Fuzzy-Logic-Based Approach for Identifying Objects of Interest in the PRIDE Framework

Zeid Kootbally, Craig Schlenoff and Raj Madhavan[*]
National Institute of Standards and Technology
100 Bureau Drive
Gaithersburg, MD, USA
{zeid.kootbally, craig.schlenoff}@nist.gov, raj.madhavan@ieee.org

Sebti Foufou
University of Burgundy
Laboratoire LE2i, UMR CNRS 5158
Dijon, France
sebti.foufou@u-bourgogne.fr

ABSTRACT

On-road autonomous vehicle navigation requires real-time motion planning in the presence of static and moving objects. Based on sensed data of the environment and the current traffic situation, an autonomous vehicle has to plan a path by predicting the future location of objects of interest. In this context, an object of interest is a moving or stationary object in the environment that has a reasonable probability of intersecting the path of the autonomous vehicle within a predetermined time frame. This paper investigates the identification of objects of interest within the PRIDE (PRediction In Dynamic Environments) framework. PRIDE is a multi-resolutional, hierarchical framework that predicts the future location of moving objects for the purposes of path planning and collision avoidance for an autonomous vehicle. Identifying objects of interest is an aspect of situation awareness and is performed in PRIDE using a dangerous zone, i.e., a fuzzy-logic-based approach representing a hazardous space area around an autonomous vehicle. Once objects of interest are identified, the risk of collision between the autonomous vehicle and each object of interest is then evaluated. To illustrate the performance of a dangerous zone within PRIDE, preliminary results are presented using a traffic scenario with the high-fidelity physics-based framework for the Unified System for Automation and Robot Simulation (USARSim).

Keywords

4D/RCS, autonomous vehicle, dangerous zone, fuzzy logic, fuzzy space, long-term prediction, moving object prediction, object of interest, PRIDE, situation awareness

[*]R & D Staff Member, Computational Sciences and Engineering Division, Oak Ridge National Laboratory, Oak Ridge, TN 37831, USA.

1. INTRODUCTION

Road traffic driving for autonomous vehicles (AVs) is continuing to gain traction both with researchers and practitioners. Funding for research in AVs has continued to grow over the past few years, and recent high profile funding opportunities have started to push theoretical research efforts into worldwide development of the most advanced projects. A leading example of the state of the art in autonomous driving is the Defense Advanced Research Projects Agency's (DARPA) series of grand challenges. In 2007, DARPA presented the Urban Challenge [1] (Victorville, CA, USA), a research and development program on AVs with the goal of developing technology that will keep warfighters off the battlefield and out of harm's way. This event required each participating team to build an AV capable of executing simulated military supply missions while merging into moving traffic, navigating traffic circles, etc.

As demonstrated by the DARPA challenges, one of the main goal of AVs is to reduce the number of casualties in traffic accidents. The National Highway Traffic Safety Administration (NHTSA) [12] reported 42 642 killed people and 2 575 000 injured in motor vehicle crashes for the year 2006. It was also reported that one cause (after speeding) of these accidents is misjudgment due to carelessness. To reduce fatalities, many efforts have led to the enhancements of road designs, imposition of laws and regulations, and improvement of situation awareness (SAw) of the drivers.

Consequently, much effort has been directed towards trying to understand the "human factors" component in vehicle accidents. As pointed out by Sukthankar [20], a primary challenge to create an AV that can competently drive in traffic is the task of tactical reasoning, i.e., the AV should be able to decide which actions to perform in a particular driving situation, in real-time, given incomplete information about the rapidly changing traffic configuration. Humans are able to understand highly dynamic and complex environments via their cognitive capabilities. One component of these cognitive capabilities is SAw, namely, the human's ability to perceive the environment, comprehend the situa-

tion, project that comprehension into the near future, and determine the best action to execute [5, 6]. Researchers' hypothesis is that an AV with human-like SAw capabilities should improve the mission success of future AV systems [2]. Research has shown that poor SAw is an important cause of driving accidents [22], hence, an AV should have good capability of early recognition of obstacles and danger prediction. Adopting the idea that SAw is a key component in driving safety, the AV community has given considerable amount of attention on this topic.

The research interest of this paper bears upon a level of SAw of how other vehicles in the environment are expected to behave considering their situation. When humans drive, they need to understand how each object in the environment moves according to the situation they find themselves in. To address this need, PRIDE (PRediction in Dynamic Environments), a multi-resolution hierarchical framework has been developed. This framework provides an AV planning system with information that it needs to perform path planning in the presence of moving objects [16]. PRIDE supports the prediction of the future location of moving objects at various levels of resolution, thus providing prediction information at the frequency and level of abstraction necessary for planners at different levels within the hierarchy.

