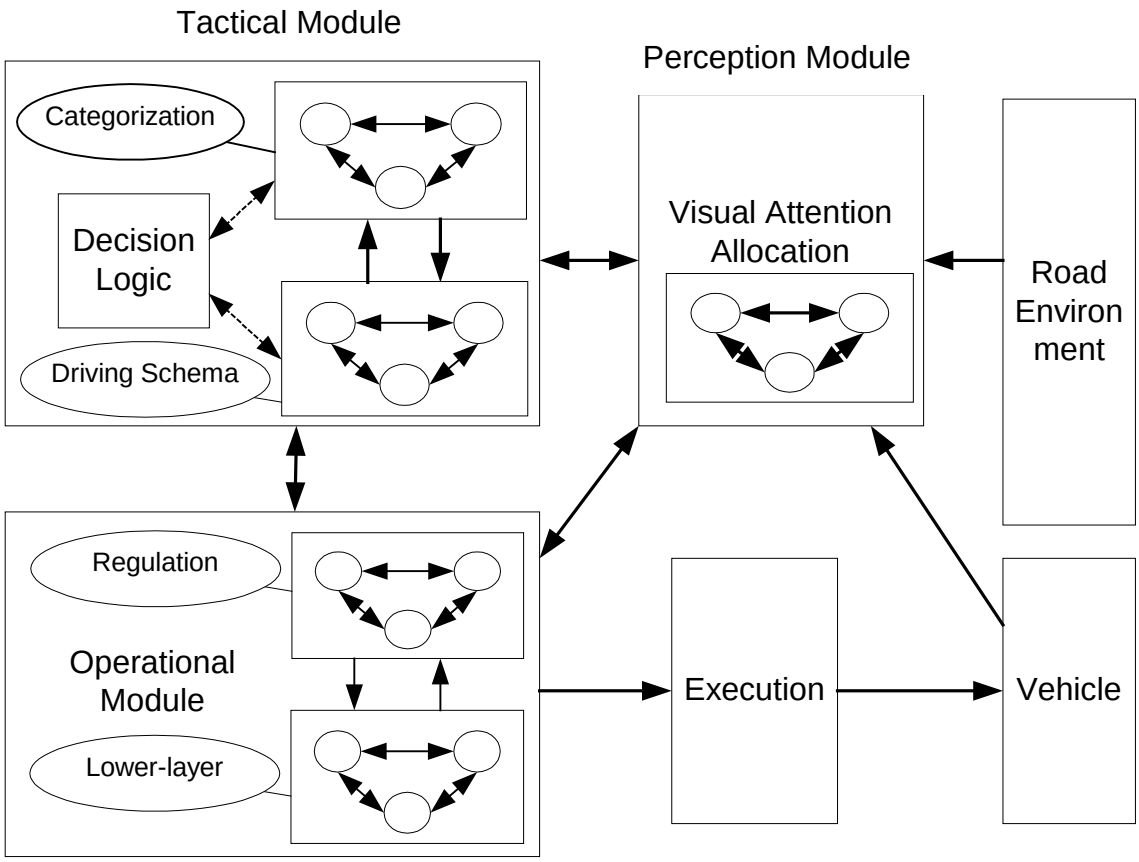


Figure 3 General architecture of the human driver model

A hierarchical and hybrid structure is used for the implementation of the tactical and operational modules. Use of the hierarchical structure brings many advantages in the implementation point of view. Since a module is composed of several different layers, one of them can be easily modified to improve the model and expanded to add more functions of the model. Moreover, an additional layer can be placed between layers, if it is necessary, without changing the whole module structure. For instance, in the proposed tactical module, a two-layer structure has a categorization and a driving schema layer to perform driving maneuver such as following and overtaking. Adding another driving maneuver like exiting a highway can be done by simply, by incorporating the corresponding structure in the tactical module with limited programming labor by modifying the interface structure.

As mentioned shortly, the hybrid structure is used to deal with both continuous and discrete event at the same time. In the other words, all decision, categorization, and control behaviors of a driver have discrete events based on their own principles but once a discrete event is chosen, the corresponding continuous event with respect to time continues unless any other discrete event happens. To realize this phenomenon, the hybrid structure is proposed in frame of finite state machines. Since SHIFT is a language for implementation of a hybrid system and SmartAHS is based on it, all finite state machines for the human model component will be based on it as well. Furthermore, the

hybrid structure is placed in a layer of the above hierarchical structure. Therefore, the hierarchical and hybrid structure can be combined together.

3 Module implementations

The module implementations will be described here with an emphasis on the assumptions, models and equations underlying the driver behavior simulation. As SmartAHS is currently a highway simulation tool of automated vehicles focusing on platooning and car-following situations, the effort of the implementation will be directed toward driver behavior on the highway. This justifies why certain choices have been made for the implementation of each module, like the reduction of perception to the processing of the presence, range and range-rate of a vehicle ahead and only considering highway driving in the driver knowledge database. Nevertheless, the development to the perception module by the addition of models processing other aspect of the driving environment is doable and one of the goals for the next development steps of the model. Along these lines, the addition of other driving environments is envisaged beyond the current implementation.

Each module implementation will be presented, starting with the perception module, followed by the description of the tactical module, the operational and execution module will be presented together and the interaction with the vehicle model will be a subpart of the operational/execution module description.

3.1 Perception module

The perception modeling focuses on the visual sense for now. It permits the categorization process and the search of the environment and the dashboard when requested. The three aspects, which will be detailed here, are the visual attention allocation, focused on deliberately directed visual attention, the range-rate perception model and finally the formalism used to represent these information for the model.

3.1.1 Visual attention allocation

The reproduction of the visual attention allocation is one of the keys for reproducing human distraction or delay for a reaction. Two types of control of the visual attention are usually described. In the first case conspicuous[2] objects automatically attract the driver's attention (bottom-up). In the second case, the driver's attention is deliberately directed toward his/her environment (top-down), for the search of expected properties of the relevant objects for the task, e.g. location, color, shape (Theeuwes,1991). For the purpose of the simulation, we focused on the second type of control.

Therefore we considered that by default, driver's attention is directed in front of the vehicle to the focus of expansion. Then, a shift provoked by the driving task can bring the need to check some information (e.g. possibility to overtake, actual speed, etc.).

[2] Conspicuity refers to the efficiency with which an object is capable of attracting attention

Other tasks can be considered, such as turning a radio on or off. Most of these visual movements have been heavily studied in the Human Factors field (Rockwell 1988, Bhises et al.1986, Wierville 1993). The time of a fixation on one part of the environment or on one device can be deduced from literature.

For the purpose of implementation of the visual attention, a finite state machine is designed as shown in Figure 4. A center state, Range & Range-rate, is to update the range and range-rate information in every viewing time (VT). When range-rate is changed or scanning message is arrived from driving schema, the state is moved to either Velocity or Side. Then, each state goes back to the default state, Range & Range-rate, after receiving either velocity or side information in an adjacent lane. Also data update depends on time parameters: Velocity check time (Tv), Scanning time (Ts). Finally, the last state, Others, represents other traffic visual attention behaviors. For instance, answering a phone, turning on a radio, and reading and interpreting traffic signal and sign are included in the state. Each behavior can be modeled as pure time delay (Td) and initiated by external command (Cmd). Each of these parameters, at the exception of others, corresponds to a glance. As the mean glance lengths tend to vary from experiment to experiment, a set of value per "studies" could be constructed. The interest would be to allow the user of the simulation to select the most appropriate set for his/her study or compare the different set of value impact.

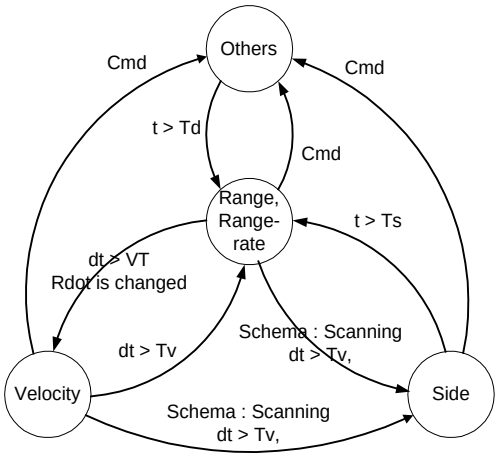


Figure 4: Schematic Diagram of Visual Attention

3.1.2 Range and Range-Rate perception

The first and second of four scaled data, which are perceived and processed in the perception module, are range and range-rate. Thresholds of subtended angle change and angular velocity are introduced to describe drivers' ability to perceive and scale the range-rate (Hoffmann, 1996). At distances where the rate of change of visual angle is less than 0.003 rad/sec, drivers' perception based on a "looming" effect is unable to discern

differences in range-rate when the object is 1.8 m wide. Using $R \cdot \theta = d$ and differentiating the geometric equation with respect to time, the following result can be derived:

$$\dot{\theta} = -\frac{d \cdot \dot{R}}{R^2} \tag{1}$$

where R and d are the range and the width of the forward car respectively, $\dot{R}$ is the perceived range-rate, θ and $\dot{\theta}$ represent the visual angle and the rate of change of visual angle respectively. At $R < \sqrt{|\dot{R} / 0.00164|}$ from the equation (1) and just-noticeable increments of $\delta R / R$ = 0.12, drivers scale perceived range-rate in a practically linear relationship to R. The car following model based on the above range-rate perception model is also suggested by Fancher et al (1998). This range-rate perception model will be also used in the proposed regional decision map later and combined with the following additional information in the map.

Observing that a driver maintains a comfortable time gap to the leading vehicle as his/her local driving objective when the range is greater then the threshold above, we have modified this model with some experimental data (Ohta, 1993) of driving objectives and control behavior. A time gap is defined as:

$$T_g = \frac{R}{V} \tag{2}$$

where V is the speed of the following car. Therefore, the third and fourth scaled data are the speed and the time gap. When a driver looks at the speedometer in the vehicle, he/she updates the velocity information and regulates the preferred speed. The comfortable time gap is derived from individual time gap choice. Ohta (1993) categorized the mean time gap values observed on a typical Japanese highway into four kinds of subjective distinct zones called the danger zone, critical zone, comfortable zone, and pursuit zone. The limits of the time gaps are 0.6, 1.1, and 1.7 s respectively. Hence, a driver is in the comfortable zone when time gap is between 1.1 and 1.7 second. Even though these were based on a relatively small sample, and by Japanese social norms, they serve as important factors (whose values could be adjusted later with American driving data) in a decision model of the tactical module.

The final scaled information is Time-to-Collision (TTC). Based on kinematics, the TTC is:

$$TTC = -\frac{R}{\dot{R}} \tag{3}$$

According to Horst (1991), the decision for braking action is based on the TTC available from the optic flow field. In Horst's experiments with twelve male student drivers, TTC value ranged from 2.1 to 2.9 s for normal, non-emergency braking and from 1.2 to 1.9 s for hard braking when they are instructed to leave braking until the last possible moment.

3.1.3 Regional decision map

The regional decision map represents an interface between perception and categorization. This map allows representing the driver perception of comfort and safety while following a vehicle. Then, it permits either to shift from schema to schema or to manage the behavior within a schema. The design of this map will be presented first and followed by a description of its application to other vehicles than the one present in front.

3.1.3.1 Map principle

The decision is an important factor in the tactical module with respect to safety and comfort. Since the decision is based on a goal, perceived information, knowledge and rules from previous experiences, it is more preferable and realistic to use dynamic and adjustable decision logic rather than static and fixed method.

From this and the perception model described above, Figure 5 is an illustration of our fused decision logic. It can describe the driver's perception and subjective feelings in car-following behavior, where each zone is based on time gap when current velocity is 60mph (26.5 m/s) as an example. Zones I, II, III, and IV are the pursuit, comfortable, critical, and dangerous zones respectively where the driver cannot detect the range-rate directly. Since the range perception model of a driver is considered, the range threshold is ±7.95 m when the time gap is 2.5 second, as shown in the figure. Furthermore, Zones V and VI are in the approaching region, where range-rate is negative and perceptible to a driver. Conversely, Zone VII is the separating zone. Zones V and VI are categorized by TTC when the range-rate is perceived. Under the assumption that normal braking is applied when the TTC is below a certain value, we can generate the Zone VI for the driver to start the normal braking.

Although Zones I ~ IV are chosen through the time-gap which a driver prefers and how he feels in each zone, they can be reshaped by other traffic conditions such as current traffic density and weather condition. That is, each range for a zone will be scaled on basis of the above traffic condition. For instance, the comfortable zone can be defined as follows:

$$R_{comfort} = f \cdot T_{comfort} \cdot V \tag{4}$$

where $T_{comfort}$ is the time-gap value which could be between 1.1 and 1.7 second based on Ohta's experiments (1993) and f is the traffic condition factor and function of other conditions as:

$$f = f(td, wc, rc, \ldots) \tag{5}$$

where *td* is the traffic density, *wc* is the weather condition, and *rc* is the road condition. The traffic condition factor is a value between 0 and 1. Figure 6 represents the scaled regional decision map for following maneuver when it is assumed that the scaling factor is a linear function of the traffic density.

