DESIGNING A MULTI AGENT MODEL WITH BDI ARCHITECTURE TO PREVENT ROAD ACCIDENTS

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Abstract: Today, with progress and developments have been done in motor cars, cars have been produced with high speed and acceleration. But this increasing in speed and acceleration, have caused many concerns about tragic driving accidents and events. Until now, many models have presented about prevention of accidents, in order to reduce these concerns. In this paper, we are going to design a multi agent model with BDI architecture to decrease road accidents. The proposed multi agent model, has been designed for automotive brake system. To cover the uncertainty of the proposed model and its language variables, the fuzzy mechanism has been used to implement it. It’s shown using the multi agent approach, efficiency, flexibility and validity of such systems can be improved considerably.

Keywords: Agent, BDI, Multi agent, Road accident, Controller
1. Introduction

Not surprisingly, transportation and traffic systems are objects of concern as they play an important and indispensable role in society. As the driver has become an important facet of modern traffic systems, models used to represent such a domain need to consider the uncertainty inherent in human behavior, which increases the modeling complexity (Rossetti et al. 2002). Despite of major advances in increasing safety, accidents still occur in the highways considerably, in this regard, it can be mentioned that modeling and simulation enable engineers to identify degree of impact of effective factors in accidents. So far, many models with different approaches have been presented to determine the effective factors in severity of road accidents and probability of crash (Koekelman and Kweon, 2001).

Multi-agent system (MAS) is a sub-field of the distributed artificial intelligence (DAI), which has received an increasing interest in the last few years. The rapid evolution in the available computational resources, both in hardware and in software, which support a widely physically distributed computing environment, has contributed to this trend. The increasing demand for suitable tools to represent the complexity inherent in some application domains is a factor that also inspires developments in the MAS field (Rossetti et al. 2002). A multi agent system is a set of entities that interact together to solve a problem or to reach a goal that is beyond the individual capabilities or knowledge of each separate entity working alone (Naji, et al. 2004). These agents can gather information from environment through some sensors and influence on the environment by drivers (Weiss, 1999). Agents offer several potential advantages over more traditional centralized approaches (Naji, et al. 2004), they are well suited to large-scale distributed and dynamic systems (Mauer, 1995). Agents present scalability and flexibility since more agents can be added as the problem size increases. They may offer improved robustness and reliability since the failure of some agents may be at least partially compensated for by the actions of other agents in the system (Jennings, et al. 1998). Traditionally, it has been assumed that agents are constructed using computer software but it is now possible to implement agents to a more general environment in which agents can reside in both the software and hardware of the system (Barr, 1998; Hartenstein, 2001). One of the capabilities of these systems is sensor fusion. The ability of the system to perform a given task appropriately is dependent on the quality of the sensory information which is in turn related to the quality of the sensors. Data fusion helps us to overcome these obstacles by integrating information from two or more independent sensor readings. These combining readings from several different kinds of sensors can reduce uncertainty and provide more precise information than reading data from a single sensor (Naji, et al. 2004).

More recently, new-generation traffic network models have also emerged from scratch, attempting to explicitly incorporate better representations of driver behavior (Cantarella and Cascetta, 1995; Liu et al., 1995; Mahmassani and Jayakrishnan, 1991). In this sense, agent-based techniques seem to be a very appropriate approach to model such a domain (Rossetti et al. 2002). In fact, the main benefit of Multi-agent systems is that they allow the simulation of complex phenomena that cannot easily be described analytically (Doniec et al. 2008).

In this paper, because of the above-mentioned advantages of Multi-agent technology, we decided to deal with a multi-agent model that able to prevent road accidents. For this reason, we used the well-known Belief, Desire, Intension (BDI) architecture that is a practical reasoning architecture, in which the process of deciding what to do resembles the kind of practical reasoning that we appear to use in our everyday lives (Weiss, 1999). Using this model, we
aim to support driver in the way that he can have more confidence and convenience during driving.

