

Toward More Realistic Driving Behavior Models for Autonomous Vehicles in Driving Simulators

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ABSTRACT

Autonomous vehicles are one of the most, if not the most, encountered elements in a driving simulator. Their impact on the realism of the simulator is critical. For autonomous vehicles to contribute positively to the realism of the hosting driving simulator, they need to have realistic appearance and, possibly more importantly, realistic behavior. This paper addresses the problem of modeling realistic and human-like behaviors on simulated highway systems by developing an abstract framework that captures the details of human driving at the microscopic level. This framework consists of four units that together define and specify the elements needed for a concrete human-like driving model to be implemented within a driving simulator. These units are: the perception unit, the emotions unit, the decision-making unit, and the decision-implementation unit. Realistic models of human-like driving behavior can be built by implementing the specifications set by the driving framework. Four human-like driving models have been implemented based on the driving framework: 1) a generic normal driving model, 2) an aggressive driving model, 3) an alcoholic driving model, and 4) an elderly driving model. These driving models provide investigators with a powerful tool for generating complex traffic scenarios in their experiments. The behavioral models were incorporated, along with 3D visual models and the vehicle's dynamics model, into one entity, that is the autonomous vehicle. An experiment was conducted to evaluate the driving behavior models. It showed that subjects perceived the autonomous vehicles with the described behavioral models as having a positive impact on the realism of the driving simulator. The experiment also showed that the specific driving models were identified correctly by the subjects in most cases.

INTRODUCTION

Drivers on real roads demonstrate different naturalistic behaviors that make the driving environment very rich in terms of possible scenarios and outcomes. They react to their instantaneous driving conditions and also act to change or escape these conditions if they are undesired or perceived as unsafe. Simplifying traffic behaviors in driving simulators and replacing it with a homogeneous simplistic model that is a collection of pre-made decisions might suffice in some cases. However, it could lead to some drawbacks: 1) the sense of presence in the driving simulator may be negatively affected because of the unrealistic behavior of autonomous vehicles, 2) the homogeneousness of the autonomous vehicles' behavior will make it predictable to the subject operating within the driving simulator and might effectively lead to the production of misleading results since a subject may adjust performance to exploit his knowledge about other vehicles in the environment, and 3) the generation of some traffic scenarios may not be supported by a simplistic model of autonomous vehicles. Providing an implementation of human-like driving behavior models within a driving simulator would provide its users with a realistic driving experience that may have a considerable impact on the validity of such a simulator and the credibility of driving studies performed on it. The use of human-like models that act differently in different situations eliminates the repetition and predictability of autonomous vehicles' behavior.

Modeling of Autonomous Vehicles' behavior in driving simulators

Michon introduced the hierarchical control structure for the driving task with emphasis on the cognitive nature of driving and suggested it as basis for a comprehensive driving behavior model (5). The hierarchical control structure divided driving into three levels of control: 1) a strategic level that primarily addresses route planning in addition to other general considerations like evaluation of time and cost, 2) a maneuvering or tactical level that addresses maneuver control like gap selection and lane changing, and 3) an operational or control level that addresses the direct low-level control of the vehicle. Almost all modern studies have used the hierarchical control structure model for simulating driving behavior or at least have been influenced by it. The strategic level has no time constraints, decisions at the maneuvering level take place in seconds, and decisions at the control level take place in milliseconds (9).

Decision-making for an autonomous vehicle within a driving simulator is generally modeled in one or more of three different approaches:

- 1) Rule-based models that rely on knowledge bases organized into specialized modules that handle different situations like negotiating turns or different actions like changing speed (3, 11)
- 2) State machines models that encode driving behavior into states that represent low-level driving sub-tasks (2). Hierarchical concurrent state machines add the concepts of hierarchy and concurrency to state machines in addition to providing communication capabilities between different states (7).
- 3) Probabilistic models that base their decisions on empirical data that characterize different kinds of real driving behavior and on probability distributions that are approximated from these data. (12, 13).

Autonomous vehicles, among other elements of driving simulators, are unique in that they are perceived by the simulator's user as being controlled by other drivers. An entity that represents an autonomous vehicle within a driving virtual environment as only a realistic 3D representation of a vehicle and a valid dynamics model is simply not enough. Like real human drivers, virtual human drivers are expected to demonstrate different naturalistic behaviors within the virtual driving environment.