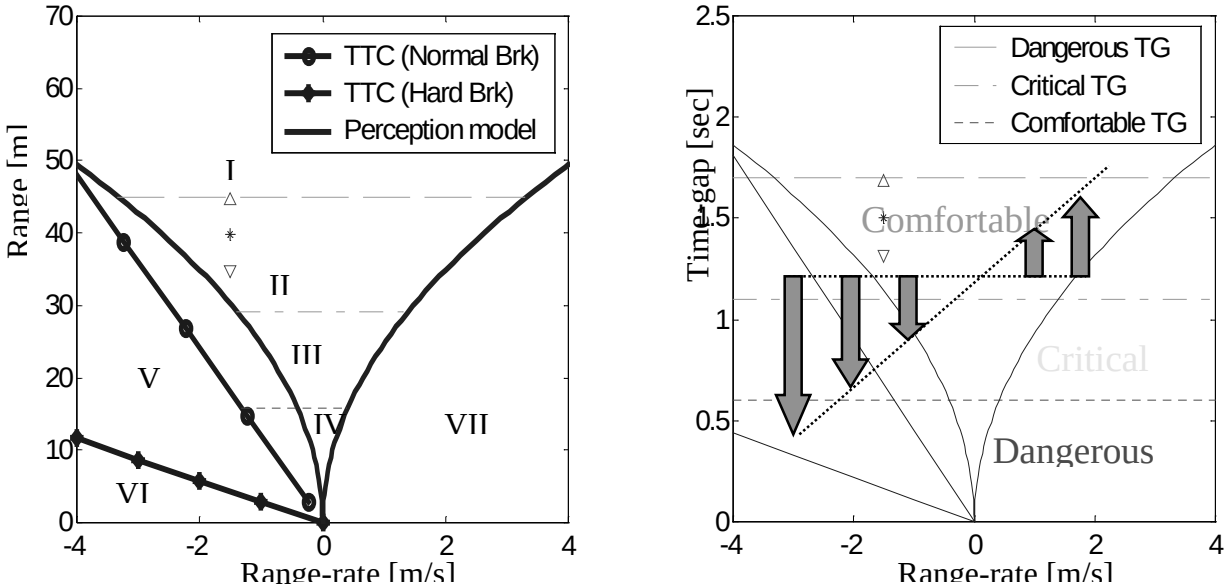


Figure 5: Regional Decision Map for Following

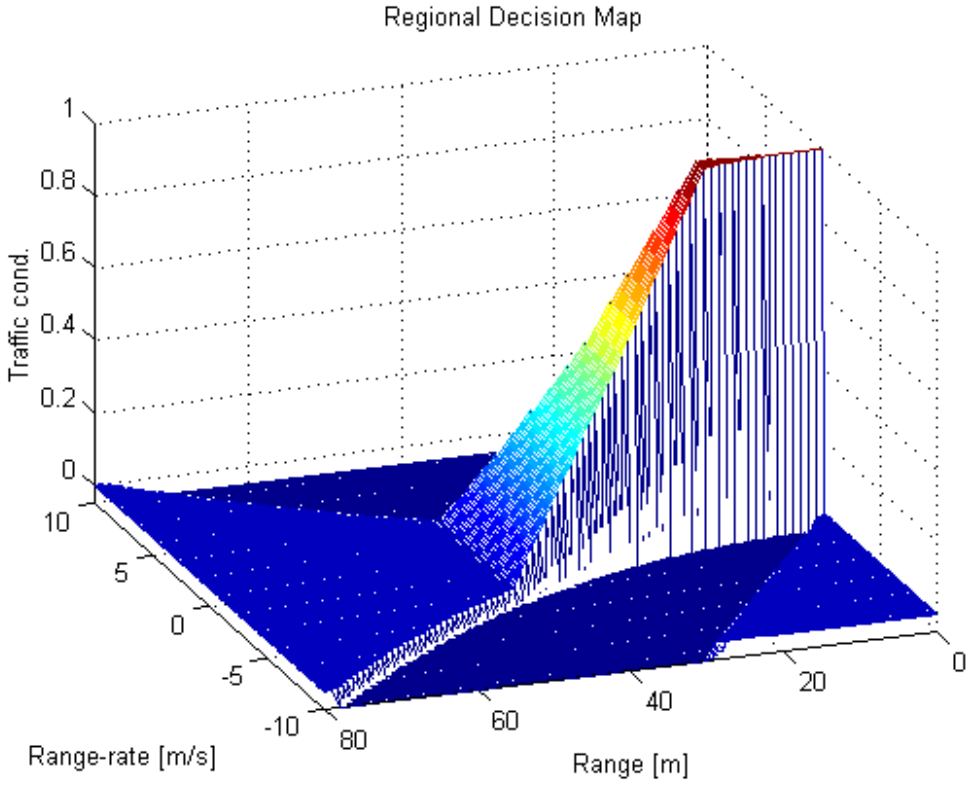


Figure 6: Regional Decision Map with Traffic Condition Factor

3.1.3.2 Application of the map principle to other vehicles

A range and range-rate perception model with respect to a vehicle in a next lane has not been introduced in the literature. When there is a rear vehicle in the adjacent lane, a similar decision map based on the same range-rate perception model than above 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 (i.e. only one map at a time can be consulted).

The minimum longitudinal safety distance (MSD) that a vehicle initially has to maintain in order to avoid any collision for lane changing/merging scenarios is calculated by Jula et al. (1999) (see Figure 7). That is, if the current range is less than the MSD, there will be a collision during lane changing. Thus, the MSD is used to check safety for a lane change maneuver, and becomes the dangerous line in the second decision map. Furthermore, a MSD threshold is considered to take human perception error into account (MSD_{max} and MSD_{min} in Figure 8). Finally, as we did in the first decision map, TTC is proposed to define a critical and a comfortable zone for lane change.

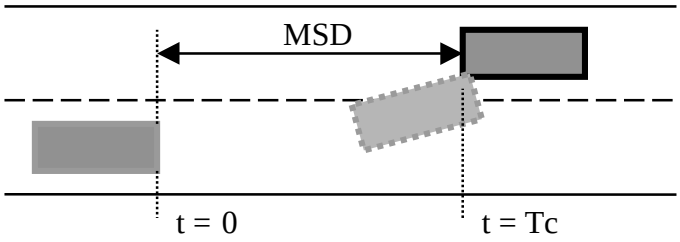


Figure 7: Minimum Safety Distance in Two-lane Highway

Figure 8 contains two regional decision maps, on which are performed Safety 1 and Safety 2 in the overtaking schema. First, zone I is obtained by calculating the MSD, which is an uncomfortable zone where a collision could happen during lane change maneuver. Zone II is a marginally safe zone where human perception error and personal preference are considered. They are defined by TTC, which is one of the design parameters and tuned based on characteristics of each driver. The other zones are grouped in a comfortable zone for lane change. This comfortable zone can be divided by use of the same 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 of lane change so that the driver maintains the comfort time gap after completing the lane change.

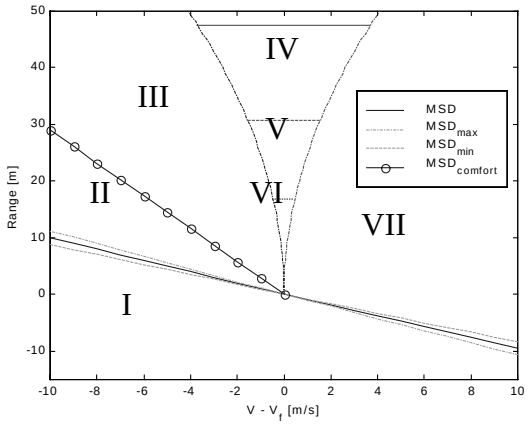


Figure 8: Regional Decision Map for Overtaking

3.2 Tactical Module

This module represents the processing of the current situation and the anticipation of the different future states necessary when driving. It is composed of a knowledge base, and a categorization process. The original knowledge base included in COSMODRIVE has been adapted by removing the schemas for familiar places. Another difference is due to our focus on highways; thus the road environment and the driving schema are only for this infrastructure. This also leads us not to consider for now the place recognition process.

As stated in the cognitive research (e.g., Dubois and Fleury, 1993), an experienced individual processes information and decision through a categorization of the situation. This process consists of the reduction of the environment to some features salient for the current goal that will be matched to some schemas. In other words, when the human being learns how to drive, he builds some schemas of the situation he meets, such as intersection with a traffic light, intersection with a stop sign, driving on highway and so on. These schemas represent the typical cases and are associated with a set of rules, expectancies and requests. This formalism for representing the driver's knowledge structure and information processes explains why the driver can manage high time constraint situations. The more experience the driver acquires on an environment, the more schemas he will develop and the more automatic the schema activation and realization will be.

The units of the driving knowledge database are described as schema. We will provide a description of the database structure and the categorization process.

3.2.1 Driver knowledge database

The amount of knowledge necessary for driving is quite considerable. Because of the time constraint associated with the driving activity, the retrieval of knowledge associated with a driving situation has to be a fast process (Dubois and Fleury, 1993). One method to achieve quick retrieval is to organize the knowledge to be retrieved in categories. The organization of human knowledge in categories has been demonstrated at many levels. Our assumption is that driving knowledge can be organized in different fashions, depending on the reason of the categorization, and that while driving; this knowledge is structured in a hierarchy based on the driving environment and the traffic level. The elements in the categories are the tasks to be performed.

3.2.1.1 Knowledge organization

As stated earlier, the first application of the simulation is highway driving. Figure 9 is a representation of the knowledge as organized for this environment.

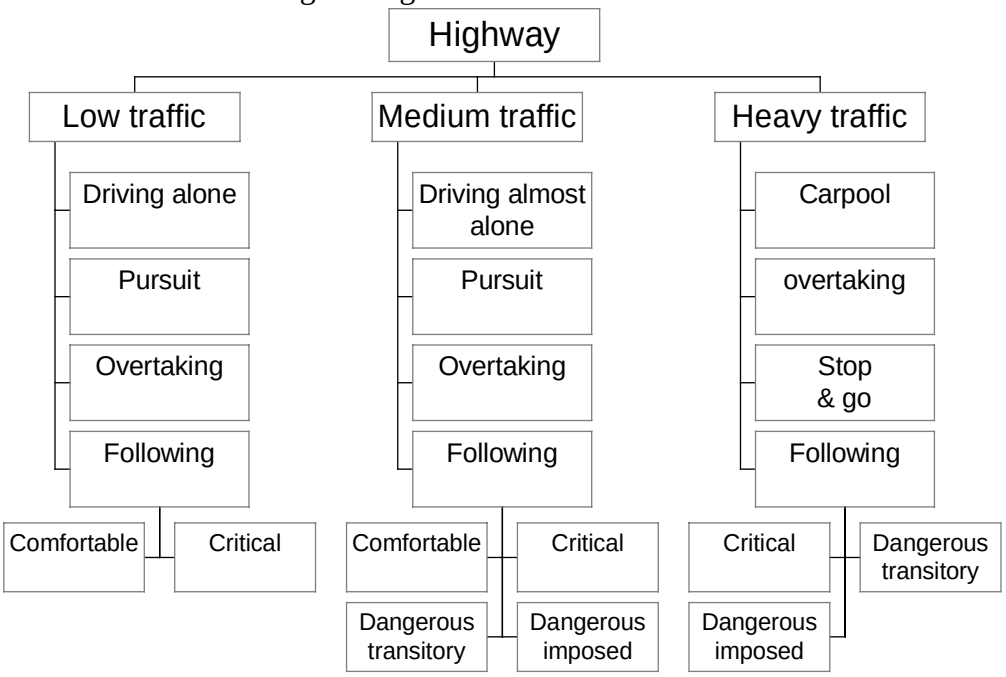


Figure 9: Driver's knowledge database

For presentation convenience, the schemas are associated with a level of traffic. In fact, each set of schemas is "dynamically constituted" based on the 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 condition is that going to a schema present in the same subset is faster than changing to the schema in a different subset. For example, being in a low traffic condition and in a pursuit schema –i.e. reaching a slower vehicle, the driver will expect to change to a

following or overtaking mode, but not to a stop and go mode. In the latter case, the appropriate procedure, braking, would take longer to instantiate than proceeding with the same acceleration.

3.2.1.2 Schemas description

A schema is to be considered as a "frame" present in the driver's knowledge database and updated with the facts of the current situation composed of: i) a road structure, ii) a local goal, iii) a set of actions, iv) expected events. In the case of the following schema for example, the local goal is to remain in a comfortable zone while following the leading vehicle. This local goal has to satisfy a more general goal, which concerns the desired velocity. A general architecture of the driving schema for implementation is organized at different levels. On top level are a few schemas: accessing a highway, driving alone, following, overtaking, and exiting the highway. The transition conditions rely on the traffic situation. For example, if the driver is alone on the highway, one of the expectancies will be to reach a slower vehicle. If this expectancy is met then he will shift to either following or overtaking, depending on the range and range rate with the reached vehicle.