2. Background

Kim et al. (1994) investigated the relationship between crash type and severity using Log linear model. They used crash data forms that have been completed by police at the site of the crash in Hawaii State. Finally, they considered head-on crashes and rollover as most severe ones. Besides emphasizing on the effects of weather conditions and crash type on crash severity, Voget and Bared (1999) obtained a relationship between rural two-lane road crash severity and its contributing factors. Khattak et al. (1999) defined factors such as careless driving, exceeding speed, alcohol use, younger or older drivers (<25 or >25), wet road, road turns, road grade, etc as increasing factors of crash severity and some other factors as decreasing factors using ordered Probit model. In prior studies some of works have been done using artificial neural networks as the modeling approach for crash severity and its relating factors. Kockelman and kwoen (2001) investigated on models of crashes including two-vehicle, single-vehicle and all other types of crashes, separately. Because of the difference in the nature of crashes and their cause, it is suggested to separate them in order to get the best results in the model. Finally, he identified the head-on impact collision, high speed, rollover, alcohol use, older age, overtaking maneuver, night crashes, etc as high severity crashes and rear or lateral impact collisions and day crashes as low severity ones. Abdelwahab and Abdel-Aty (2001) classified crash severity into three injury severity levels that is related to two-vehicle accident occurred at signalized intersections. They used MLP for classifying data and classified 65.6% and 60.4% of cases for the training and testing data, respectively. Abdelwahab and Abdel-Aty (2004) also applied multilayer perception and fuzzy adaptive resonance theory to analyze driver injury severity in traffic accidents. The results indicated that gender, vehicle speed, seatbelt use, vehicle type, point of impact and accident location can affect in probability of injury severity. Dursun Delen et al. (2006) developed eight binary neural models to classify accidents by level of injury severity from no-injury to hard-injury and conducted sensitivity analysis to identify the prioritized importance of crash-related factors. Milton et al. (2008) demonstrate a modeling approach that can be used to better understand the injury-severity distributions of accidents on highway segments, and the effect that traffic, highway and weather characteristics have on these distributions. The approach they use allows for the possibility that estimated model parameters can vary randomly across roadway segments to account for the variability in the data.

Chen and Jovanis (2000) obtained a relationship between crash severity and its associated factors using Log linear model. They used 408 observations of bus crashes in a freeway in Taiwan during of 1985 to 1993. They considered the crashes fatalities with crash injuries because the crashes fatalities were with low number. Chen and Jovanis emphasized on the importance of proper classification of a number of data such as the time of crash. Frontal impact collisions, driving in late hours of night or early morning and driver fault were introduced the main factors which have considerable affects on crash severity. Kockelman and kwoen (2001) investigated on models of crashes including two-vehicle, single-vehicle and all other types of crashes, separately. Because of the difference in the nature of crashes and their cause, it is suggested to separate them in order to get the best results in the model. Finally, he identified the head-on impact collision, high speed, rollover, alcohol use, older age, overtaking maneuver, night crashes, etc as high severity crashes and rear or lateral impact collisions and day crashes as low severity ones. Abdelwahab and Abdel-Aty (2001) classified crash severity into three injury severity levels that is related to two-vehicle accident occurred at signalized intersections. They used MLP for classifying data and classified 65.6% and 60.4% of cases for the training and testing data, respectively. Abdelwahab and Abdel-Aty (2004) also applied multilayer perception and fuzzy adaptive resonance theory to analyze driver injury severity in traffic accidents. The results indicated that gender, vehicle speed, seatbelt use, vehicle type, point of impact and accident location can affect in probability of injury severity. Dursun Delen et al. (2006) developed eight binary neural models to classify accidents by level of injury severity from no-injury to hard-injury and conducted sensitivity analysis to identify the prioritized importance of crash-related factors. Milton et al. (2008) demonstrate a modeling approach that can be used to better understand the injury-severity distributions of accidents on highway segments, and the effect that traffic, highway and weather characteristics have on these distributions. The approach they use allows for the possibility that estimated model parameters can vary randomly across roadway segments to account for the variability in the data.
for unobserved effects potentially relating to roadway characteristics, environmental factors, and driver behavior. Doniec et al. (2008) focus on road traffic simulation, specifically the design of a road traffic simulation tool to be able to deal realistically with road junctions. They propose a multi-agent behavioral model based on (1) the opportunistic individual behaviors that describe the norm violation and (2) the anticipatory individual abilities of simulated drivers that allow critical situations to be detected. Ydenius (2009) investigated how crash severity depends on various road environments. In this study, crash severity was shown for various speed limits, crash types and road surface friction. Data used were from 422 frontal vehicle crashes in Sweden with recorded crash pulses. The findings of the current study showed that the average change of velocity was $46 \pm 4.1 \text{ km/h}$ higher on roads with a 90 km/h speed limit than on roads with a 70 km/h speed limit. This study shows that the average impact severity of crashes depends not only on the struck object itself, but also on the traffic environment in which the crash occurs.