This paper presents a fuzzy-logic-based methodology to identify objects of interest within a dangerous zone for an AV. A dangerous zone is defined as a space with a potential of hazard. Once objects of interest have been identified, the risk of collision is then evaluated for an AV with each object of interest inside the dangerous zone. A simulated scenario using the Unified System for Automation and Robot Simulation (USARSim) [4] shows preliminary results and demonstrates the performance of a dangerous zone within PRIDE for identifying objects of interest.

The remainder of this paper is organized as follows: section 2 gives an overview of the PRIDE framework. Section 3 describes SAw within PRIDE and goes into detail about objects of interest. Section 4 describes the concept of dangerous zone used to identify objects of interests in the environment. Section 5 discusses the performance of a dangerous zone and section 6 concludes this paper.

2. THE PRIDE FRAMEWORK

PRIDE is a multi-resolutional hierarchical framework that provides an AV planning system with information required to perform path planning in the presence of moving objects. This framework supports the prediction of the future location of moving objects at various levels of resolution. PRIDE is based on the 4D/RCS architecture [8], which provides a reference model for unmanned vehicles on how their software components should be identified and organized.

The PRIDE framework provides moving object predictions to planners running at any level of the 4D/RCS hierarchy at an appropriate scale and resolution. The underlying concept of PRIDE lies in the incorporation of multiple prediction algorithms into a single, unifying framework.

At the higher levels of the framework, the prediction of moving objects needs to occur at a much lower frequency and a greater level of inaccuracy is tolerable. At these levels, moving objects are identified as far as the sensors can detect and a long-term (LT) prediction algorithm predicts where those objects will be at various time steps into the future. Higher-level reasoning processes need a global rep-

resentation of the environment to compute the future location of an AV. PRIDE uses the road network database [14] (RND) to access different information about the road networks, including individual lanes, lane markings, intersections, legal intersection traversability, etc. The lower levels of the framework use estimation theoretic short-term (ST) predictions based on an extended Kalman filter (EKF) to predict the future location of moving objects with an associated confidence measure. Complete details on the LT and ST prediction algorithms can be found in previous efforts [11, 16].

PRIDE currently integrates the Mobility Open Architecture Simulation and Tools (MOAST) framework along with USARSim [17]. This integration provides predictions incorporating the physics, kinematics and dynamics of AVs involved in traffic scenarios. MOAST is a framework that provides a baseline infrastructure for the development, testing, and analysis of autonomous systems[1]. MOAST implements a hierarchical control technique which decomposes the control problem into a hierarchy of controllers with each echelon (or level) of control adding additional capabilities to the system. USARSim is a high-fidelity physics-based simulation system that provides the embodiment and environment for the development and testing of autonomous systems. USARSim utilizes high-quality 3D rendering facilities to create a realistic simulation environment that provides the embodiment of a robotic system. The system architecture on the integration of PRIDE with the MOAST and USARSim frameworks is described in previous work [11].

PRIDE also handles drivers' aggressivity. In this context, the aggressivity represents the style and driving preferences of a driver. For example, one would likely assume that a conservative driver will remain in his lane whenever possible and will keep a gap between his vehicle and the leading vehicle. Conversely, an aggressive driver would have a higher probability of changing lanes and would be more apt to tailgate the leading vehicle. One may also find that the aggressivity of the driver may change over time, e.g., the driver can be very aggressive when trying to get to a certain lane, but become more passive when he gets there. The PRIDE framework addresses all the driver types and situations mentioned above. Experiments and corresponding results performed on aggressivity can be found in previous work [15].

3. SITUATION AWARENESS

To make assumptions of the future positions of moving objects, PRIDE has access to a level of SAw of how other vehicles in the environment are expected to behave considering the road traffic situation. An AV should be able to plan a path while avoiding any collision with obstacles or other moving objects on the road. The AV also requires knowledge of the environment and knowledge on the status of other objects in the environment to be able to drive tactically. The modeling of other vehicles is the most important aspect of tactical driving [20]. It is straightforward to model speed and relative positions, however, it is a challenging task to model the future behavior of the drivers.

SAw was first discussed in connection with pilot perfor-

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[1] Autonomous systems in this context refer to embodied intelligent systems that can operate fairly independently from human supervision.

mance in air-to-air combat and was seen as the critical difference between fighter aces and ordinary pilots [7, 10]. Since its original conception, numerous definitions of SAw have been proposed. The work presented in this paper uses the formal definition from Endsley [6] where SAw is described as *[An expert's] perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future.*

3.1 Situation Awareness Model

The model of SAw within the PRIDE framework is being developed based on a three-level model provided by Endsley [6], as sketched in Figure 1.
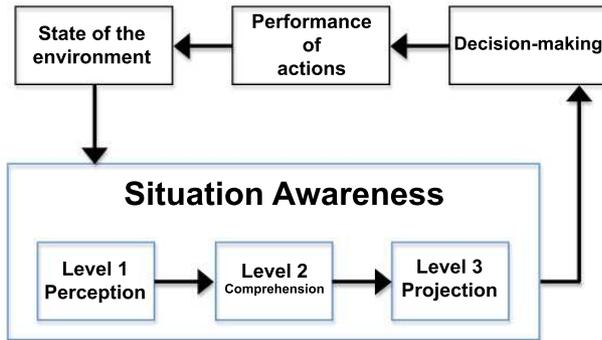

Figure 1: Endsley's model of situation awareness (from [19]).