As discussed above, the driving schemas are in the knowledge database and their task is to systematically organize the driving behavior. Especially general driving maneuvers such as driving-alone, car-following and lane-changing case will be focused and designed here. A finite state machine is proposed to realize implementation of driving schema. The driving schemas composed of the simplified discrete states are shown in Figure 10. In the case of driving-alone schema, it is assumed that a driver scans road environment as a function of his/her expectancies. One of them is to reach a slower vehicle. At this moment, the driver will prepare a switch to either the following or overtaking schema by estimating the range-rate. This range-rate is associated to an index that will activate the appropriate schema. Its objective is to maintain a driver's desired speed. To achieve the goal, environmental road data including the adjacent lane is perceived and processed. Then corresponding data as well as message commands will be generated and sent to an operational module.

In the following schema (see Figure 5), Safety 1 is performed through a decision map, which is described in the Section 3.1.3. Since a goal of the following maneuver is here to track a comfortable zone by the above hypothesis, two control states, range-rate and time-gap control state, are included in the following driving schema. The main role of those states is to activate local controllers in the operational module in order that a driver can apply proper control action to achieve the goal. Transition of the two control states is based on the perceived range-rate under the prerequisite that safety for following is guaranteed. As shown in the figure, the transition from the range-rate control to the time-gap control state happens when the perceived range-rate is zero and vice versa. If the driver feels dangerous, the Check Safety 1 goes to a Read Command state after updating the adjacent information through the Scanning state.

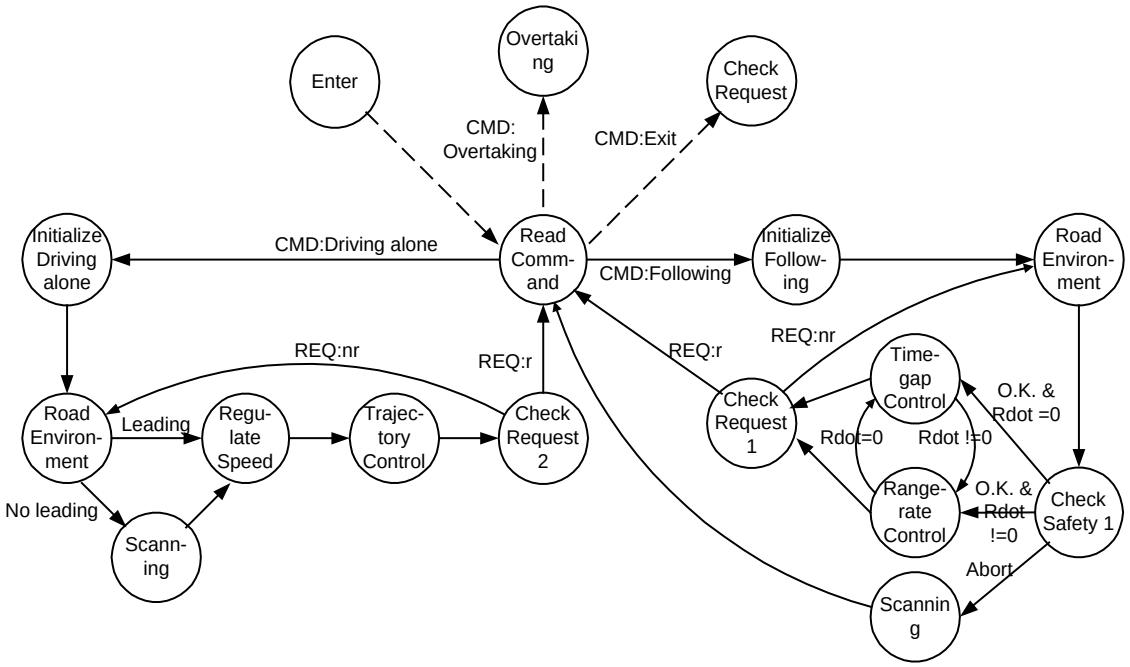


Figure 10: Schematic Diagram of Car –following and Driving-alone Schemas

Figure 11 presents the finite state machine of the overtaking schema as it is in the knowledge base. The lane-change control state in the figure is linked with the regulation layer in the operational module in order to execute the lane change maneuver. Two safety-check logic based on the two regional decision maps, which are described in the section 3.1.3, are proposed. The Safety 2 in the figure works based on the second regional decision map (see Figure 8). If the driver is in the dangerous zone, the state goes to "Check Range & Range-rate" and "Read Command". If he is in the critical zone, the state stays unless he is in either the dangerous or comfortable zone. Otherwise, the state goes into Lane-Change Control state. Then it will activate the corresponding local controller in the operational module. The Safety 1 is performed by use of the first decision map (see Figure 5) for car following with respect to a leading vehicle in the adjacent lane.

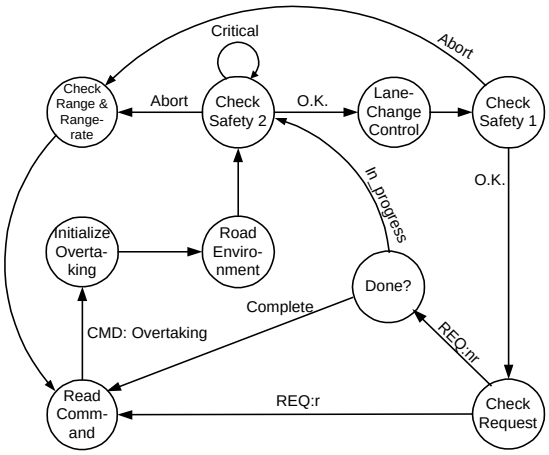


Figure 11: Schematic Diagram of Schema for Overtaking

3.2.2 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.

Here also, a finite state machine is proposed to implement the categorization in simulation and is shown in Figure 12. Since a straight highway is assumed to have multiple lanes rather than a single lane, the overtaking maneuver is considered so that a driver does not necessarily apply braking for a slower leading vehicle and can overtake it. Interactions of the two schemas depend on transition conditions based on a decision logic that follows later in detail. Two buffers and two channels are used to interface between the driving schema and the categorization as used to link between a coordination layer and a regulation layer for vehicle automation. They are used to communicate with a driving schema (see Figure 3.2): Command (CMD), Flag (FLAG), Request (REQ), and Response (RES). The interaction is facilitated by the presence of two buffers that can be used to store the commands (CMD) and responses. The channel has only binary information, such as response/ no response or request (r)/no request (nr).

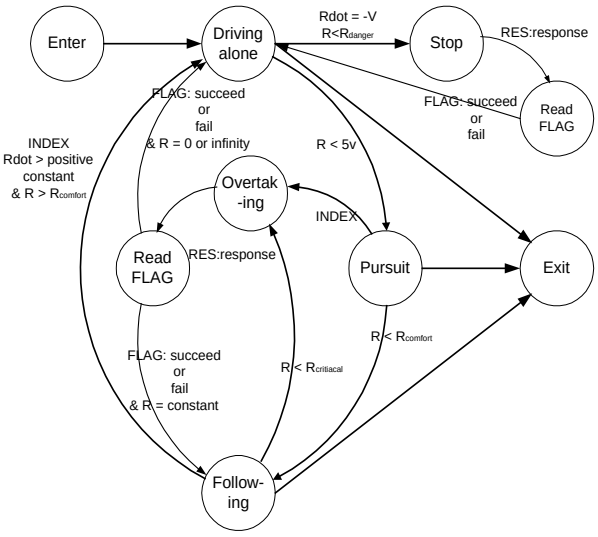
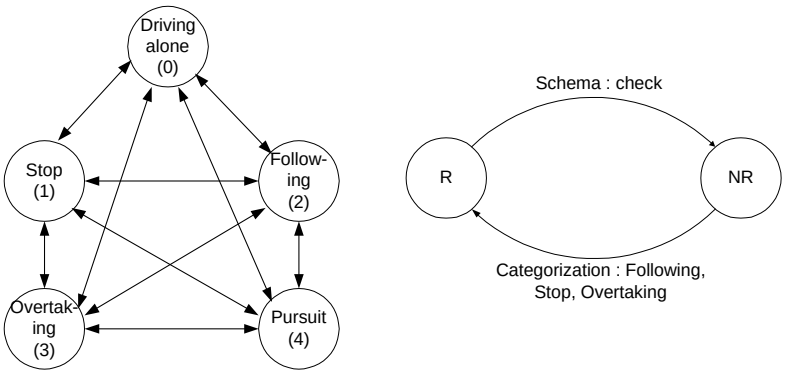
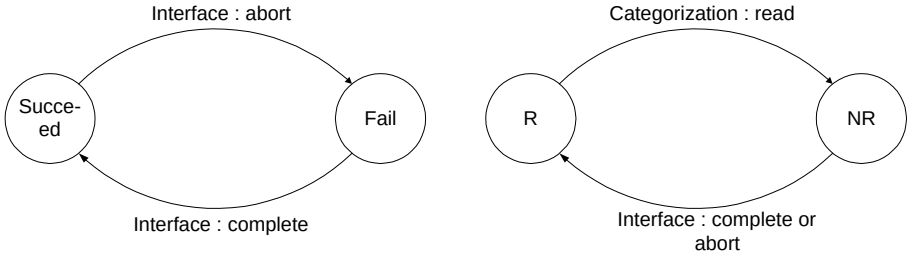


Figure 12: Schematic Diagram of Categorization



(a) Command (CMD) and Request (REQ)



(b) Flag (FLAG) and Response (RES)

Figure 13: Interactions between Categorization and Driving Schema

3.3 Operational/ Execution Modules

The operational module interacts with the perception and the tactical modules as shown earlier in Figure 1. Its task is to receive error signals and commands from the tactical module and translate them to throttle, steering and braking input for the actuators on the vehicle. For this purpose it utilizes several continuous time control laws that make use of the information provided by the perception module to calculate the actuator inputs required for a particular maneuver. For instance, if the driver wants to maintain the preferred speed when any leading vehicle is not detected, the operational module involves a control law for preferred velocity tracking as well as vehicle dynamics and human-factors considerations.

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 operation module is proposed: regulation and lower-level layer. Consequently, a four-layered hierarchical structure is built into the tactical and operational modules as presented in Figure 14.

Based on Figure 5, a hypothesis is that a driver will minimize the time leading up to Zone II, i.e., the comfortable following zone, and maximize the time within Zone II. According to the hypothesis, the control objective for following a car is to be in the Zone II, the control behavior will reflect this.

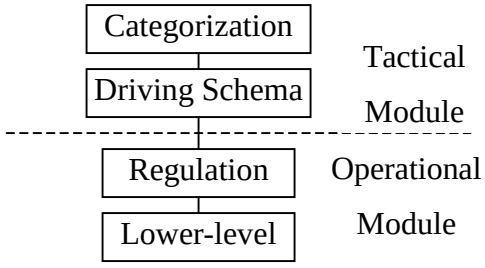


Figure 14: Hierarchical Structure of Tactical and Operational Module

For instance, suppose that the driver is located in Zone V. Since a driver has the perception of closing (range-rate), he begins to reduce velocity in order to traverse either to Zones II, III, or IV. Once the driver enters Zone II, he feels comfortable, and he will maintain current throttle pedal position. However, if the driver enters Zone IV, he will decelerate using either brake pedal or engine brake to avoid a rear-end crash. Otherwise, he will choose a schema between changing of lane and following a leading car, based on road environment information such as the positions of the vehicles in the adjacent lane.

3.3.1 Regulation Layer

Four different controllers are proposed for performing four driving maneuvers in the categorization (see Figure 12): following, driving alone, pursuit 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 comfort zone based on the time-gap and range-rate perception model (see Figure 15).

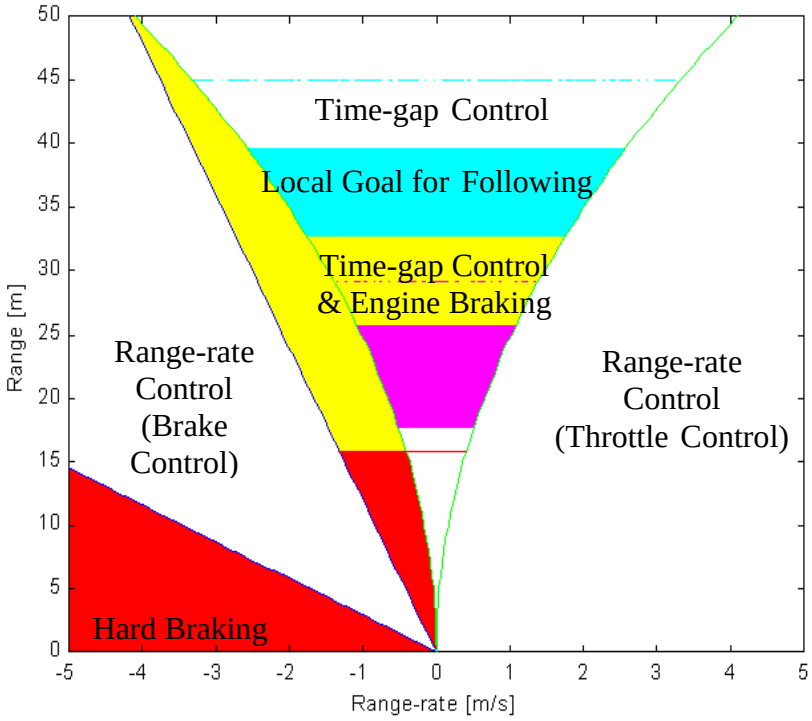


Figure 15: Description of the control used in the different region of the map

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. That is, when time-gap for the comfortable zone is selected between a comfortable time-gap, T_{comf}, and a critical time gap, T_{crit}, desired range for the time-gap control is defined as follows:

$$R_{des} = \begin{cases} T_{comf} \cdot V & if \quad R > T_{comf} \cdot V \\ T_{crit} \cdot V & if \quad R < T_{crit} \cdot V \\ R & otherwise \end{cases} \tag{6}$$

where R is the distance between a leading and a following vehicle. Feedback error for the time-gap control is:

$$S_1 = R_{des} - R \tag{7}$$

If the range is between $T_{comf} \cdot V$ and $T_{crit} \cdot V$, the feedback error will be zero, which means there is no change of control input in the lower-level layer. For the range-rate control, the feedback error is defined as:

$$S_2 = V - V_l = -\dot{R} \tag{8}$$

where V_l is the velocity of a leading vehicle and $\dot{R}$ is the perceived range-rate based on the range-rate perception model. Furthermore, the trajectory control is designed to keep a desired speed that is chosen by the driver. The lane-change control is proposed to change a lane 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 as done above.

