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Driver Behavior Model Based on Ontology for Intelligent Transportation Systems

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***Abstract*— Intelligent transportation systems are a set of technological solutions used to improve the performance and safety of road transportation. A crucial element that affects road safety is driver behavior, because driver errors are usually the principal cause of traffic accidents. Therefore, understanding and modeling human driver behavior is extremely important for the safety of the road transportation. In this paper, a driver behavior model based in ontology for intelligent transportation system is proposed. The ontology will allows predicting different undesirable situations, such as traffic accidents, and road congestion, taking into account the environment information and the driver behavior.**

Keywords-ontology; inteligent transportation systems; model; driver behavior

I. INTRODUCTION

Intelligent Transportation Systems are the set of applications and technological systems created with the aim of improving safety and efficiency in road transport. These systems allow to control, manage and monitoring the different elements of roads.

The continuing evolution of intelligent transportation systems has ushered in a new era of interconnected intelligent systems, which certainly has been a quantitative leap in safety of road transport. These systems enable the exchange of information between different applications, and the subsequent analysis to improving the safety of drivers and eases travel and comfort in road travel.

One of the factors that affect road safety is driver behavior. There are various studies [1] which found that driver errors are usually the major contributor in more than 90% of the traffic accidents. Therefore, understanding, analyzing and modeling human driver behavior in a realistic way is extremely important in enhancing the safety of the road transportation.

Due to its high degree of expressiveness, the use of ontologies is suitable to ensure greater interoperability among software agents and different applications involved in intelligent transportation systems [2]. Ontologies are useful not only to modelling the different elements involved in road transportation, such as vehicles, infrastructure and driver behavior, but also facilitates the interaction and the exchange of information from different sources.

In this work we propose an ontology-based model of driver behavior, to be integrated in and intelligent transportation architecture. The driver behavior will be used to predict and avoid traffic accidents and to optimize the routing management.

The paper is organized as follows. Section II presents the state of the art in the driver behavior modelling field. Section III is a brief background about ontologies and its main components. The description of the driver behavioral model and the ontology is presented in section IV. In section V an example of the use of the ontology is showed. Finally, the conclusions and lines of future work are summarized in section VI.

II. RELATED WORK IN DRIVER BEHAVIOR MODELING

There are some previous works focused in driver behavioral models. Michon [3] provides a simple two-way classification, in which he first distinguishes between models that are behavior oriented, and those that are motivation oriented. He differentiates, by the order hand, between taxonomic and functional models.

According to [3], a taxonomic model is related to facts and relationships between facts. Taxonomic models of driver behavior are exemplified by trait models and by task analysis. Trait models describe relationships between driver characteristics without incorporating dynamic functions. These models are motivation oriented and have historically concerned the statistical identification of the accident-prone driver [4][5]. In [6] they provided a review of the study of individual differences in road traffic crashes and concluded that the differential crash involvement paradigm should be abandoned. A driving task analysis is behavioral oriented model. It is essentially a description of facts about the driving task, the behavioral requirements, and the ability requirements for performing that task. The principal example in this category is the task analysis presented in [7] and [8], which partitioned the driving task in some major tasks, divided into elementary tasks. Today the descriptions of these tasks constitute an exhaustive inventory of automobile driving.

Regarding functional models they can be motivational or cognitive models, and behavioral, such as mechanistic and adaptive control models. Motivational driver models make explicit assumptions about the driver's mental state [3]. Risk homeostasis theory (RHT) [9] is perhaps the most familiar motivational model. RHT posits that a driver acts on the basis of a target level of accident risk. A more recent and well-cited motivational model is a task-capability interface (TCI) [10]. TCI describes the interaction between the

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determinants of task demand and driver capability. The task demand is determined by factors such as the environment, other road users and speed, with capability being determined by training, education and experience. Motivational models take the form of a comprehensive theory, often covering the entire driving task. Critics of motivational models, however, have pointed to an overreliance on confirmation rather than refutation, lack of specificity and impreciseness [11].