This paper describes a framework for modeling driving behavior at the microscopic level. The proposed framework captures the details of human driving tasks and subtasks on two-lane highways (1). These details are captured in abstract terms that do not define any driving pattern nor do they correspond to any categorical human driving behavior observed on the road at the microscopic level of the driving task. This framework serves as a base model for almost any concrete human-like driving model by injecting empirical data that define and characterize such a model. The driving framework consists of modular components that facilitate extending this framework into different categories of human-like behaviors such as aggressive driving, alcoholic driving, novice driving, etc. The driving framework is used to generate generic driving models that conform to common driving rules and represent normal driving behaviors with slight differences including speed selection and distance estimation. In addition, three specific concrete human-like driving models are built based on this framework: an aggressive driving model, an alcoholic driving model, and an elderly driving model.

These driving behavior models were incorporated with other components of autonomous vehicles. This task was concluded by defining an autonomous vehicle object with four components that intimately work together: a driving behavior model, a 3D presentation model, a dynamics model (6), and a sound model (10). The driving behavior model applies control signals, GAS, BRAKE, and STEERING, to the dynamics model. The dynamics model translates these signals into a vehicle's displacement and orientation. The changes in the vehicle position and orientation are applied by the simulator to the 3D presentation model. The vehicle's sound model changes the intensity of the sound based on data provided by the dynamics model.

The Driving Behavior Framework and Driving Models

The proposed framework captures the details of human driving tasks and subtasks on two lane highways (1). These details are captured in abstract terms that do not define any driving pattern nor correspond to any categorical human driving behavior observed on the road at the maneuvering and control levels of driving as defined by the hierarchical control structure. It serves as a base model for concrete human-like driver models by injecting empirical data that define these models.

The proposed driving framework defines four categories of driving characteristics. Each category serves to indicate a certain pattern of driving behavior and all categories together serve to define a pattern of driving behavior. The four categories of driving characteristics are the following:

1. Driving characteristics related to perception: characteristics that define how a driver of a certain driving pattern perceives the driving environment, e.g. what speed he considers appropriate, what distance he considers close, etc
2. Driving characteristics related to motivation: characteristics that define how a driver of a certain driving pattern responds emotionally to the driving environment, e.g. what makes him feel satisfied with his speed, what makes him feel unsafe, how anxious he becomes when he feels unsafe, etc.
3. Driving characteristics related to decision-making: characteristics that define how driver of a certain driving pattern makes decision at the tactical level, e.g. what makes him want to change lanes, what makes him tailgate other drivers, etc.
4. Driving characteristics related to decision-implementation: characteristics that define how a driver of a certain driving pattern implements his decision at the control level, e.g. how good he is in speed perseverance, how skillful he is in maintaining his lane position, etc.

In connection to the four categories defined above, the proposed driving framework has been divided into four units with each unit corresponding directly to one of these four categories. The major four units of the driving characteristics are:

1. The Perception Unit (PU)
2. The Emotion Unit (EU)
3. The Decision-making Unit (DMU)
4. The Decision-implementation Unit (DIU)

These units work concurrently and exchange data among each other to achieve and implement a driving decision. Each of the above listed units uses one or more Fuzzy Logic techniques to transform data and to make or implement decisions. Figure 1 shows the architecture of the driving framework and the relationship between this framework and the simulator's environment.

The Perception Unit (PU)

The perception unit main role is to fuzzify a driving model's environment by converting numerical raw data provided by the simulation into qualitative presentation that resemble a human driver's perception of his environment. A driver on the road does not have access to a numerical representation of his environment. He cannot tell the exact distance in feet and inches between his vehicle and other vehicles on the road. He can tell however if that distance is far or close and to what extent that distance fits that description. A driver on the road does not know exactly how many inches away he is driving from the center of the lane but he can tell whether he is far to the left or to the right, or if he is approximately in the center.

It is based on this qualitative description of the environment that drivers on the road make and implement their decisions. The Perception Unit contains the elements needed by driving models to understand and analyze their driving environment in human-like terms. Its role hence is very important

since most, if not all, decisions and actions of a driving model are affected by its perception and understanding of the world around it.