Each controller is activated by a message from the driving schema as shown in Figure 11. The message is chosen in the tactical module based on the categorization and decision map. Once a controller is activated, the corresponding desired value and feedback error would be calculated and sent to a lower-level layer, which will be described next.

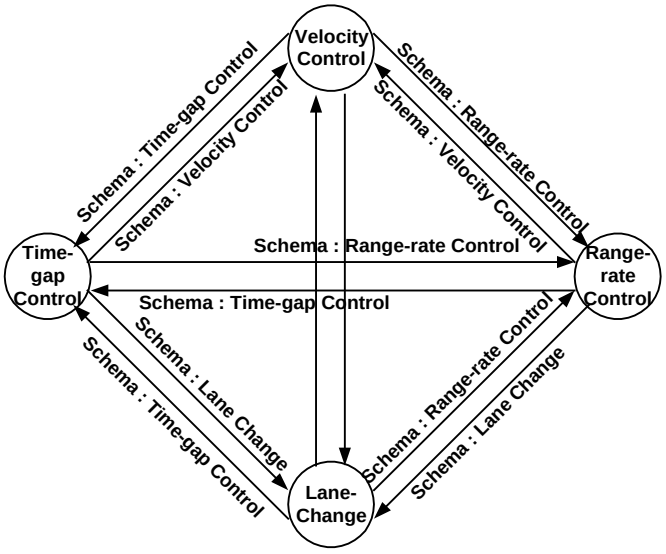


Figure 16: Schematic Diagram of Regulation Layer

3.3.2 Lower-level Layer

It is assumed that the driver is skilled at manipulating the actuators in the vehicle to obtain the desired speed and time-gap. Under that assumption, control inputs to a vehicle are calculated in the lower-level layer based on a vehicle model which can be included in the simulation. For instance, in the case of a two-dimensional dynamic model, a throttle angle, a brake pressure, and a steering angle should be calculated and acceleration for a kinematic model should also be provided. A sliding control approach has been used in the operational module in order to achieve a goal of each driving maneuver. Four different sliding surfaces can be defined in the controllers of the above regulation layer and one of them will be chosen. Then, its 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. More detailed description related to the proposed operational module will be presented later.

3.3.2.1 Vehicle Model

Various levels of vehicle model have already been developed and included in libraries of simulation tool, Smart-AHS. Choice of a specific model is based on purpose of simulation and computation capacity. Here, two different vehicle models, kinematic and two-dimensional dynamic vehicle model, will be used in both macro- and micro-level simulations and described next. Since lateral motion dynamics is much more complicated than longitudinal one, the lateral vehicle dynamics will not be described here but more detailed description can be found in Pham (1996).

Kinematic Vehicle Model

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. Since each vehicle is assumed to be a lumped mass, simple kinematics can be applied. Then, the vehicle model is derived:

$$\ddot{x} = a \tag{9}$$

where x is the distance and a is the acceleration of the vehicle.

$$T \cdot \dot{a} + a = u \tag{10}$$

where T is the time constant which can be determined by experimental driving data and u is the desired acceleration.

Two-Dimensional Dynamic Model

A three-state vehicle model is introduced for the purpose of controller development in this section. Modeling of each vehicle component for simulation is described here. A longitudinal vehicle model is simplified to a one-state model based on kinetics. It is assumed that a right and a left side of a vehicle are symmetric so only a half car model could be considered. By balancing the forces in the longitudinal direction and using the moment balance law, the longitudinal equations of motion are:

$$J_e \cdot \dot{w}_w = M_e - h \cdot F_{tr} - M_r - M_b \tag{11}$$

$$m \cdot \dot{v} = F_{tr} - F_d \tag{12}$$

where M_e is the driving torque and J_e is the effective rotational inertia of wheels:

$$J_e = J_w + \frac{J_{eng}}{R_g^2} \tag{13}$$

where J_{eng} is the rotational inertia of engine, w_w is the wheel speed, h is the effective wheel radius, and M_b denotes the braking torque. F_{tr} is the tractive force and m is the mass of the vehicle. M_r is the rolling resistance moment and is taken as an

experimentally determined constant. Finally, F_d is the aerodynamic drag force and has the form:

$$F_d = C_a \cdot v^2 \tag{14}$$

where C_a is the aerodynamic drag coefficient. At this point, we make the first simplifying assumption that no slip occurs at the wheels. Then,

$$\begin{aligned} v &= h \cdot w_w \\ \dot{v} &= a = h \cdot \dot{w}_w \end{aligned} \tag{15}$$

Using this assumption and substituting the expressions for the tractive forces in Equation (11) and (12) yields:

$$\dot{v} = \frac{M_e - M_b - M_r - C_a \cdot h \cdot v^2}{m_e} \tag{16}$$

where m_e is the equivalent moment of inertia and defined as:

$$m_e = \frac{J_{eng} + R_g^2 \cdot (J_w + m \cdot h^2)}{R_g^2 \cdot h} \tag{17}$$

3.3.2.2 Design of Lower-level Controller

Control inputs to a vehicle are calculated in the lower-level layer: a throttle angle, a brake pressure. A sliding control approach has been suggested to develop a representation of the operational module. A sliding surface error for the time-gap control is:

$$S_1 = R_{des} - R \tag{18}$$

Differentiating the above equation, the sliding surface is:

$$\dot{S}_1 = \dot{R}_{des} - \dot{R} = T_1 \cdot \dot{V} - \dot{R} = -\Lambda_1 \cdot S_1 \tag{19}$$

where Λ_1 is a constant gain and $\dot{R}$ is the range-rate. Since the range-rate is zero due to the threshold of range-rate perception, desired acceleration is:

$$a_{des} = \dot{V} = -\frac{\Lambda_1 \cdot S_1}{T_1} \qquad \text{where} \quad T_1 = \begin{cases} T_{comf} & if \quad R > T_{comf} \cdot V \\ T_{crit} & if \quad R < T_{crit} \cdot V \\ C & otherwise \end{cases} \tag{20}$$

where C is the constant. For the range-rate control, the sliding surface error is defined as:

$$S_2 = V - V_l = -\dot{R} \tag{21}$$

where V_l is the velocity of a leading vehicle. After following the same procedure, we obtain the desired acceleration.

$$a_{des} = \dot{V} = -\Lambda_2 \cdot S_2 \tag{22}$$

where Λ_2 is a constant gain and it is assumed that velocity of the leading vehicle is constant.

In order to calculate either the desired acceleration or throttle pedal position, one of longitudinal vehicle dynamics, (9) and (12), is considered. For the time-gap control, the

desired acceleration of the kinematic model combining the equation (9) with the equation (20) is:

$$u = a_{des} = -\frac{\Lambda_1 \cdot S_1}{T_1} \tag{23}$$

In the case of the dynamic model, combining the equation (16) with the equation (20), the desired engine torque is:

$$M_{eng,des} = (r \cdot F_r + r \cdot C \cdot v^2 - m_e \frac{\Lambda_1 \cdot S_1}{T_1}) \cdot R_g \tag{24}$$

where R_g is the gear ratio. The desired throttle angle is obtained from the engine map.

$$\delta = f(M_{eng,des}, V) \tag{25}$$

For the range-rate control, the same approach is used to calculate both the desired acceleration and engine torque respectively.

$$\begin{aligned} u = a_{des} &= -\Lambda_2 \cdot S_2 \\ M_{eng,des} &= (r \cdot F_r + r \cdot C \cdot v^2 - m_e \cdot \Lambda_2 \cdot S_2) \cdot R_g \end{aligned} \tag{26}$$

Similarly, desired braking torque can be calculated from the equation (16) when the driving torque becomes a minimum value with respect to current speed.

4 CASE STUDY AND SIMULATION

There are many driving situations for highway driving. These can be categorized into normal and emergency driving. Of these, several cases, were investigated through the simulation of different scenarios. In the normal driving case, following and lane changing maneuver were simulated. In the emergency driving case, two possible situations were distinguished: one was due to lack of visual attention and the other was due to the limitation of physical performance such as the vehicle braking performance. All simulations were performed in the frame of Smart-AHS and all human driver components were implemented by SHIFT.

4.1 Normal driving

For normal driving case, the driver is assumed to be attentive to the driving activity, i.e., in simulation terms, there is no external command in the visual attention allocation. Therefore, all visual attention is distributed in front and sides to perform either following or lane-changing maneuver.

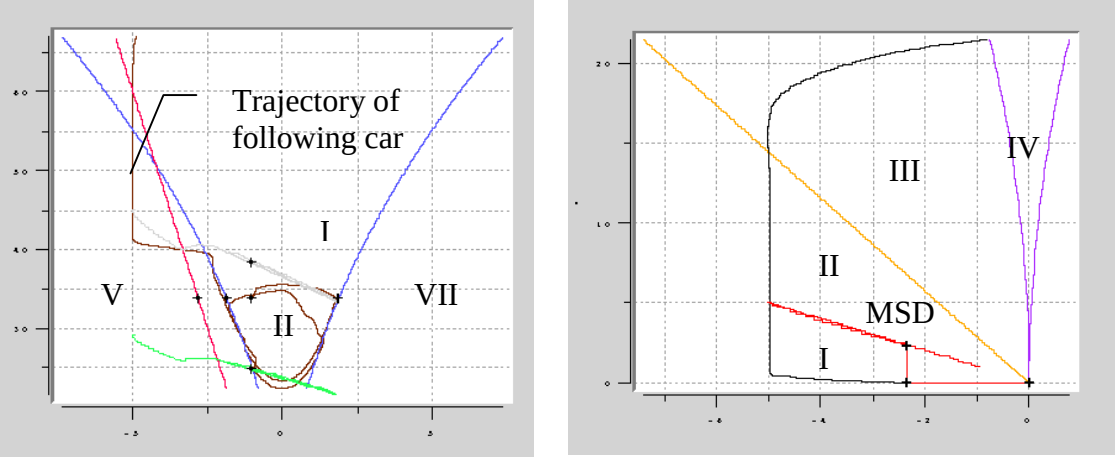
4.1.1 Car-following Case

Two vehicle models that are described in 3.3.2.1 can be used for simulation. For simulation efficiency, we used a simple kinematic vehicle model. On the other hand, in the micro-simulation, a power-train vehicle model (or two-dimensional dynamic model), including engine, transmission and tire components, was used in order to describe driver throttle and brake control in more detail. A specific driving situation using both vehicle models has been simulated and each will be described.

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. If the power-train vehicle model is included in simulation, Figure 17(a) 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 (or Regional decision map II) is used to confirm safety for lane change. For the given example, the range is assumed to be less than MSD (see Figure 17(b)). That is, the driver is in an uncomfortable or a dangerous zone for lane-changing. Thus, the speed is reduced to stay in the initial lane and to maintain a comfortable time gap.

In the case that the simple kinematic model is used to increase computation speed and accommodate hundreds of vehicles in a macro-simulation, the same regional decision maps are shown in Figure18. In order to represent a different type of a driver, who has a different control pattern, engine braking is considered in the operational module. That is, engine braking instead of braking is applied in Zone III and X in the Figure 18.

Consequently he tracks a comfortable zone, Zone II, slowly rather than braking immediately.