The mechanistic model is based in the principle of "Unsafe at any speed", so this type of model has not gained popularity in the field of driver behavior. However, some specific problems have been tackled successfully with them, particularly in the area of car following [12], [13].

Adaptive control models are used for driver assessment through parameter identification techniques [14]. In contrast to motivational models, adaptive control models provide precise quantitative results. A common characteristic of many adaptive control models is that despite being able to accurately fit the measured data they are not good at making predictions. For example, the optimal control model of human behavior [15] contains many free parameters which hamper its usefulness and predictive ability [16].

There are other methodologies for modeling driver behavior which combine different modelling approaches. OFFIS [17] models the driver behavior with a combination of two modelling methodologies; the cognitive and the probabilistic. This approach is based on the assumption that driving a car involves different cognitive layers concurrently, while these interact with each other. Knowledge processing is done on three stages, taking into account the cognitive workload that is used for the knowledge processing, the cognitive stage, the associative stage and the autonomous stage. Processing at the autonomous level is highly automated and requires the lowest workload, whereas processing at the cognitive level is very explicit and requires a high workload.

COMSODRIVE is a theoretical framework [18] based in the mental representation of the driving situation. This mental model is built in Working Memory from perceptive information extracted in the road scene, and from permanent knowledge stored and activated in the Long Term Memory. Driver's mental representations are a "goal driven" model of the road environment.

The Driver Model proposed by KIT (Knowledge Information Technology Ergonomics) includes two modules: the first one is the Decision Model and the second one is the Control Model [19]. The aim of the Decision Model is of determining the desired path and speed for the car, according to the input collected from the vehicles and the environment, and providing them to the Control Model which has the aim of choosing the task to perform. The Driver Model main target it has always been considered that the vehicle is driven at the highest "intended" speed, depending on driver characteristics, traffic, road and weather conditions and maximum allowed speed. The internal state of the driver is taking into account.

In [20] a methodology that can elicit prior knowledge for explaining human driving behavior in specific environments is presented. They first collect human driving data from trials performed on a virtual driving simulator and identify individual driving behaviors. Then collect prior knowledge of driving behavior model by interviewing the subjects of the simulation and select meaningful prior knowledge. Finally they construct a driving behavior model that can explain the human subject's actions based on hypothetical reasoning.

III. OVERVIEW OF ONTOLOGIES

Ontology is the most expressive knowledge representation form. It provides a common vocabulary in a given domain and allows defining, with different levels of formality, the meaning of terms and the relationships between them [2]. Ontologies facilitate the design of exhaustive and rigorous conceptual schemas to allow communication and information exchange between different systems and institutions.

A. *Ontology Elements*

The components of ontologies are classes (concepts), relations, axioms and individuals. The classes or concepts in the ontology represent any entity that provides some information and contain properties. Relations represent interactions between classes. Among the most common relations we can find is inheritance, which is usually called taxonomic. Taxonomy is a class hierarchy, where each class is also called node. Axioms are used to define the meaning of ontological components, and individuals are concrete instances of a particular class.

IV. THE PROPOSED DRIVER BEHAVIOR MODEL

The driver behavior model we propose is shown in Fig. 1. The model is composed of a knowledge base and a reasoning module.

The knowledge base is divided into two parts: The ontological one and the rule base one. The ontological module is form using information from the driver and the environment. A traffic general ontology store the whole environment knowledge, including vehicles, infrastructure items (e.g. roads, bridges, traffic signs, traffic lights) and weather conditions. The driver behavior ontology has the knowledge related to driver characteristics, perception and cognitive state to perform the different driving tasks. The rule base contains the rules that are necessary to follow to perform the different driving task.