The Perception Unit's variables in the driving framework are assigned values from a symbolic domain. Every assignment of a symbolic value to a linguistic variable should be coupled with a certain degree of truth in assigning such a value. The perception unit constantly transforms the numerical values provided by the driving environment into symbolic ones and thus renders such an environment as if it is being seen through a human eye. To accomplish this task, the perception unit uses a set of fuzzifiers or fuzzification objects. Each fuzzifier handles a certain category of variables and is used by the perception unit to fuzzify all variables within that category. The speed fuzzifier, for example, uses a certain set of numerical values provided by the environment and transforms them into one or more symbolic values, e.g. "low" or "normal", each associated with a certain degree of truth. This fuzzifier is used by the perception unit to handle the speed of the vehicle controlled by the driving model itself as well as the speeds of the surrounding vehicles. Each variable of the perception unit has one and only one fuzzifier.

The perception unit in the driving framework defines the linguistic variables needed by driving models as well as the symbolic domains of these variables. It does not specify, however, how numerical values are mapped to symbolic ones. The rules and functions for such a mapping are left to be defined by the driving models derived from the framework.

The driving speed fuzzifier for example is used by the perception unit to provide the driving model with a qualitative description of the instantaneous speed of any vehicle in the environment. The instantaneous speeds of all these vehicles are defined in the perception unit as linguistic variables. The value of a linguistic variable has two components, a qualitative and a quantitative component. The perception unit in the driving framework defines only the domain of the qualitative values that the instantaneous speed linguistic variable can take. The rules for mapping a set of numerical values into a value for the speed linguistic variable is left to be defined by the driving models derived from the driving framework. This allows different driving models to see the same set of numerical values related to a vehicle's instantaneous speed in different qualitative terms. The instantaneous speed linguistic variable of a vehicle in the environment is defined at the driving framework level as:

Linguistic Variable	: instantaneous speed
Domain	: {"low", "normal", "above normal", "high" }
Fuzzifier	: Speed Fuzzifier

This presentation would allow a derived driving behavior model to describe its speed in one or more of the following statements at the logical level of the driving model knowledge:

- Speed is low
- Speed is normal
- Speed is above normal
- Speed is high

Each statement of the above defines a fuzzy set but stops short of providing the membership function of that set.

It is required that any driving model derived from the driving framework define the needed membership functions and thus enable the speed fuzzifier to render the model's instantaneous speed symbolically. A driving behavior model, for example, might choose to describe its instantaneous speed in one of the above listed statements based on the numerical value of the instantaneous speed and the numerical value of the desired speed. The desired speed in turn can be a function of the speed limit, weather conditions, road conditions, etc. This can be expressed in the form of a numerical function, y , defined accordingly as:

$$y = f(\text{speed limit, weather conditions, road conditions, etc})$$

The driving behavior model should then provide membership functions that would map any value of y to one or more of the above listed statements as shown in Figure 2.

Expectedly, a driving model that is built to simulate an aggressive driver should define a different mapping than that defined by a model built to simulate a conservative driver. Different autonomous vehicles thus will perceive the same driving environment differently. Comparing an aggressive driving model and a conservative driving model, what is perceived as low speed by the first might be perceived as normal speed by the second and what is perceived as enough distance for the first might be perceived as too close to the second. These two vehicles, in addition to other vehicles in the environment, are going to react differently to the environment. Each of them would make decisions and implement them based on how each sees the world. The fuzzy membership functions of the fuzzy variables of a driving model derived from the framework should be defined based on observed and collected data from the category of driving behavior that the model is trying to simulate.

The Emotions Unit (EU)

The emotion unit in the driving framework is based on the theory proposed by risk-avoidance models (4). It makes the driving task balanced around the two often-conflicting factors of safety and efficiency. Its role is to capture the emotional status of the driving model in terms of the model's satisfaction with its performance, mainly speed, and in terms of the model's discomfort with the surrounding traffic conditions, mainly when forced to drive at a high speed or when being tailgated by another vehicle. Low satisfaction generally triggers decisions that would potentially increase the speed, e.g. changing to a faster lane or, if in the fast lane, tailgating the leading vehicle to force it to speed up change to the second lane. High discomfort, on the other side, triggers decisions that would potentially lead to a safer situation, e.g. going to a slower lane if the model was forced to drive at a speed that is perceived as unsafe or if it was tailgated by another vehicle.