(a) Regional Decision Map I (b) Regional Decision Map II

Figure 17: Longitudinal Following Simulation in the Regional Decision Maps (Power-train vehicle model)

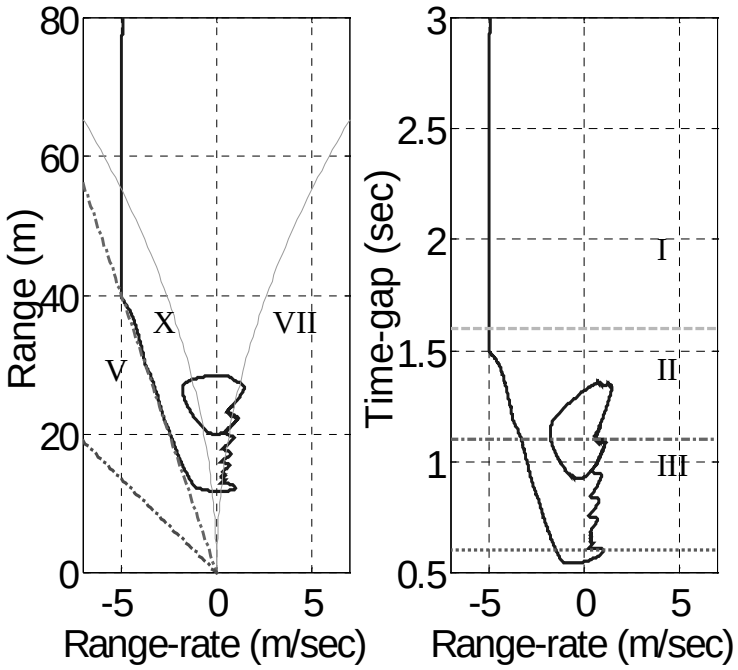
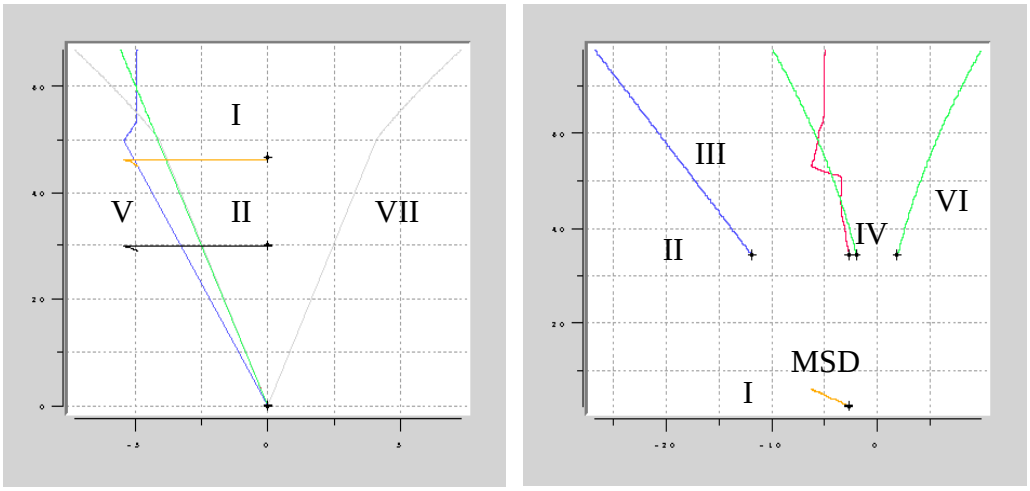


Figure 18: Longitudinal Following Simulation (Kinematic Vehicle Model)

4.1.2 Lane-Change Case

It is assumed that overtaking can happen when the driver is in the zones IV, V, or VI (see Figure 5) because the driver may feel uncomfortable and/or enter into a dangerous situation when following the preceding car. As was done in the longitudinal following case, we will consider both the computational overtaking schema and regional decision map with respect to an adjacent lane so that the driver organizes the overtaking behavior systematically and ensures safety during overtaking.

Figure 19 presents the regional decision maps for following and overtaking as well as the trajectory with respect to a leading vehicle in the next lane. The given initial conditions here are the same than 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 (see figure 19 (b)). After completing the lane-change, all information arrives from decision map I as the driver is in a new following situation.



(a) Regional Decision Map I (b) Regional Decision Map II

Figure 19: Overtaking Simulations in the Decision Maps

4.2 Emergency Case

Many driving situations can cause an emergency event on the highway. Potential problems are visual distraction and poor braking performance under hard braking of a lead vehicle. The two situations could happen either independently or simultaneously. In simulations, each situation was considered independently and as a worst-case scenario.

4.2.1 Emergency caused by hard braking of the leading vehicle

Since each vehicle has its own characteristics of braking performance, it is not easy to define a minimum distance to avoid rear-end collision. If both maximum deceleration of a following car and current deceleration of a leading vehicle are known, based on kinematics, the minimum distance can be defined as:

$$R_{\min} = \frac{1}{2}\left(\frac{V^2}{a_{\max}} - \frac{V_l^2}{a_l} \right) + V \cdot \tau \qquad (27)$$

where a_{max} and a_l are the maximum deceleration of the following one and the deceleration of the leading one respectively, and τ accounts for the system and driver delays. Therefore, when the leading vehicle decelerates with a_l, if the range is less than R_{min}, the collision cannot be avoided even though the maximum braking, i.e. maximum deceleration is applied. Otherwise, the collision will not happen with the maximum deceleration. Moreover, the parameter, τ, is an important factor to calculate the minimum distance. It is not a constant but a variable and is related with visual attention, which is described next. That is, if a driver is distracted visually or by something else, the value will increase and results in increment of the minimum distance.

4.2.2 Emergency caused by visual distraction

It is assumed that driver's visual attention is distracted by some external commands. The external commands account for other traffic visual behaviors such as answering a cellular phone, turning on a radio, or reading and interpreting traffic signals and signs. As mentioned before, the behavior is modeled as pure time delay and initiated by external command.

A worst-case scenario will be used to illustrate the difference between the normal and emergency case. When a leading vehicle decelerates at –0.39g, responses of a following one are represented in Figure 20 and in Figure 21 where VA lines are the case where there is the external command and Attentive is the case without any external command. Under the assumption of the worst-case scenario, a driver is assumed to be in visual distraction during 2 second at first. In the given scenario, much deviation of range and time-gap is shown, compared with attentive case (see Figure 20), and larger deceleration by braking is required to go back to either a comfortable or a critical zone (see Figure 21).

In consequence, the simulation results show that hard braking situation can be turn into unexpected hard braking situation with adding visual distraction, which is one of the emergency cases. Furthermore, if there is a limit of braking performance, as mentioned in the previous section and larger deceleration of a leading vehicle is given, a rear-end collision can happen due to lack of visual attention.

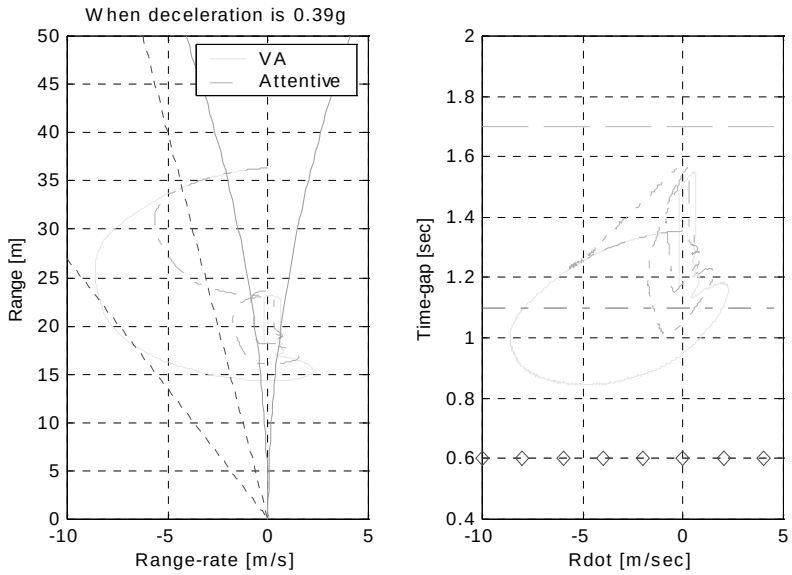


Figure 20: Comparisons between Attentive and Inattentive Case Simulation

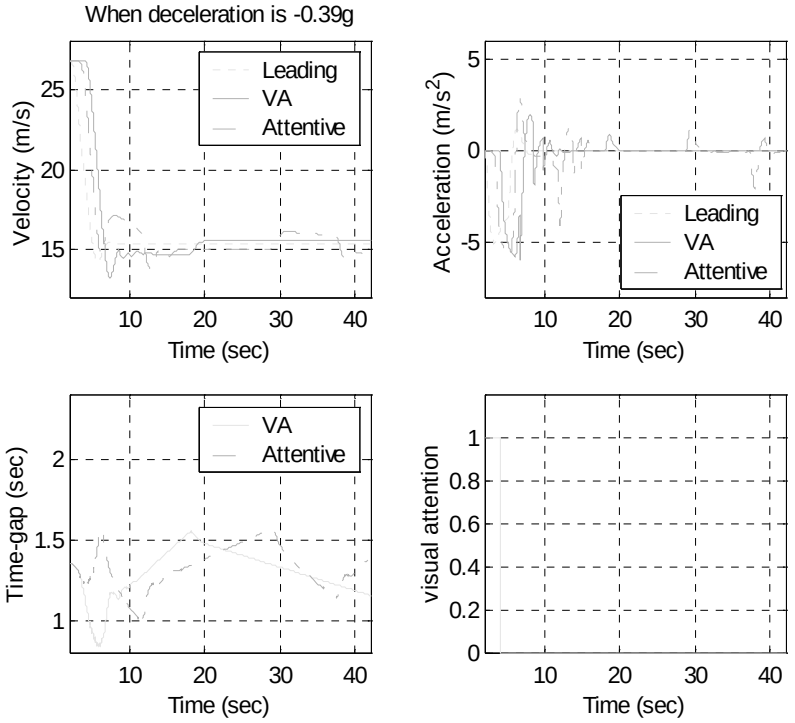


Figure 21: Time Responses of Attentive and Inattentive Cases

5 Calibration

The simulation results in the previous chapter are quite sensitive to variations in the parameters of the model (e.g., time-gap thresholds, TTC for braking or gain constants). Therefore, in order to improve the "human-like" aspect of the simulation, it is necessary to tune these parameters using real-world data. Two different methods are usually applied in order to collect data for driving behavior description. One consists of collecting data at one location, over a few hundreds meters. This method permits to gather some information for a lot of different drivers but does not describe accurately the evolution of driver's velocity or time-gap over a long period of time. The other method is to instrument a vehicle that is driven in real traffic by one person for a long period of time. This method has the advantage of providing interesting insight about the way a driver behaves. From this behavior it is possible to set more accurate model parameters, i.e. velocity, range, range-rate. It also allows the possibility to deduce other parameters from them, such as TTC and thresholds for the different zones considered for following.

The data used for the calibration were collected by the University of Michigan, Transportation Research Institute (UMTRI) during the Intelligent Cruise Control – Field Operation Test (ICC-FOT). These data partially fit the needs of the model. UMTRI provided the data for the 108 voluntary drivers who participated in the test corresponding to certain specification, i.e.:

- manual driving (the two other situations were Conventional Cruise Control and Intelligent Cruise Control),
- velocity superior to 55 mph (24.5 m/s),
- presence of a leading vehicle in the radar range (about 100 m).

The provided data are only on the form of vehicle-data, there is no description of the traffic environment. In order to focus on following behavior, it was decided to isolate the events for which the time gap was below 2 sec. over a steady period of at least 30 sec. The boundary of 2 sec (time gap) has been chosen because it corresponds to the limits of the range-rate perception and is closed to Otha's results (time-gap limit for comfortable following is 1.7 sec.). Therefore, the tuning of the model concerned only situation of close "following".

5.1 Driving Behavior Parameters

There are two critical parameters which are considered here: one is a mean time-gap value where the range-rate is not perceived based on the proposed perception model and the other is a mean time-to-collision value where either engine brake or brake is initiated.

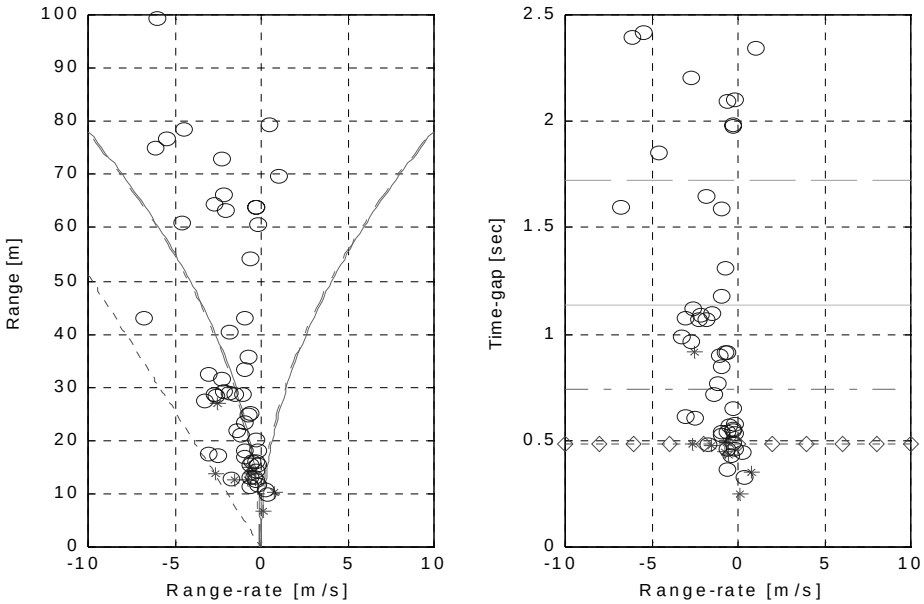


Figure 22: Engine Brake and Brake Initiation of Driver 56

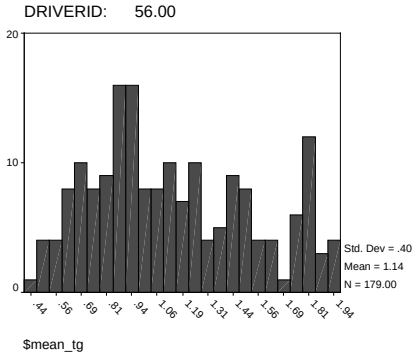
In order to obtain the above values, it was necessary that the driving data reproduced from the original FOT data through filtering and restricting conditions. For instance, one of filter design technique (Zero-phase forward and reverse digital filtering) was used to filter out range-rate and velocity data. Also it is assumed that driving duration for each event should be at least greater than 30 second in order that the event is regarded as following behavior. That is, any event, which did not last 30 second was not considered for calculation of the mean time-gap.