A crucial aspect when working with ontologies is the mechanism of reasoning, which is simply the ability to obtain new knowledge from knowledge already available using inference strategies. In this work the reasoning module is responsible of choosing the rules to apply to perform the current driving task. The rules will be applied following the specific goal and taking into account the input data retrieved from the ontologies. We have a task hierarchy in which each driving task is split into smaller tasks (subtasks) to facilitate the processing and the final goal accomplishment. The rules will be interpreted by the reasoner to produce an output in form of actions. We used the Pellet reasoner [21], which is a tool for reasoning with ontologies. It is implemented all in Java; it is freely available and allows checking the consistency of the ontology.

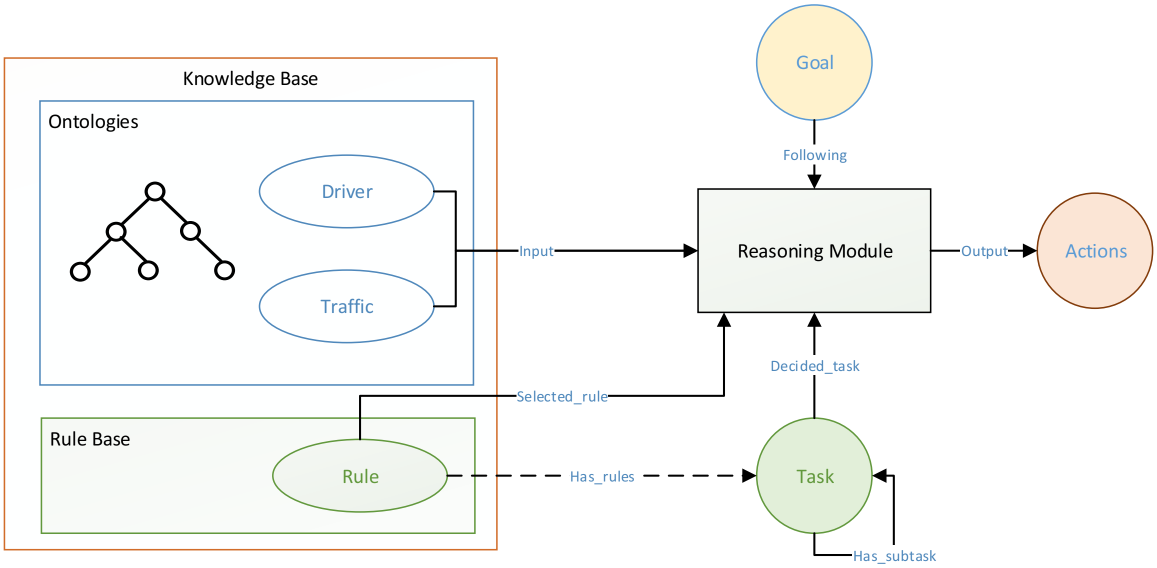

Figure 1. Driver behavior model.

A. *The driver behavior ontology*

An ontology that relates the different entities involved in the driver behavior has been developed. The ontology was implemented in OWL-RDF language [22] using protégé [23]. Fig. 2 shows the principal classes and relations identified in the driver behavior ontology.

The main class of this ontology represents the driver. The principal attributes of the drivers related to the behavior are: the age, the number of years of experience driving, the gender, the number of kilometers driven and the number of accidents in which he/she was involved.