The emotions unit does not propose any direct decisions to improve the agent's emotional state; it only tries to capture that emotional state in response to the driving environment as it is perceived by the perception unit. Because of its emotions unit, a driving model does not implement driving actions based simply on current traffic conditions. Instead, the model is more concerned about satisfying its own

emotional needs. In that sense, the decision-making and decision-implementation processes are going to be motivated by the emotional needs of the model rather than by the current environment conditions. The emotions unit thus plays an important role in shaping the driving task as a reflective task rather than a reactive one. It makes the model an active player in the environment that initiates actions rather than being a passive one that only does what the local environment directly allows it to do.

The current design of the emotions unit has taken advantage of the fact that the driving models are deployed in a simulation program. In these settings, complex emotional variables that characterize individualistic patterns of driving are generally overlooked. The emotions unit in its current design has five variables. These variables define together the following characteristics of an emotion:

1. Type of the emotion
2. Intensity of the emotion
3. How that emotion was generated or induced
4. The surrounding social rules that may encourage a person to express or suppress his emotions.

These characteristics were defined by Picard as the major factors that influence the mapping between emotions and their physical expression (8).

The type of emotions that can be captured in the current design are satisfaction and discomfort in accordance with the risk-avoidance model (4). Each of these two types is defined as a linguistic variable in the emotions unit whose value reflects the intensity of it at a time. The conditions that generate these emotions every time are induced by the emotions unit based on data available through the perception unit. The social rule factor is simplified in the emotions unit through using a constant value that indicates the urge of the model to improve his emotional state; this constant is called the “demeanor” of the driving model. If the driving model is assigned a higher demeanor value, it is more likely to express its emotions physically. If on the other hand it is assigned a lower demeanor value, it is more likely to suppress its emotions. The agent’s desire in improving its emotional state, i.e. express its emotions physically, is captured in two variables, the model’s desire to increase its satisfaction and the model’s desire to decrease its discomfort. The values of these two variables determine the direction in which the decision-making and decision-implementation processes will proceed. The relationship between the emotions unit and other units in the driving framework is shown in Figure 3.

Similar to the perception unit, the emotions unit in the driving framework does not specify the rules that would produce a certain value for any of its linguistic variables. Driving models derived from the framework should provide the rules that would produce a certain description of the model’s emotional state and its urge to improve this state at a certain instance of time. The emotional state as captured by the emotions unit initiates the decision-making process in the decision-making unit and the urge to improve that state dictates the willingness to take risks by the decision-implementation unit when carrying out decisions.

The Decision-Making Unit (DMU)

The DMU is the inference engine at the tactical or maneuvering level of the driving framework and the driving models. The DMU's role within the driving framework and driving models extended from it is to make a decision that might potentially serve the emotional needs of the driving model by increasing satisfaction or by decreasing discomfort, whichever is more urgent to the model. If the model does not have any certain emotional needs at a certain instance of time, the DMU role is to continue with the same driving performance, i.e. remaining in the same lane and maintaining the desired driving speed.

Based on the emotional state of a driving model, largely determined by its perception of its environment, the DMU searches through all possible avenues to find the most benefiting decision to make at the maneuvering level. However, the DMU is not responsible for implementing its decisions. This task is left to the decision-implementation unit whose job is to wait for an appropriate traffic situation to start implementing an already-made decision. The separation between making a decision and actually implementing it comes from the fact that real drivers do not normally implement decisions as they make them. An obvious example is that a driver might decide that he wants to change lanes even if it is not appropriate to do so at the time when the decision was made. With that decision in mind, the driver would wait for an appropriate condition to implement the decision or he might even participate in creating such an appropriate condition by adjusting his speed. The DMU investigates the driving environment globally for actions that would serve emotional needs, be it efficiency, safety, etc., and then the Decision-implementation unit investigates the driving environment locally to see when it is best to carry out these decisions.