Since the FOT data provided objective data about following, the threshold for defining the following zones described earlier were to be determined with engine brake and brake action. The assumption underlying this choice is that the engine brake is applied when the driver goes into either critical zone or range-rate perception threshold zone and the brake is performed if the driver thinks the following situation is becoming dangerous. Figure 22 presents initiation of the engine brake and brake actions of Driver 56. In the figure, "*" stands for braking and "o" represents engine braking. Furthermore, there were criteria applied before doing statistical analysis. First, any engine brake and brake event of which time-gap was greater than mean time-gap was excluded because such action could be for tracking the desired speed rather than following the leading vehicle. Second, any event, which occurs in the positive range-rate plane, was not considered in calculating the range-rate perception threshold since it could be assumed that this event happens due to not the range-rate control but the time-gap control. Under these restrictions, the range-rate perception threshold and critical zone were obtained statistically.

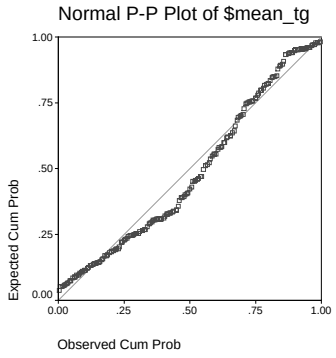
One approach to define the comfortable zone is to use the time-gap distribution under the above condition of at least 30 second duration following. Two methods could be proposed to determine the comfortable following zone. First, if the time-gap distribution

can be assumed as a normal distribution in some cases, the zone can be found using both mean and standard deviation. Second, there is a relatively large peak in the tail of the distribution around time-gap at 1.7 seconds, which is usually greater than mean time-gap. According to range and velocity distribution in the latter cases, both distributions are approximately normal. That is, if the range is getting larger in a high speed which is relatively greater than a mean velocity, the driver tend to maintain the current speed rather than track the velocity of a lead car. Otherwise, a driver could speed the velocity up to reduce the range. Then the time-gap will not be changed with large variation and cross the upper limit of the comfortable zone. For instance, the time-gap distribution and normal approximation of Driver 1 and 56 are shown in figure 23 and figure 24.

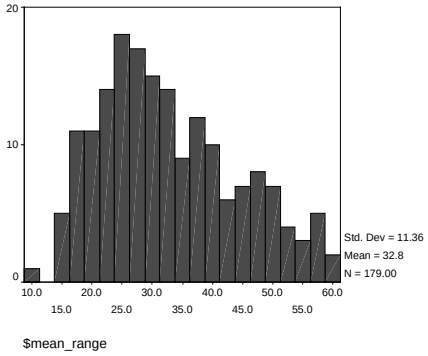
In the figure 23(a), there is a large peak in the tail of the time-gap distribution and it results in deviation with respect to the normal distribution as shown. The corresponding range and velocity distributions (see figure 23(c) and (d)) were investigated and there was no peak in the tail. This could mean that a driver does not often exceed a specified speed in a large range and it results in the peak in the time-gap distribution. This suggest that the initiation time-gap of the last peak can be considered as an upper limit of the comfortable zone. Based on the above approach, comfortable boundaries of all test drivers are listed in Table 1.



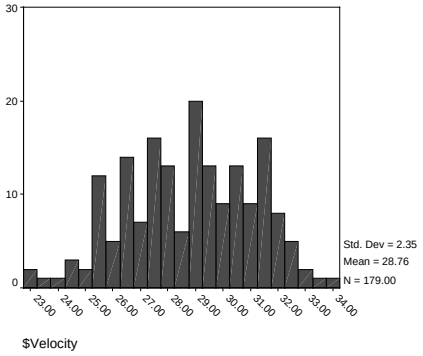
(a) Time-gap Distribution



(b) Normal Distribution Approximation

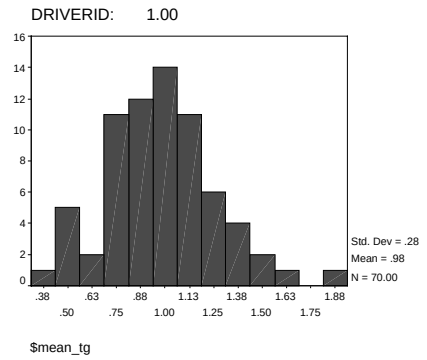


(c) Range Distribution

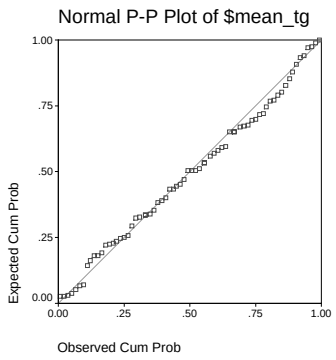


(d) Velocity Distribution

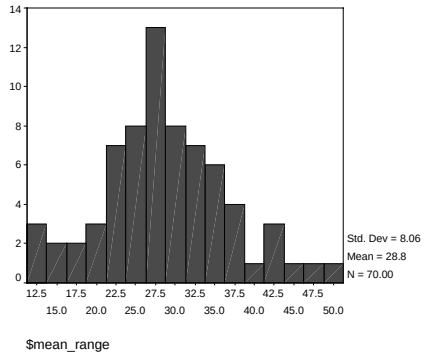
Figure 23: Distributions and Normal Distribution Approximation (Driver 56)



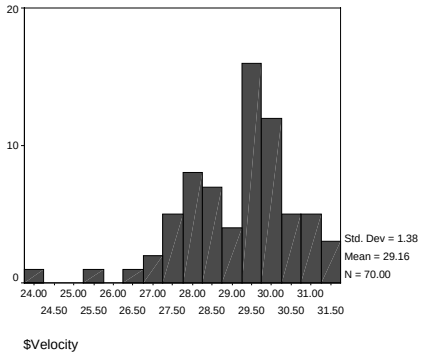
(a) Time-gap Distribution



(b) Normal Distribution Approximation



(c) Range Distribution



(d) Velocity Distribution

Figure 24: Distributions and Normal Distribution Approximation (Driver 1)

Alternatively, Figure 24 presents an example of a driver without any peak in the tail. As seen in the figure 24(b), the time-gap distribution is very close to the normal distribution. Since the velocity in the Figure 24(d) is relatively small during following maneuver, Driver 1 seems to smoothly track the velocity of a leading vehicle and results in no peak in the time-gap distribution tail. In this case, the comfortable time-gap boundarie can be chosen by use of the mean and standard deviation under the normal distribution approximation. Mean and standard deviation of time-gap of all drivers are also listed in the Table 1.

DriverId	StyleID	Age	Gender	mean_tg	min_ttc	error	Tg_critical	Tg_brk	mean_TTC	Tg_comfortable
1	4	40-50	Female	1.003	11.8668	0.595	0.8251	0.6599	22.7748	N/A
4	4	20-30	Male	0.9	4.6399	0.303	0.7879	0.7083	13.6244	1.72
5	3	40-50	Female	0.998	7.3021	10.53	1.061	1.0732	10.5275	1.66
6	3	40-50	Female	1.476	28.264	0.254	1.2877	No Brake	N/A	N/A
7	3	60-70	Male	1.094	5.2991	0.508	1.0373	0.8813	13.59	1.78
8	2	40-50	Female	0.793	10.1009	0.197	0.9629	0.884	20.7699	1.78
9	1	40-50	Female	1.335	16.0387	0.243	1.1709	1.313	N/A	1.78
10	4	20-30	Female	0.693	6.4832	0.329	0.6596	0.4399	22.0893	1.35
12	4	40-50	Female	0.844	5.757	0.238	0.7313	N/A	5.757	N/A (1.22)
14	4	40-50	Male	1.539	8.8114	0.553	1.1127	0.3478	8.8114	N/A
15	5	20-30	Female	1.27	8.6076	0.653	1.0452	0.8934	11.7555	N/A

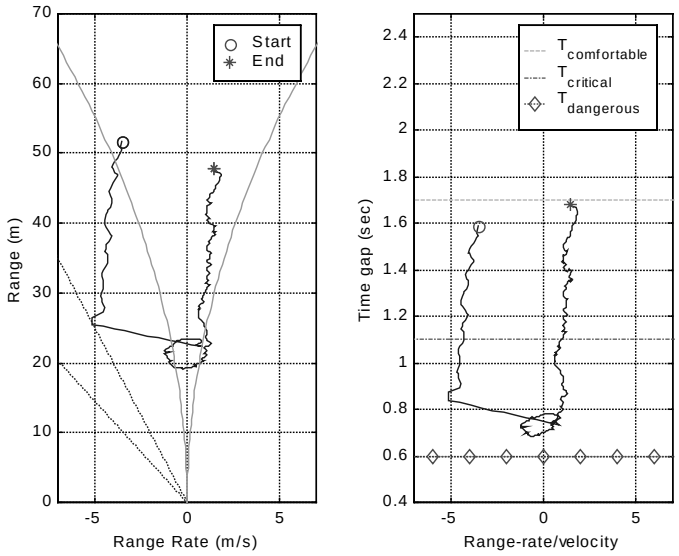
DriverId	StyleID	Age	Gender	mean_tg	min_ttc	error	Tg_critical	Tg_brk	mean_TTC	Tg_comfortable
17	5	40-50	Male	1.514	6.3553	0.17	1.1121	0.7113	6.5275	N/A
18	5	60-70	Male	1.504	25.8651	0.487	0.971	No Brake	N/A	N/A
20	1	60-70	Male	1.104	17.9737	0.395	1.6633	1.4974	N/A	N/A
21	4	40-50	Female	1.131	12.2742	0.044	0.9472	0.974	12.2742	N/A
23	2	40-50	Female	1.422	14.4047	0.55	1.2137	N/A	N/A	1.66
25	2	40-50	Female	1.31	12.6367	0.446	1.3466	0.9549	N/A	1.66
26	5	40-50	Female	1.242	15.4725	0.805	1.0918	0.4001	N/A	1.47
29	3	40-50	Female	0.942	8.3042	0.949	0.9312	1.4116	N/A	1.28
30	3	20-30	Female	1.373	15.005	0.761	0.9021	1.024	15.005	N/A
31	4	20-30	Female	1.121	4.0309	0.229	0.8426	0.7519	19.7804	1.34
32	5	60-70	Male	1.129	5.3305	0.239	1.0954	0.6847	14.6035	1.72
33	5	20-30	Male	1.144	14.338	0.225	1.2494	0.8727	14.338	1.6
34	5	40-50	Male	1.154	6.4239	0.545	0.9892	0.9028	11.007	1.78
35	1	40-50	Male	1.365	11.4997	0.315	1.275	1.2338	11.4997	1.59
39	5	20-30	Female	1.138	141.02	1.604	1.3091	No Brake	N/A	N/A
40	3	60-70	Male	1.142	8.6324	0.557	1.1356	1.0503	17.4464	1.72 (1.65)
41	1	20-30	Male	0.798	2.5759	0.154	0.572	0.5345	7.5925	1.35
42	4	20-30	Female	0.96	10.0706	0.259	0.8038	0.9726	13.4948	1.41
44	1	20-30	Female	0.96	7.7187	0.875	1.1936	1.4169	11.8017	N/A
45	2	20-30	Female	1.16	11.9297	0.364	1.1019	N/A	N/A	1.35
46	2	60-70	Female	1.666	13.909	0.472	1.2116	1.119	16.6528	N/A
47	3	60-70	Male	1.192	26.8643	0.496	0.9914	1.2105	N/A	1.85
48	2	60-70	Female	1.701	N/A	N/A	1.0697	No Brake	N/A	N/A
49	5	20-30	Female	1.066	8.0075	0.535	0.9211	0.8772	16.9382	1.72
50	1	20-30	Female	0.992	6.4492	0.221	0.9116	1.1339	9.7182	1.47
51	1	20-30	Female	0.758	5.8113	0.092	0.8395	0.6141	21.5188	N/A
52	4	20-30	Female	0.856	4.3847	0.147	0.6045	0.7087	10.58	0.91
54	5	20-30	Male	1.383	7.0859	0.712	1.1773	1.0725	16.5699	1.6
55	3	20-30	Male	1.669	6.9989	0.042	0.8992	0.9334	7.5643	N/A
56	5	20-30	Female	1.139	5.1131	0.214	0.7372	0.4821	16.5328	1.72
59	4	20-30	Male	0.917	6.2122	0.464	0.6776	0.6273	15.4439	N/A
61	3	20-30	Male	1.2	7.0812	0.343	1.0175	0.9594	8.6796	1.47 (1.78)
62	1	60-70	Male	1.05	16.6462	0.535	0.95	1.0565	16.6462	N/A
63	3	20-30	Male	1.205	8.7634	0.614	0.9972	0.8609	14.3996	1.78
65	5	60-70	Female	1.14	8.7361	0.469	1.1158	1.0397	8.8643	1.41
66	3	60-70	Male	1.096	9.1897	0.34	1.1415	0.8361	20.0596	N/A
67	2	60-70	Female	0.986	38.8888	0.868	1.3349	1.3307	N/A	N/A
68	5	20-30	Male	1.08	5.3962	0.652	0.9683	0.9063	13.931	1.78
69	5	60-70	Female	1.826	8.7099	0.684	1.0493	0.6949	N/A	N/A
70	2	60-70	Female	1.269	14.2646	0.639	1.2698	1.1302	14.2646	1.85
72	5	60-70	Female	1.505	13.1964	1.286	1.1341	0.9918	13.1964	N/A
73	4	20-30	Female	1.036	3.9519	0.302	0.6991	0.6207	14.6705	1.78
75	3	40-50	Male	1.389	8.3106	0.496	1.3516	1.0584	14.7221	N/A
76	4	20-30	Male	0.978	5.0338	0.196	0.7883	0.7559	20.4431	1.78
77	5	60-70	Female	1.162	7.138	0.609	0.8385	0.7591	12.3326	1.78
78	3	40-50	Male	1.26	6.2552	0.386	1.0644	0.9987	9.829	N/A
79	3	20-30	Female	1.346	12.703	0.033	1.0273	1.0253	12.703	1.85
80	4	40-50	Female	1.113	5.0647	0.346	0.7188	0.5732	15.3512	1.78
81	5	40-50	Male	1.156	4.3384	0.578	1.0528	0.8925	15.8674	1.47
82	3	60-70	Female	1.36	9.701	0.732	1.1685	1.3461	N/A	1.72
83	2	60-70	Female	1.719	16.5326	0.732	1.2423	0.6362	N/A	N/A
84	5	40-50	Female	1.155	14.1752	0.468	1.2173	N/A	N/A	1.72
85	4	60-70	Male	0.808	2.2616	0.244	0.6565	0.5887	14.0204	N/A
87	4	20-30	Female	0.713	3.7628	0.147	0.6358	0.5822	15.8464	N/A
88	4	40-50	Female	0.981	6.2795	0.568	0.8385	0.8134	18.584	1.78