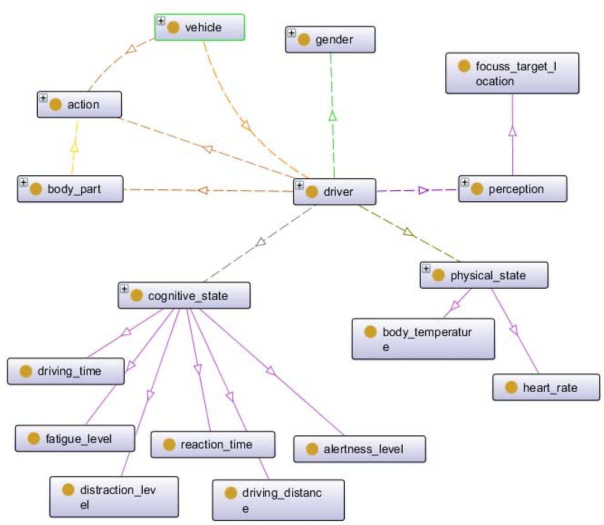

Figure 2. Driver behavior ontology

The driver has a set of cognitive state concepts related to the concentration in the driving task, such as the different levels of alertness, distraction and fatigue; the driving distance, the driving time and the reaction time. This last concept represents the time elapsed since an event occurs, until the driver reacts by executing an action.

The physical state is a group of concepts related to the physical condition of the driver which can affect the behavior, such as the body temperature and the heart rate.

Another important group of concepts is related to the perception of the driver from the environment. These concepts are principally deal with the infrastructure elements the driver can locate in his/her visual camp. Querying over these concepts is possible to detect if traffic signs or other infrastructure items have been seen by the driver. With this information it is possible to calculate the reaction time of the driver and predict if there is any unusual behavior.

Fig. 3 shows the set of concepts related to the actions that the driver can perform and the relations with the driver body parts and the vehicle parts involved in that action.

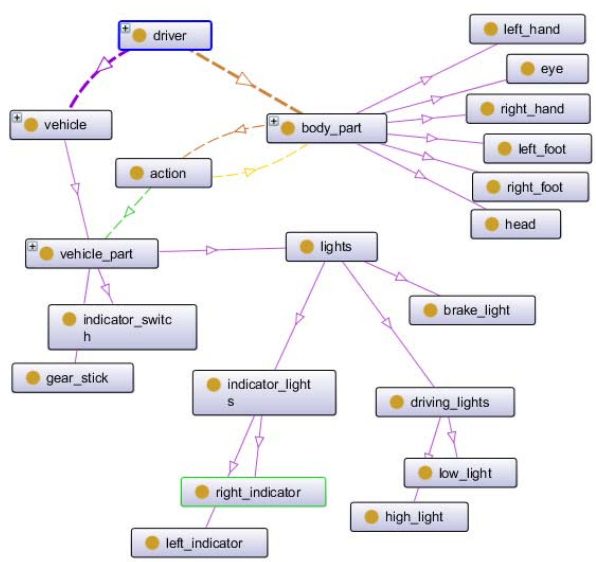

Figure 3. Driver, vehicles and action relations in the behavior ontology

As we can see in Fig. 3, there is a driving relation between the driver and the vehicle, but there is also another important connection between them: the action concept. The main idea is that drivers have a set of actions related with some driving tasks (e.g. steering movement, accelerate, braking) that they can take. Each action involves different driver body parts and vehicle parts. For example: The accelerate action involve the right foot (body part) of the driver and the accelerator pedal (vehicle part) of the vehicle.

B. *The rule base*

The rules to reasoning with the ontology have been developed using the Semantic Web Rule Language (SWRL) [24]. We also use SWRL rules to define different actions that a driver needs to take to accomplish all the driving tasks.

In this work we use the rules proposed in [20] to describe the typical actions that drivers take in different traffic situations. These rules were obtained from experiments with a 3-D traffic simulator. In TABLE I. taken from [20] we show a small set of rules related to the use of the accelerator pedal.

The first rule means that if the vehicle is on a curve, then the typical action of the driver is release the accelerator. The second rule means that if the vehicle is going straight, then the driver steps on the accelerator. If the subject is driving uphill, the usual action is accelerating; whereas, he/she releases the accelerator if he/she is driving downhill (rules 3 and 4). Rules from 5 to 8 say that if the driver sees a curve ahead or a downhill ahead, then he/she releases the accelerator. However, if the subject sees a straight ahead or an uphill ahead, then he/she steps on the accelerator. The last two rules mean that if the vehicle is over the desired speed, the driver accelerates, while if the vehicle is under the desired speed, the driver releases the accelerator.