The DMU is composed of sets of fuzzy if-then rules. These rules are grouped together in the DMU in the form of decision trees. Each decision tree is designed to handle a certain emotional need of the driving model. A decision tree is composed of nodes linked with each other through decision paths that each ends with a final-decision node. Based on the emotional state of the model, the DMU determines which decision tree is to be processed in search for decisions. Decisions are achieved by traversing that decision tree in a process that can yield more than one decision at once. Decisions are weighed while they are being achieved and the decision with the highest weight is chosen as the decision that best serves the emotional needs of a driving model.

A decision tree is composed of nodes connected to each other through links. A node can be either a parent node or a decision node. A decision node exists only on the leaves of the decision tree and indicates a driving decision. Each parent node is associated with a linguistic variable as the criterion of that node. A parent node in a decision tree has as maximum number of children that equals the number of possible values of the linguistic variable acting as its criterion with each possible value leading to one of the children. A possible value for the node's criterion leads only to one node; however more than one possible value can lead to the same child node.

Each parent node simulates part of the antecedent of a fuzzy if-then rule and each decision node simulates the consequent part of a fuzzy if-then rule.

Figure 4 explains how a set of if-then rules can be constructed as a decision tree. Modeling a set of if-then rules in the form of decision trees makes extending that set a very flexible task. Decision trees offer a much more convenient and manageable approach toward implementing fuzzy if-then rules. At the same time, they provide a mechanism for assigning weights to decisions as they are being achieved as will be explained in the next section.

Decision-making in a decision tree is done through recursive traversal of the decision tree. Processing a decision tree starts with visiting its root node which like any other node should be associated with a linguistic variable as its criterion. Each value of this criterion leads to another node that could be either another part node or a decision node indicating that a decision has been achieved. The criterion values are inquired at the time of the decision-making; nodes associated with values retrieved as possible values for that criterion at that time are visited and the process is repeated again until a decision node is reached indicating the end of one path. Since a decision tree can yield more than one decision at the same time, a min-max approach is used to select the final decision. The weight of a decision is selected as the minimum quantitative value among all linguistic variables whose qualitative components have contributed to that decision. The decision with the maximum weight is then selected and submitted to the decision-implementation unit.

The Decision-Implementation Unit (DIU)

The DIU is the inference engine at the control or operational level of the driving framework and the driving models. Decisions made by the DMU at the maneuvering level need to be approved and scheduled by the DIU. If the DIU finds the traffic conditions appropriate for implementing a decision made by the DMU, it starts doing so. If the traffic conditions were found inappropriate for implementing such a decision by the DIU, its role becomes to maintain the driving speed and avoid colliding with other vehicles in the environment until the traffic conditions are deemed appropriate for implementing that decision. However, this decision may be replaced by that time by another decision even before it is implemented in response to changes in the environment.

Once a decision, achieved either by the DMU or by the DIU, is ready to be carried out, the DIU translates this decision into GAS, BRAKE and STEERING signals. These signals are passed to the autonomous vehicle's dynamics model, which uses these signals to determine the next position and orientation of the autonomous vehicle. Other data is provided to the dynamics model through the driver model only once, e.g. the vehicle's mass or maximum acceleration, and through the simulator's environment, e.g. road conditions. Having the behavioral model control the vehicle through its dynamics model instead of sending desired speed and orientation explicitly provides more flexibility in modeling the driving task at the operational level. Another advantage of having the DIU controls the vehicle through control is that the same driving model would perform differently if driving two different types of vehicles. If a driving model is built to simulate a novice driver tested on a regular vehicle and on a large truck, its

lack of driving skills would be more apparent and his driving mistakes would be aggravated when it is associated with the dynamics of a large truck versus a regular vehicle.

In addition to the signals passed to the dynamics model of the autonomous vehicle, the DIU sends left turn and right turn signals that update the status of the vehicle and inform other vehicles on the road about its intention to change lanes or make turns. These signals go to the simulator to make them available to other vehicles. The relationship between the DIU, the vehicle dynamic model, and the simulator's virtual environment is shown in Figure 5.

The DIU uses decision trees to determine whether traffic conditions are safe for implementing a DMU decision. A decision tree that checks for distance to leading vehicle is traversed to determine whether or not to implement a decision to increase speed. Similarly, a decision tree that checks for distance to following vehicle is traversed to determine whether or not to implement a decision to reduce speed. Finally, a decision tree for checking distance to vehicles in the neighboring lane is traversed to determine whether to or not to implement a decision to change lane or pass a vehicle.