DriverId	StyleID	Age	Gender	mean_tg	min_ttc	error	Tg_critical	Tg_brk	mean_TTC	Tg_comfortable
89	3	20-30	Male	1.159	5.3781	0.606	0.9475	0.847	11.1266	1.78
90	5	60-70	Female	1.32	7.8296	0.763	1.0763	1.1435	8.7783	1.72
92	5	40-50	Male	1.375	16.0619	0.832	1.2167	1.5103	N/A	1.85
93	3	20-30	Male	1.275	12.4197	0.512	1.2467	0.9838	19.4391	1.72
94	5	40-50	Male	1.083	11.0142	0.43	0.9325	1.2739	11.0142	1.78
96	5	40-50	Female	1.175	8.099	0.461	1.0753	0.8691	14.8549	1.72
97	5	60-70	Female	1.308	6.9039	0.539	0.9333	0.6741	6.9039	1.85
98	1	20-30	Male	1.378	10.9961	0.322	1.0883	0.897	18.4279	1.47 (1.78)
99	4	40-50	Female	1.308	8.0608	0.635	1.0085	0.8578	16.2807	N/A
100	5	40-50	Male	1.027	6.9602	0.364	0.7979	0.7746	10.0729	1.78
102	2	40-50	Male	1.349	7.6356	0.516	1.3306	1.1338	16.6914	1.78
103	1	60-70	Male	1.663	10.8436	0.84	1.445	1.6797	10.8436	N/A
104	5	40-50	Female	1.329	13.2188	0.884	1.4143	1.3988	13.2378	1.72
105	5	40-50	Male	1.11	8.2192	0.616	0.9904	0.6172	15.1122	1.78
106	2	60-70	Female	1.127	12.7139	0.163	1.5974	2.1181	N/A	N/A
107	1	60-70	Male	1.513	15.6701	0.677	1.3602	1.4161	19.6709	N/A
108	2	60-70	Male	1.444	16.3027	1.156	1.0195	0.9992	N/A	N/A
109	4	20-30	Male	1.028	7.5259	0.275	0.6438	0.5507	12.118	1.47
110	5	60-70	Male	1.124	10.912	0.749	1.1065	0.9006	23.5251	1.72
111	4	40-50	Male	1.045	5.6172	0.364	0.8046	0.7181	16.1508	1.47
112	5	40-50	Male	1.265	5.6738	0.712	1.3364	1.1541	11.2498	N/A
113	2	60-70	Male	1.454	14.7102	0.696	1.2678	0.9946	16.3358	N/A
114	4	20-30	Male	0.739	5.2591	0.104	0.4997	0.4997	16.8076	N/A
115	2	60-70	Male	1.103	20.2193	1.019	1.2434	1.022	N/A	N/A
116	2	60-70	Male	1.623	19.1602	1.66	1.5589	1.5276	N/A	N/A
117	5	40-50	Male	1.255	9.2094	0.128	0.9249	No Brake	N/A	N/A

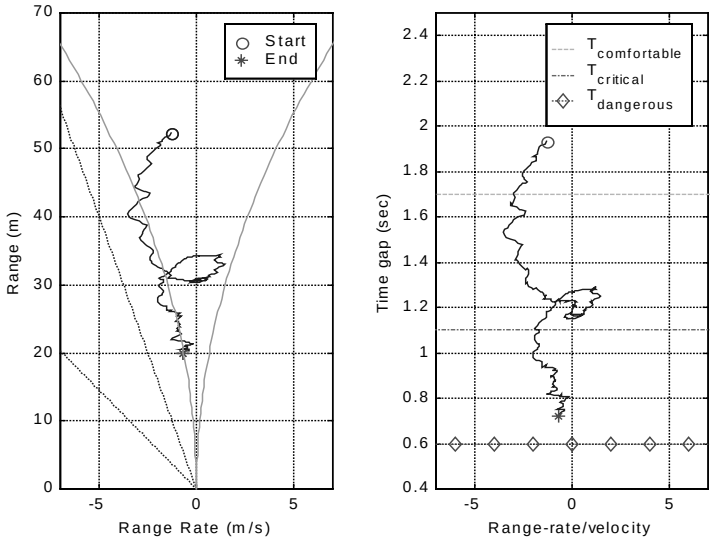
Table 1: Derived values from 92 UMTRI ICC FOT Drivers

5.2 Driver's Characterization

Selection of execution behaviors such as brake, engine brake, throttle control and time-gap is an important factor when categorizing drivers. For instance, figure 25 shows different driving pattern for one following event under different initial conditions. Each graph has two decision maps (see Section 3.1.3 for decision maps description): range-rate vs. range and range- rate vs. time-gap. In the former figure, a following vehicle was initially about 4m/s faster than a leading vehicle. When the following vehicle passed the range-rate perception threshold, which was set by the 5.6 second TTC line, a braking force was activated and the range-rate approached a zone where the range-rate was not perceivable. Once into a critical zone, the driver reduced velocity by means of engine brake and resumed the following maneuver in the comfortable zone. The latter figure also shows a real longitudinal following event for a driver whose driving style was categorized as "Planner". This event lasted 40 seconds. The driver approached the comfortable zone and stayed there while the leading vehicle kept a constant speed. At the end, the leading vehicle slowed down. Consequently, the following vehicle was entering the critical zone. Although the next event is not shown here, the driver finally returned to the comfortable zone by reducing speed. As a result, control action such as the engine brake and brake will be regarded as driving behavior factors.



a)



b)

Figure 25: Experimental Examples of different control pattern

As one would expect it, the behavioral differences among the ICC-FOT drivers are numerous. Nevertheless, even if behavior varies a lot among drivers, a classification of these drivers can be realized upon their following tendency characteristics. Fancher et al. (1998) proposed a very interesting classification of drivers based on two parameters: one represents the tendency for following (far or close) and the other the velocity tendency (faster or slower than the leading vehicle). Each of these tendencies has been represented on an axis. Then a "central zone" around these axes was determined. The central zone limits are 0.6 and 2.25 sec. for the following distance (under .6 is considered close, higher

than 2.25 is considered "far") and -.075 and .075 m/s for the velocity tendencies (under -.075 is slower and above .075 is faster). Each time occurrence without this zone is used to determine the driver profile. There are five categories with the following characteristics:

-**Ultra-Conservative**: this driver tends to be far from the leading vehicle and/or at a slower pace than the followed vehicle

-**Planner**: here also the driver tends to be far but also to go faster than the preceding vehicle

-**Hunter/Tailgater**: those drivers tend to go faster than the preceding vehicle and follow closely

-**Extremist**: in this category are drivers are extreme in more than one of the tendency, this group is the less homogeneous in their tendencies.

-**Flow-Conformist**: the drivers in this group do not show real tendency

As we focused on "close" following events with a time gap smaller than 2 seconds and our boundaries for faster/slower are different (perception model), the benefit of the transfer of this drivers categorization to our analysis is limited. Rather than five categories, the two groups we identify would be the "Hunter/Tailgater" versus the rest of the drivers. The explanation is that both "Planner" and "Ultra-Conservative" drivers are identified based on far following situations that were not considered here. The models parameters developed in the previous part will first be discussed using this group classification, then, the relationship between the parameters and the group will be analyzed.

A one-way Analysis of Variance (ANOVA) was performed for each measure used as a model parameter. The data were analyzed separately for the driving style, age and gender. The statistically significant results are shown in Table 2. The differences rely on the parameters describing the low boundary for following behavior. While some effect could be identified for the driving style and age factors, there is no significant effect for the gender factor.

	mean_tg	min_ttc	error	Tg_critical	Tg_brk	Mean_TTC	Tg_comfortable
Driving style	***	***	**	***	***		
Age	**	***	*	***	*		
Gender							

*p<.01, **p<.001, ***p<.0001

Table 2: Model parameters per driving style, age and gender - Overview of statistically significant test

In order to analyze the differences between the groups, the upper and lower limits of the confidence mean have been plotted (cf. Figure Driving style "repartition" per model parameters) for both driving style and age. The differences between the driving styles have been analyzed with a Dunett C test (as the variances are not homogeneous between the groups). The results are shown in Table 3. The same procedure has been applied for the age group comparison (results also shown in Table 4).

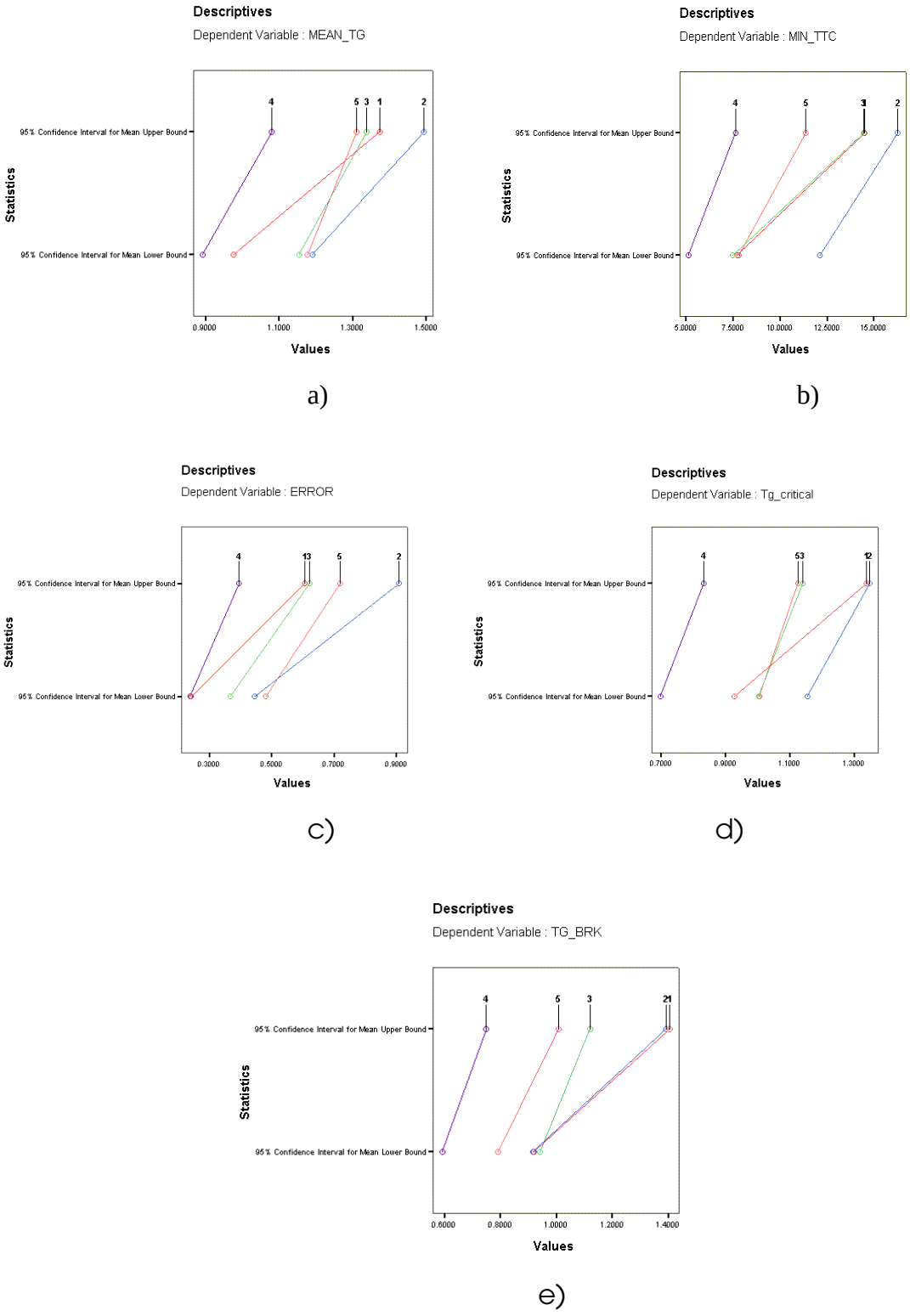


Figure 26: Driving style "repartition" per model parameters

Figure 26 shows that the difference between groups for the five parameters are mainly due to the Hunter-Tailgaters (group 4 in the figure). The mean time gap of this group is smaller than the one of the driving style Ultra-Conservative (group 2), Planner (group 3) and Flow-Conformist (group 5) (cf. Figure 26 (a)). There is no significant difference between the Hunter-Tailgaters and the Extremists (group 1) because of their proximity for the lower bound. This can also be explained by the fact that the Extremists are not homogeneous around one tendency. The Hunter-Tailgater is the only "marginal" group here.