Generally, the above-referenced works represent different results on the effects of influential factors associated with crash severity. Actually, in each of these investigations, the increasing or decreasing factors of crash severity identified by considering available data type, whereas the work presented in this paper investigates accident prevention and prediction.

3. Research framework

The proposed model in this study was designed in the way that it can inform driver on safe speed, and distance and also optimum braking point. In addition, the model provides a set of information for driver about speed and its restrictions, road status and weather condition. In this way, it can support driver against potential dangerous situations and improve driver calmness. We have used agent-based technology to present this model.

3.1 Agent base technology

Agent-based techniques form an attractive paradigm for building real-time parallel applications because they have several high-level characteristics: flexibility, modularity, concurrency, reactivity, proactiveness, reasoning, learning, autonomy, communication, and cooperation. When agents are effectively implemented, they can react to environmental changes by adapting to unpredictable events. This responsiveness to the environment is one of the most important and basic requirements for intelligent systems (Naji, 2008). Agents are autonomous computational entities that can perceive the information concerning their environment through sensors and affect the environment in an appropriate manner using some form of actuators. Agent systems operate asynchronously and in parallel and can offer increased speed and efficiency (Naji, et al. 2004). Figure 1 shows an intelligent agent model interacting with its environment.

![Intelligent Agent interacting with its environment](image)

3.2 Multi-agent System with BDI architecture

The formalism used for the agents is derived from the well-known Beliefs, Desires, and Intentions (BDI) architecture that are described extensively in the technical literature (Naji, et al., 2002). It's a type of agent architecture containing explicit representations of beliefs, desires, and intentions. The architecture addresses how the beliefs, desires, and intentions of the agents are represented, updated, and processed to determine the agent's actions. In BDI architectures, decision-making reflects the practical reasoning that we each carry out every day in furtherance of our
goals. The basic components of BDI architecture are data structures representing the beliefs, desires, and intentions of the agent (Weiss, 1999). The Beliefs refer to a set of information that agent has about itself and the environment which may be false. This forms informational state of the agent. Desires represent a set of high level objectives and goals that the agent is trying to achieve. Desires must be realistic and not conflict with each other. The intentions refer to the agent’s deliberative state in which the detailed sequences of actions, or plans, made to the environment and other cooperating agents through actuators (Naji, et al. 2004; Weiss, 1999).

The BDI model is attractive for several reasons. First, it is intuitive—we all recognize the processes of deciding what to do and then how to do it, and we all have an informal understanding of the notions of belief, desire, and intention. Second, it gives us a clear functional decomposition, which indicates what sorts of subsystems, might be required to build an agent. But the main difficulty, as ever, is knowing how to efficiently implement these functions (Weiss, 1999).

3.3 Operational Definitions of Research Framework Components

In this part, we present Operational definitions of components which mentioned in research framework (Figure 2).

1. The Long Range Radar (LRR): this radar is able to detect obstacles like cars, trucks or guardrails and trees up to a distance of 150m. Besides the range and the angle of an obstacle, it gives also information about the relative speed of this obstacle using the Doppler Effect.