The DIU uses steering and pedal modules to send the GAS, BRAKE, and STEERING signals to the vehicle's dynamics model. These modules determine the degree of driving skills in the driver behavior model at the operational level. They also play an important role in models that are required to demonstrate impaired driving skills like alcoholic driving. The pedal module in the current design defines only the granularity of the increase in GAS or BRAKE signals that a driving model can send to the vehicle's dynamics in one step. The values of GAS granularity and BRAKE granularity do not have to be the same. The smaller the GAS and BRAKE granularity values are, the more skilled a driving model in controlling its speed is.

The steering module introduces a human error to the model's ability to steer in a perfect manner. A driving model has to continuously control the steering wheel in order to follow the desired path while changing lanes, passing another vehicle, driving on curves, or even maintaining an appropriate lane position on straight roads. An ideal model would be able to send the exact steering signal to the vehicle's dynamic model required to achieve a desired vehicle's orientation. The steering module shapes the model's ability and skills in controlling the vehicle's orientation. To do so, the steering module changes the perfect steering signal by a weaving value, that can be increased or decreased based on the steering skills of the driving model. The steering module has another factor that determines the sensitivity of a driving model to its lane position. This factor works closely with the lane position linguistic variable. The higher the sensitivity factor is, the more likely the driving model to start correcting his steering in early stages is.

The DIU allows a driving model to have an alertness factor with a value between zero and one that alters the model's ability to consider all requirements before implementing a decision. If the alertness factor of the model is low, it is more probable that one or more important requirement, chosen randomly, for implementing a decision are not going to be considered by the model before it starts implementing that

decision. The alertness factor partially determines the model's ability to avoid accidents, which might alter a specific traffic condition from a relatively safe condition into an accident-prone one.

EVALUATION

A generic driving model that represents normal driving behavior was generated from the driving framework. In addition, three types of erratic driving models were developed from the driving framework, aggressive driving model, alcoholic driving model, and elderly driving model. Membership functions were defined for each possible value of each linguistic variable in both the perception unit and the emotions unit based on each driving model's characteristics. Decision trees were defined for the decision-making unit and the decision-implementation unit to simulate the decision-making and decision-implementation of each driving pattern. Also, values were set in the steering and pedal modules to exhibit the skills of each driving pattern at the control level. Each driving model was built based on the broadly observed characteristics of that model. General characteristics for each model were documented and mapped to certain membership functions, decision trees, or factors in the steering and pedal modules. Variations within each driving model are supported through different means to enable experiment designers to aggravate or alleviate the erraticism of a driving model, e.g. make an aggressive driving model more aggressive or less aggressive or make an alcoholic driving model more drunk or less drunk. Each autonomous vehicle in the environment has its own copy of all elements of the driving model with which it is associated. This makes it possible to have autonomous vehicles in the environment that are associated with the same driving model yet each of them represents a slight variation in implementing this model from the other autonomous vehicles. Ten subjects were asked to participate in an experiment designed to assess the impact of the behavioral models on the realism of the simulator and to validate the erratic driving models described above.

Analysis of the collected data showed that subjects have perceived the autonomous vehicles with behavioral models to have increased the presence within the simulator. On scale of 1 to 5 where 1 indicated a highly negative impact and 5 meant a highly positive impact on the simulator realism. The average value was 4.1. The steering and pedals activities of the autonomous vehicles were rated as 3.5 on a scale of 1 to 5 with 1 as entirely not realistic and 5 as entirely realistic.

To validate the implemented erratic driving models, subjects were asked, while driving, to associate certain autonomous vehicles with a driving pattern from a list that included {aggressive, normal, alcoholic, novice, elderly, and conservative}. The actual answers of the subjects were compared against the expected answers and a binomial test was applied to the results to find out whether subjects were more likely than not to identify an autonomous vehicle with its expected type. Analysis of the subjects' answers showed that the aggressive and alcoholic driving patterns are more likely to be detected as such. The elderly driving pattern was found less likely to be identified as such by the participants. However, it was found less likely to be identified as normal behavior. This result can be explained in the light of the highly diverse driving characteristics generally exhibited by elder drivers.