The measures between the groups are also different for the min-TTC. Here the differences concern the Ultra-Conservatives and the Flow-Conformists as well as the Hunter-Tailgater with these two groups. The Ultra-Conservatives display higher min-TTC. The Extremists and Planners show a much greater difference between the higher and lower values for the confidence interval than the other groups. It should also be noted that the Extremists overlap the Planners for the upper bound and they are overlap with the Flow-Conformists for the lower bound, which can explain why they do not appear as having a difference with the other groups.

The parameter error (cf. Figure 26 (c)) is associated to the min-TTC parameter. However, the Hunter-Tailgater drivers are still detached of the other groups, but the repartition of the other groups differs from the previous graph min-TTC. Here also, the main difference exists between the Hunter-Tailgaters and the Ultra-Conservatives as well as the Flow-Conformists. The Extremists and the Planners show some smaller errors than the Flow-Conformists for both the upper and lower bound but do not appear to be significantly different of the other groups.

The parameter, critical time gap, also permits the identification of two more differences. The significant differences here are between the Ultra-Conservatives, with the Flow-Conformist and the Planners, and the Hunter-Tailgaters, with the four other groups.

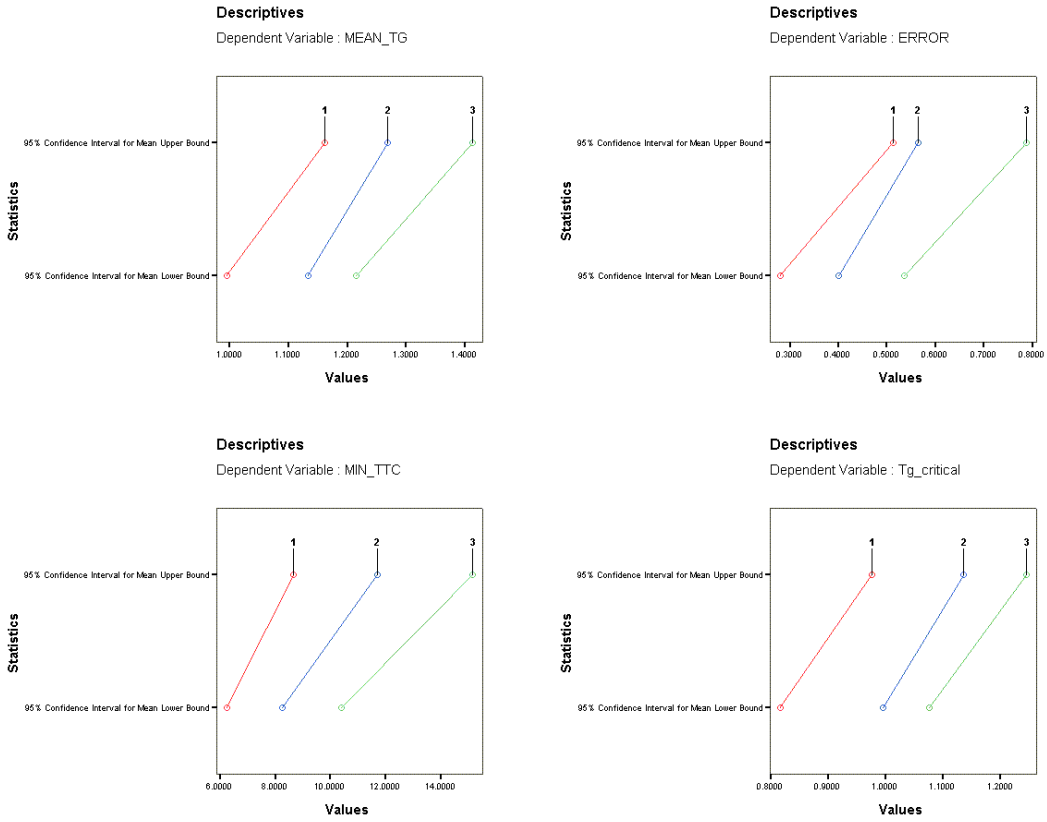
Finally, the difference between groups observed for the tg-braking parameter is attributable to the Hunter-Tailgaters, for which a significant difference can be observed with all of the other groups.

					95% Confidence Interval	
Dependent Variable	(I) STYLEID	(J) STYLEID	Mean Difference (I-J)*	Std. Error	Lower Bound	Upper Bound
MEAN_TG	4	2	-.3561	7.395E-02	-.6154	-9.6774E-02
		3	-.2600	7.142E-02	-.4505	-6.9455E-02
		5	-.2584	6.293E-02	-.4240	-9.2809E-02
MIN_TTC	2	5	4.6084	1.5707	.6583	8.5586
	4	2	-7.8264	1.6673	-11.3494	-4.3035
		5	-3.2180	1.3701	-6.3343	-.1017
ERROR	4	1	-.1074	.1076	-.3988	.1840
		2	-.3601	9.987E-02	-.7156	-4.5384E-03
		3	-.1772	9.455E-02	-.3928	3.848E-02
		5	-.2834	8.330E-02	-.4868	-8.0028E-02

Tg_critical	2	3	.1804	6.303E-02	7.529E-03	.3532
		5	.1866	5.659E-02	2.147E-02	.3517
	4	1	-.3693	6.679E-02	-.6887	-4.9845E-02
		2	-.4871	6.078E-02	-.6588	-.3154
		3	-.3067	5.870E-02	-.4458	-.1677
		5	-.3005	5.172E-02	-.4300	-.1711
TG_BRK	4	1	-.4919	9.998E-02	-.8692	-.1146
		2	-.4831	9.731E-02	-.8516	-.1146
		3	-.3602	8.954E-02	-.5326	-.1877
		5	-.2288	8.032E-02	-.4212	-3.6354E-02

* The mean difference is significant at the .05 level.

Table 3: Comparison between driving style groups



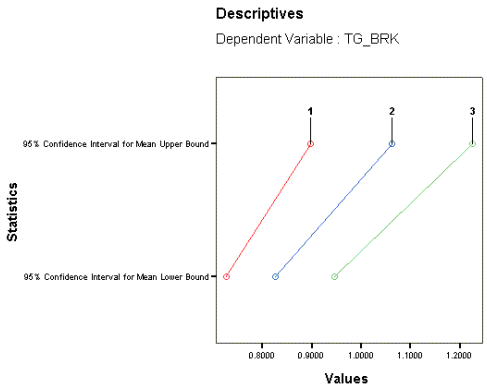


Figure 27: Age group repartitions per model parameters

The analysis of the age groups shows that the main difference is between the young and older drivers, except for the parameter time-gap critical, for which all groups are significantly different.

					95% Confidence Interval	
Dependent Variable	(I) AGE	(J) AGE	Mean Difference (I-J)*	Std. Error	Lower Bound	Upper Bound
MEAN_TG	1	3	-.2364	5.845E-02	-.3927	-8.0041E-02
MIN_TTC	1	3	-5.3391	1.2669	-8.5733	-2.1049
ERROR	1	3	-.2662	7.584E-02	-.4732	-5.9157E-02
Tg_critical	1	2	-.1701	5.334E-02	-.2985	-4.1635E-02
		3	-.2649	5.468E-02	-.4054	-.1244
TG_BRK	1	3	-.2741	7.925E-02	-.4727	-7.5540E-02

* The mean difference is significant at the .05 level.

Table 4: Comparison between age groups

In summary, the Hunter-Tailgaters and the Ultra-Conservatives are the two “extreme” groups, as the Hunters always display the smallest values and the ultra-conservatives have the higher. The repartition of the other groups varies slightly among the different parameters. Therefore, the lack of differences between the Extremists, the Planners and the Flow-conformists probably results from the restriction criteria applied to the data set used here. The variation of position of the Extremists can be justified by the way this category had been determined, as the criterion was to be extreme on more than one axis. They appear extreme either on the hunter tailgaters, (cf. Figure 26 (a) and (c)) or on the Ultra-Conservatives (cf. Figure 26 (d) and (e)). The other salient result is that the older drivers show a clear tendency to have higher model parameters values than their young counterparts. Therefore, two types of profiles can be considered for the simulations. One profile using the characteristics of the driving style with three main styles: Hunter-Tailgater, Flow-Conformist/Planner and Ultraconservative. The other profile using age as a criterion with differences between young and old.

6 CONCLUSIONS

The model presented in this report represents the first step of the conjunction of two approaches heavily involved in ITS designed, driver behavior understanding through a human factor perspective and traffic micro-simulation at the vehicle control level of detail from a control perspective. The mix of these two approaches is promising for the simulation of human control of vehicles, especially when comparing different levels of vehicle automation with human performance.

Driving behavior can be described by a sequence of continuous and discrete events. However, most of the discrete events are not based on a time-based cycles (i.e., each x seconds, perform task y) but rather of conditional form (i.e., when x occur, then perform task y). Thus, most of the challenge at the modeling step relies on how to efficiently describe these conditions (the larger the number of rules, the slower the process is) and how to express these conditions using a mathematical description. The solution used here consisted of considering a default situation and then adapts the behavior when a triggering event happens. Ordering these events as a function of their odd of appearance (a driver does not expect to react at a traffic light while driving on a highway) also increases the capacity of the system. This approach was adopted to differing degrees within the modeling effort.

The visual attention allocation represents one example of this approach. For this case, the default behavior was looking forward, with other behavior activation when a stimulus occurred. At this step of the development of the model, the other behaviors were described through the results of experiments present in the literature, leaving certain behaviors in the shade, (e.g., trigger points for eye movements). Another example for improving the condition description was the organization of the driver behavior in different levels of activity. As a result, the focus was on describing the behavior at one level of activity. To this end, the behavior was categorized, first on the various driving environments, and then as a function of the types of maneuver to perform, including the expected triggers for the other maneuvers.

A sensitive aspect of this approach is the need for accurate and appropriate data in order to tune the model. Some of the tuning has been realized base on data available in the literature. Another source was the University of Michigan Transportation Research Institute, which provided naturalistic data for highway driving. These data have been used mainly for the description of the following behavior part of the model. However, the data used were limited, as the behavior could not be analyzed for maneuvers other than steady following, leading to some restrictive choices for the sample of data used. Regardless, some interesting tuning has been realized base on this data, as well as the consideration of UMTRI driver characterizations in order to determine if some driver profiles could be deduced from the sample of data used here. The interest of such profiles would be to allow the re-creation of traffic phenomena due to driver variability.

However, this categorization of drivers still needs more development, and could also reflect driver characteristic other than following preferences. The driver population could be sorted based on age or experience, in the fashion which would best suit the goal of the simulation. The next steps of the model development will be divided between the perception module, the knowledge database and the acquisition of new data to fine tune the model. For the perception module, the accent will still be on the visual modality in order to improve the model's ability to detect other vehicles and in a manner similar to the humans. For the knowledge database, two aspects will be considered. First, the tuning of the remaining maneuvers of the current database. Second, the description of driving in other environment, such as urban driving and more specifically intersection crossing. This step is closely related to the possibility of acquiring data from which the parameter values necessary for the model development could be extracted. This goal will be pursued through the collection of naturalistic data for a few drivers but with a very detailed analysis of the driver behavior in terms of the control the vehicle and the environment condition. These developments will increase the model accuracy and effectiveness for simulations involving new systems and/or their evaluation in terms of traffic benefit or impact on driving activities.

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