2. Digital Map Data: The knowledge of the geometric information of the road is generated from maps which are commercially available for today’s car navigation systems. A list of points with non-equidistant intervals describe the roads (polygonal map), according to the shape of the real road.

3. DGPS (Differential GPS): The usage of digital map data requires the usage of a positioning system which enables the combination of sensor measurements and map data.

4. Lane detection camera: The lane detection system provides information of the own lane during velocities of more than 40 km/h. A 12-bit grayscale camera is used to obtain this lane information. The system delivers the lane shape with the parameters of the widely used quadratic equation.

5. HMI (Human-Machine Interface): HMI channels are available to provide information and warnings to the driver: a haptic accelerator pedal, a visual warning display, seat belt vibration, and audio signals.

6. ACC radar: this radar detects obstacle, and mounted on the front of the vehicle.

7. Vehicle to Vehicle Communication (VCC): enhances the selection of relevant targets.

8. Vehicle State Sensors: these sensors are installed on different parts of vehicle to detect and provide an estimation of the host vehicle's global state.

9. Fusion for Obstacle Estimation: This module gets input from the Long Range Radar. The aim is to detect and track vehicles in front of the ego-vehicle. Additional input comes via the communication channel, if another vehicle in the near of the ego-vehicle is able to detect an obstacle which is important for the scene reconstruction. The results of the module will be used in the path prediction module and to calculate the optimal maneuver.

10. Fusion for Road Geometry Estimation: This module will be described in more detail in the next section. The module gets information from the Position and Ego State Estimation module, from the Long Range Radar and the lane tracking system. Additionally, the module is using digital map data.

11. Position and Ego State Estimation: To have already reasonable position estimation for the road geometry algorithm, the vehicles position coming from the DGPS is improved by the fusion of the position with the speed
and yaw-rate from the ego-vehicle. A dynamic movement model is used for that.

12. Obstacle Path Prediction: A very important module in this system is the Obstacle Path Prediction module, because the computation of the optimal path needs an estimation, how the obstacles in the scene (other vehicles or objects) will move in the next seconds. Therefore, the current movement state of every obstacle coming from the Obstacle Estimation module will extrapolated in time and combined with other available information. The result is an estimated path for every tracked obstacle.

13. Host Vehicle Path Prediction: Also the path of the own vehicle has to be extrapolated, to allow the later comparison with the calculated reverence maneuver. The principle of this module is the same as the module above. Anyway, more information and information with higher accuracy is available at the module input, because the actual movement state of the ego-vehicle can be estimated more accurately than the movement state of other obstacles.

14. Reference Maneuver Computation: The computation of the reference maneuver is based on the aim, to find the best possible path and speed for the vehicle in a given situation. Therefore, a mathematical formulation of the goal function has been defined, that implements the rules for safe and human-like driving. The output of this module is passed to the HMI, where a warning method is selected, which is appropriate for a given situation (Gietelink et al. 2009; Weigel, et al. 2006).

4. Effective Factors in Road Accidents Occurrence

In order to use an agent-based approach for the proposed road accidents’ prevention model, having knowledge about the required parameters as inputs of agents in the model, is necessary. A list of required parameters for use in agent-based model is described in the table 1.

Table 1. Required Parameters in Road Accidents
(Weiss, 1999)
Due to complexity of parameters that are mentioned in the table I and in order to use agent-based technology to implement a agent-based model for our proposed system, this study uses an agent-based paradigm with BDI architecture for a part of the model that is showed in dashed line in the Figure 2. This part identifies parameters that effect on the brake point: sensor for determine road surface conditions (atmospheric conditions), sensor for measure vehicle slip percent, and sensor fusion for braking action point.

If the standard conditions are missed, designed agent will be able to prevent the accident by locking wheels. By considering above concepts, we develop a fuzzy multi-agent model for our proposed system that is showed with dashed line in Figure 3. In the other word, in order to exploit features and advantages of multi-agent based technology, we use this paradigm to calculate optimal brake point.