TABLE I. RULES RELATED TO THE DIVER BAHAVIOR IN ACCELERATION TASK (TAKEN FROM [20])

Nº	***Rules***	
	Antecedent	***Consequent***
1	Curve(x) ∧ IsOn(x, car)	ReleaseAccel
2	Straight(x) ∧ IsOn(x, car)	Accelerate
3	Uphill(x) ∧ IsOn(x, car)	Accelerate
4	Downhill(x) ∧ IsOn(x, car)	ReleaseAccel
5	Curve(x) ∧ InSight(x, car)	ReleaseAccel
6	Straight(x) ∧ InSight(x, car)	Accelerate
7	Uphill(x) ∧ InSight(x, car)	Accelerate
8	Downhill(x) ∧ InSight(x, car)	ReleaseAccel
9	OverDesiredSpeed(car)	ReleaseAccel
10	UnderDesiredSpeed(car)	Accelerate

V. EXAMPLE

Here we present a short example of the use of the driver behavior data model to optimize routing and avoid congestion. Let's suppose that the principal goal of the driver is to move from one point to another in the shortest possible time. Fig. 4 shows a simple traffic scenario composed of 5 roads and 6 intersections. To move from point A to point B, the car has two possible routes. The first one is showed with red dashed lines, and the second one is showed with black dashed lines.

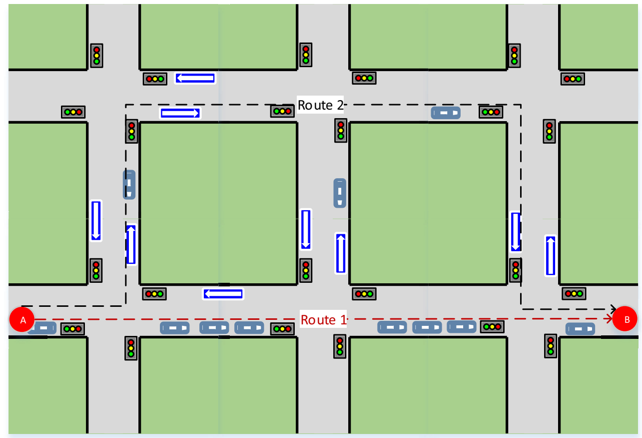

Figure 4. Routing example

The car's agent makes queries to the ontology to retrieve the information related to the traffic scenario (including the state of the roads, the location of the vehicles and traffic signs, the weather conditions), the routes and the information about the different actions that should be done to follow each route. The information related to the behavior of the driver is also in the ontology.

The prediction system, taking into account the information of the traffic scenario and the driver profile (if the driver is aggressive, moderate or passive) can predict the time to destination in the different routes. In the example shown in Fig. 4, with a naked eye, the better route might be *Route 1*, because it is the shortest and it is all straight ahead, but as we can see in the figure, that route is congested. If the driver is aggressive and is familiar with the road, to take the second route could be a better choice to gain time and to avoid congestion.

VI. CONCLUSIONS AND FUTURE WORK

In this work a driver behavior model based in ontology for intelligent transportation system is presented. The model is composed of a knowledge base and a reasoning module. The driver behavior ontology has the knowledge related to driver characteristics, perception and cognitive state to perform the different driving tasks. The rule base contains the rules that are necessary to follow to perform the different driving task. The reasoner is responsible of execute the rules to perform the current driving task to produce an output in form of actions.

The diver behavior ontology will allow predicting different undesirable situations, such as traffic accidents, and road congestion. Thus, we are working in the implementation of the prediction module, taking into account not only the environment information, but also the driver behavior. In this stage is very important classify the subjects into driving profiles according to different parameters, such as the use of the accelerator pedal, the speed average, among other issues. To achieve this classification, we plan to apply fuzzy logic techniques.

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