CONCLUSIONS

The driving framework and the driving models described in this paper serve to address this problem of building more realistic traffic at the microscopic level in driving simulators and offer techniques that facilitate the use of various types of complex human-like driving behaviors in driving experiments. The driving framework specifies the functionality required by a driving model to operate in a human-like manner at the microscopic level. This includes addressing the perceptual style of a driving pattern, its emotional needs, its approach toward decision-making, and its skills in implementing its decisions effectively and safely. This architecture of the driving framework allows an extended driving model to serve as an intelligent agent within the environment that controls an autonomous vehicle at the tactical and operational level. By doing so, not only does a driving model make its decision humanly, it also implements these decisions in a human-like manner.

Two primary advantages result from using human-like driving behavior models within a driving simulator. The first advantage is the increase in the realism within the simulator, a valuable need for any driving simulator that strives to be regarded as a legitimate representative of the real world.

The second advantage of using autonomous vehicles with human-like driving behaviors in a driving simulator is the support they provide for scenario generation. Some driving experiments may require generating a driving scenario that involves other vehicles. The driving models have built-in support for scenario generation at the microscopic level. This means that the experiment designer needs to address decisions only at the macroscopic level, i.e. define the path of each autonomous vehicle. The availability of different patterns of human driving for autonomous vehicles provides the scenario designer with a tool for testing a scenario under various circumstances and in different kinds of traffic.

The main limitation of the driving framework is that it operates only on simulated two-lane highway systems. Extending the driving framework and driving models to support other driving environments, e.g. neighborhood and urban driving environments, requires constructing new fuzzification objects for variables that characterize these environments and that are not currently available in the driving framework. The definitions of the variables of the emotions unit need then to be revised to accommodate the new variables of the perception unit. Decision trees for the decision-making and decision-implementation units need to be enhanced or changed to handle the conditions of the targeted driving environment.

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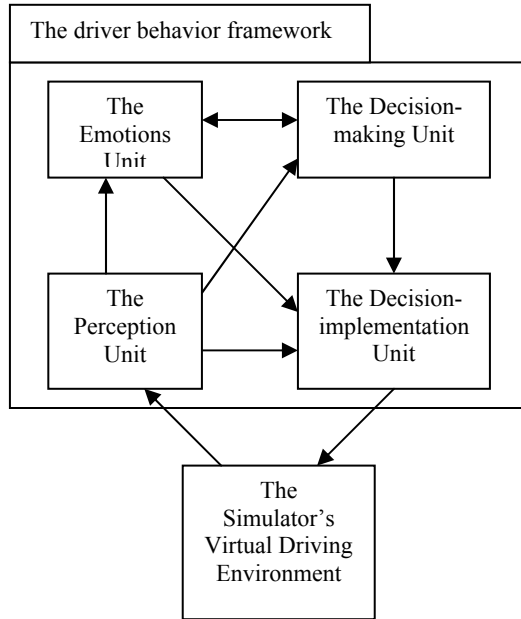


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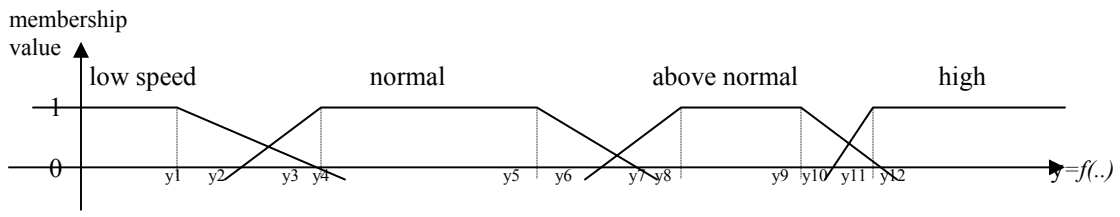


FIGURE 2 Membership functions for the driving speed fuzzy variable.