According to Figures 2 and 3 Components of BDI architecture for agents of fuzzy controller agent are shown in table 2.

<table>
<thead>
<tr>
<th>Agent Name</th>
<th>Believes</th>
<th>Desires</th>
<th>Intentions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agent1</td>
<td>U1=%current slip \ U2=% predicted slip</td>
<td>U2=U1+7*(U1-U0)</td>
<td>U2=U1+7*(U1-U0)</td>
</tr>
<tr>
<td>Agent2</td>
<td>U1=Signal of brake pressure to the pedal</td>
<td>determining road type: - dry -slippery or rainy -frozen or snow</td>
<td>Mauer state diagram</td>
</tr>
</tbody>
</table>

5. Fuzzy set theory

Fuzzy sets are introduced by lotfi zadeh (1965) as a tool for modeling uncertainties of natural language 45 years ago. A fuzzy set is defined by equation (1) as:

\[ \mu_A(x): X \rightarrow [0,1] \]  

A function is generalized characteristic, x refer to global set. for \( x \in X \), \( \mu_A(x) \) indicates that x with what degree is member of A fuzzy set. A fuzzy set is defined often as equation (2):

\[ A= \{(x, \mu_A(x)) \} | x \in X \]  

Operation on fuzzy set

Operation on fuzzy set that is designed considering with inference mechanism, will be including of one or a combination of the following operators (Phuong, 2001):

- Supplement of a fuzzy set.
- Subscription of two or more fuzzy sets.
- Community of two or more fuzzy sets.
- Combination of operators: using the Demorgan rules in fuzzy sets.

Fuzzy Expert System

Expert system is a system with linguistic variables, or numbers with internal uncertainty in its antecedent rules.
Approaches to identify fuzzy expert system

Build the fuzzy expert system is required to find relationship between input and output data. For example in medicine, input data are signs of illness and system’s output is doctor diagnosis.

Two types of approaches exist to identify system: direct approach and indirect approach, which are explained below.

Indirect approach is used when the data associated with input and output of system, is adequate to build the system and representation of different conditions of system. Modeling such system is performed based on data clustering method. This approach in medicine generally is used when the diagnosis largely depends on laboratory data.

The indirect approach, the encoded knowledge in the knowledge base is adopted from experts. In this approach, the knowledge engineer has a very important role in identify system. He uses the discussion methods with experts and trying to find input and output data (rules), relationship between them and identifies the parameters (if the variables have uncertainty). This approach is used when there is no sufficient data to identify system or consultation with experts will lead to better results (Hoppner et al., 1999).

Fuzzy expert system structure

Fuzzy algorithm is expressed as the main part in providing fuzzy rule based system. General structure of fuzzy expert system is presented in Figure 4. Expert system structure will contain four main sections which are given below (Emami et al., 1998).

1. **Fuzzification**: fuzzification module is responsible for fuzzification process. This process converts real numbers to fuzzy sets.
2. **Knowledge base**: knowledge base is general state of encoded knowledge in the knowledge base of expert system that is expressed as if-then rules.
3. **Inference mechanism**: reasoning process in the inference mechanism takes place as the following stages:
   - Community antecedences in each rule.
   - Inference rule for each relationship.
   - Community of all existing rules in the system.
   - Deduction from a set of rules using the input data in order to obtain fuzzy output.
   - Defuzzification output of system.

Considering the types of applied fuzzy mechanisms, Mamdani fuzzy model is the most important mechanism for fuzzy inference that is used in the fuzzy systems. The first fuzzy inference system was introduced by Mamdani in 1975 and due to its simplicity has many applications in fuzzy systems (Mamdani and Assilian, 1975).

4. **Defuzzification**: The input of defuzzification module is fuzzy set that is obtained of community fuzzy rules. This module convert fuzzy set to a real number based on defuzzification process. The most important method for defuzzification is using of central method that returns center of area under a curve to a number. Other methods such as mean of maximum (MOM), height and parametric methods are used for defuzzification process (Downs et al., 2001).

Our proposed controller agent is similar to mamdani model. This controller agent has eleven fuzzy rules: four rules for dry road conditions, four rules for icy road conditions, two rules for wet road conditions and one rule for wheels’ lock situation. At any time, only one set of these rules become active with regard to inputs of road type. List of fuzzy rules has been
suggested in the following. In these rules the input variables of controller agent have been named: "slip" that has been shown as $(U1-U0)$ in Figure 1, "Predicted Slip" that has been shown as U2 in Figure 2, "Previous Braking Torque" that has been shown as U2 in Figure 1 and "Braking Torque" that is output of controller agent.

1. If (DRY is true) and (Predicted Slip is not very large) then (Braking Torque is large).
2. If (DRY is true) and (Slip is large) and (Previous Braking Torque is large) then (Braking Torque is medium).
3. If (DRY is true) and (Predicted Slip is not very large) and (slip is small) and (Braking Torque is large) then (Braking Torque is large).
4. If (DRY is true) and (Predicted Slip is not very large) and (slip is medium) and (Braking Torque is large) then (Braking Torque is large).
5. If (ICE is true) and (Slip is zs) and (Previous Braking Torque is zs) then (Braking Torque is zs).
6. If (ICE is true) and (Slip is zero) then (Braking Torque is small).
7. If (ICE is true) and (Slip is small) then (Braking Torque is zero).
8. If (blockage is true) and (Predicted Slip is very large) and (slip is very large) then (Braking Torque is zero).
9. If (wet is true) and (Predicted Slip is not large) and (slip is zs) then (Braking Torque is small).
10. If (wet is true) and (Slip is small) then (Braking Torque is zs).
11. If (wet is true) and (Predicted Slip is not large) and (slip is zero) then (Braking Torque is small).

6.1 Simulation and Pseudo Code

To simulate our model the fuzzy rules are written in Matlab software. Pseudo code for fuzzy variables is described in tables 3 and 4.

Table 3. Pseudo code for fuzzy variables input

<table>
<thead>
<tr>
<th>Fuzzy variable</th>
<th>Variable values</th>
<th>Fuzzy interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{PS}_{\text{predicted slip}}$</td>
<td>$[0.01,0.03]$</td>
<td>$[0.01,0.03]$</td>
</tr>
<tr>
<td>$\text{slip}_{\text{predicted slip}}$</td>
<td>$[0.01,0.03]$</td>
<td>$[0.01,0.03]$</td>
</tr>
<tr>
<td>$\text{previous braking torque}_{\text{predicted slip}}$</td>
<td>$[0.01,0.03]$</td>
<td>$[0.01,0.03]$</td>
</tr>
<tr>
<td>$\text{braking torque}_{\text{predicted slip}}$</td>
<td>$[0.01,0.03]$</td>
<td>$[0.01,0.03]$</td>
</tr>
</tbody>
</table>

Table 4. Pseudo code for fuzzy variables output

<table>
<thead>
<tr>
<th>Fuzzy variable</th>
<th>Variable values</th>
<th>Fuzzy interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{Braking Torque}_{\text{predicted slip}}$</td>
<td>$[0.01,0.03]$</td>
<td>$[0.01,0.03]$</td>
</tr>
</tbody>
</table>

6.2 Knowledge Representation

Because of the values of variable commonly cited as linguistic variables or intervals that have uncertainty, the representation can play an effective role in increasing the measurement accuracy. Fuzzy techniques are used in order to represent uncertainty about variables' values. Parameters of input and output variables (degree of membership of variable in fuzzy set) have been calculated by library studies and consultation with experts. Experts express their opinions based on points with zero and one degree of membership (MF=0 and MF=1). With connecting these points together, trapeze and triangle membership function is created. Drawing triangle and trapeze shapes are used as common methods for present fuzzy membership functions. Table 5 shows fuzzy values and fuzzy intervals for variables such as: slip, predicted slip and previous braking in the knowledge base of system. Figure 5.(a) Shows membership function of predicted slip variable, Figure 5.(b) Shows membership function of slip variable, Figure 5.(c) Shows membership function of previous braking torque variable. Table 6 shows fuzzy values and fuzzy intervals for braking...
Torque as an output variable. Figure 5. Shows membership function for braking Torque variable.