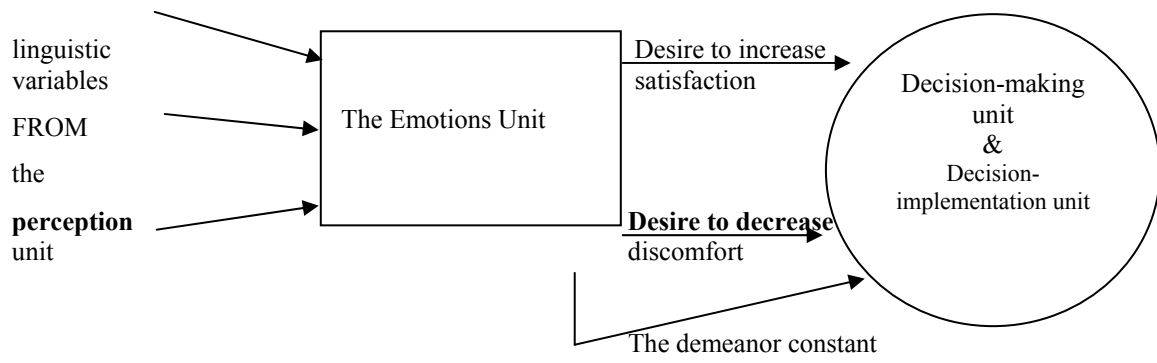


FIGURE 3 The relationship between the emotions unit and the other units of the driving framework.

IF current driving speed is low AND leading distance is far
 THEN increase speed
 IF current driving speed is low AND leading distance is normal OR leading distance is close
 THEN change lane

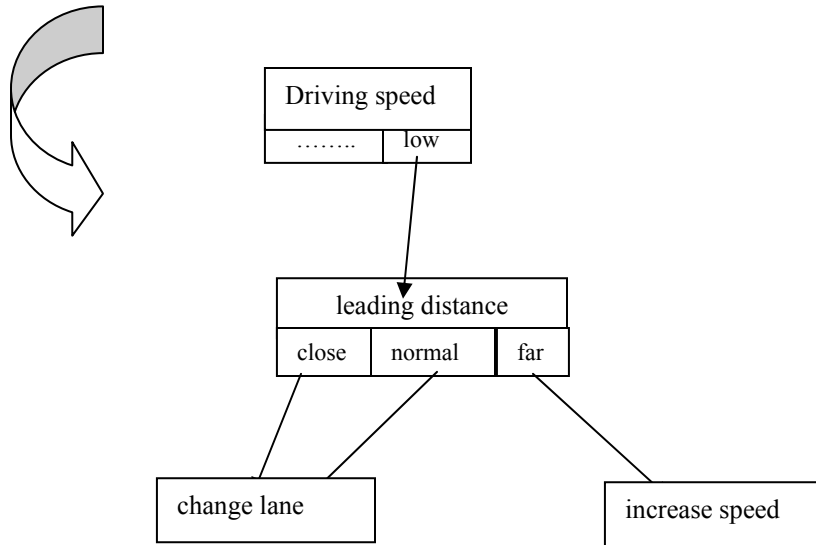


FIGURE 4 Mapping of fuzzy if-then rules from conventional format to decision-tree format.

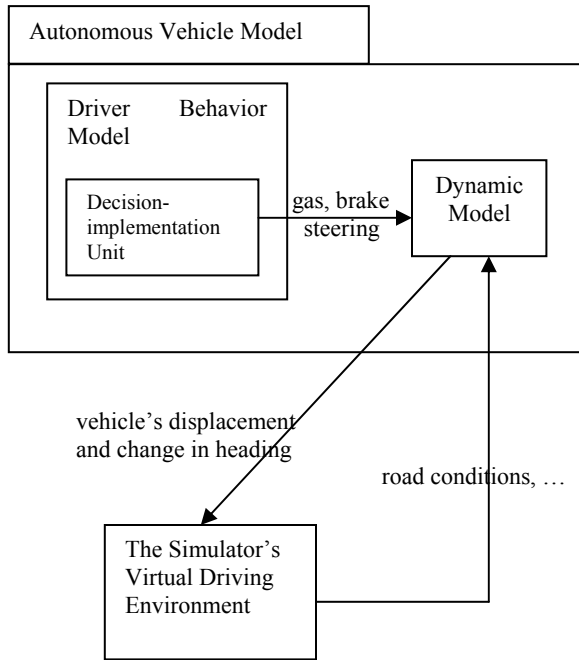


FIGURE 5 Relationship between the decision-implementation unit, the vehicle dynamic model, and the simulator's virtual environment.