Table 5. Input variables, fuzzy values and fuzzy intervals in the knowledge base of multi agent model for prevention of road accidents

<table>
<thead>
<tr>
<th>Input variable</th>
<th>Variables values</th>
<th>Fuzzy intervals</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted slip</td>
<td>Very large</td>
<td>0.0-0.15</td>
</tr>
<tr>
<td></td>
<td>Large</td>
<td>0.15-0.25</td>
</tr>
<tr>
<td></td>
<td>Zero</td>
<td>0.15-0.25</td>
</tr>
<tr>
<td>Slip</td>
<td>Small</td>
<td>0.01-0.05</td>
</tr>
<tr>
<td></td>
<td>Medium</td>
<td>0.05-0.11</td>
</tr>
<tr>
<td></td>
<td>Large</td>
<td>0.09-0.15</td>
</tr>
<tr>
<td></td>
<td>Very large</td>
<td>0.15-0.25</td>
</tr>
<tr>
<td>Previous braking torque</td>
<td>2/2</td>
<td>0-0.2</td>
</tr>
<tr>
<td></td>
<td>Large</td>
<td>0.4-1.2</td>
</tr>
</tbody>
</table>

Figure 5. (A) Membership function of predicted slip variable, (B) membership function of slip variable, (C) membership function of previous braking.

Table 6. Output variable, variable values and fuzzy intervals in the knowledge base of multi agent model to prevent road accidents

<table>
<thead>
<tr>
<th>Output variable</th>
<th>values</th>
<th>intervals</th>
</tr>
</thead>
<tbody>
<tr>
<td>braking torque</td>
<td>Zero</td>
<td>0-0.02</td>
</tr>
<tr>
<td></td>
<td>Zero_Small</td>
<td>0.0-0.12</td>
</tr>
<tr>
<td></td>
<td>Small</td>
<td>0.12-0.5</td>
</tr>
<tr>
<td></td>
<td>Medium</td>
<td>0.5-1.5</td>
</tr>
<tr>
<td></td>
<td>Large</td>
<td>1.5-5.5</td>
</tr>
<tr>
<td></td>
<td>Very_large</td>
<td>5.5-1</td>
</tr>
</tbody>
</table>

7. Conclusion

In this paper a multi agent model was presented for prevention of road accidents. Because parameters and inputs of this model are so abundant, so implementing it as a multi agent model is difficult. Therefore in order to create a clear picture of how to implement an appropriate multi agent model, only a part of proposed model that is related to brake system of vehicle is considered. Brake system is a highly non-linear system with variable parameters. Optimal state during braking can be achieved where the slip will be enough to maximize friction between wheel and road. Achieving to this goal is very difficult due to several factors including of variability of optimal operating point, changing the curve of friction coefficient-slip, lack of access or lack of efficient use of sensors related to key variables of model, and so on. Considering the benefits of fuzzy controller in the control of nonlinear and uncertain systems, an agent is used in this model that is named fuzzy controller. This agent has input variables such as: slip, predicted slip and previous baking torque. Also the output variable of this model is braking torque. If road be slippery, a signal will be sent from fuzzy controller agent to pedal of car that is caused locking the wheels and thus can prevent accidents. The proposed model uses a fuzzy multi agent approach with several advantages mainly concurrency in detecting accident conditions, and providing fast reactions against accident situation by giving warning to the driver or automatic action in the vehicle. We believe with the explained facilities which our proposed model provides for drivers it can help to prevent road accidents considerably and decrease the high statistics of accidents.

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