- Perception: this level of awareness is achieved if AVs are able to perceive different elements (e.g., vehicles, roads) in the environment as well as their characteristics (e.g., size, color, location).

- Comprehension: not only the AVs must perceive relevant information in the environment, they also must combine the perceived data to interpret the situation correctly.

- Projection: at this level, the AVs have the ability to anticipate the actions of other vehicles and predict the future states of the environment.

The perception level for an AV in PRIDE is addressed through the MOAST/USARSim framework [17] and the RND [14]. MOAST queries USARSim to retrieve the characteristics of the AVs, such as the speed, the cartesian coordinates, the orientation, and the speed rotation of the wheels. PRIDE then compares the collected information to the RND to determine the position of the AV in the environment. The query returns the type of the road where the AV is positioned, the ID of the lane, the speed limit, and the traffic flow on the lane.

At the comprehension level, PRIDE combines the elements from the perception level to present a situation for the AV. For example, a vehicle with high speed (as compared to the speed limit of the road) and high acceleration could be considered as aggressive for example. Likewise, a vehicle driving at high speed toward the same uncontrolled

intersection as the AV has a higher probability of collision than if its speed was lower. Hereby, PRIDE has the ability to understand the situation by gathering different information from different sources.

At the projection level, the LT prediction algorithm computes the future position of each AV by first computing all realistic action sequences. Then, based on a final cost for performing each action sequence, the LT algorithm chooses the action with the lowest cost, i.e., the one with the highest probability (see [16] for more details). The selected action sequence is based on the actions of other moving objects and on the situation of the AV itself. The output of the LT prediction algorithm is a collision-free path for the AV.

3.2 Object of Interest

The goal of PRIDE is to emulate human drivers' behaviors for AVs. As such, to achieve autonomous driving with human-like SAw capabilities in the presence of moving objects, the AVs have first to identify objects of interest in the environment. This section establishes the idea of identification of objects of interest, which is part of the *state of the environment* step, as depicted in Figure 1.

At its current state, PRIDE first takes into account all moving objects in the environment and then tests if any future collision is likely possible. It is obvious here that there is a need for identifying only specific objects (moving or static) and then evaluating the danger caused by each object. In real world, a driver pays attention to only a few objects around him, and obviously not to all of them. Since time constraints prevent processing all of this information at every time instant, the driver must intelligently select the information most critical to the immediate task. Focusing on some moving vehicles or static obstacles first reduces the computation time for collision, especially for a large number of vehicles and obstacles in the environment. Furthermore, identifying these specific objects constitutes a step further towards the simulation of a typical driving behavior. The AV should first focus on objects of interest in the environment that most constrain its available actions [13]. For example, when approaching an intersection with a STOP sign, the AV can safely ignore the trajectories of the vehicles beyond the intersection, since the STOP sign forces the AV to come to a halt. The AV should also make strong assumptions about objects in the environment. While observing an oncoming vehicle, the AV could note its position and velocity, then "forget" about the oncoming vehicle for some time interval, knowing that the vehicle would not be able to close the distance in that time. The AV focuses on particular objects at particular time in particular situations. These objects are termed "objects of interest" and can be defined as *a moving or stationary object in the environment that has a reasonable probability of intersecting the path of the autonomous vehicle within a predetermined time frame.* The identification of objects of interest is performed with the methodology presented in the next section.

4. METHODOLOGY TO IDENTIFY OBJECTS OF INTEREST

The methodology for the identification of objects of interest consists of two steps:

1. Building a dangerous zone around an AV to identify objects of interest.

2. Evaluating the risk of collision of the AV (called driving risk level) with any object of interest.

4.1 Dangerous Zone

Moving vehicles are subject to physical hazards coming from any direction, e.g., lateral impacts from the non-respect of rights-of-way at intersections or from a non-detected vehicle in the blind spot, and rear-end crashes usually due to inattention, following too closely, or both. Some of these accidents occur when the driver fails to maintain a safe headway from the leading car because of a perceptual inadequacy in estimating headways [21].

To effectively model the importance of an object on the road, PRIDE relates to the concept of dangerous zone (DZ) [18] to identify objects of interest in the space area around the AV. A DZ is defined as a space with a potential of hazard. Within the DZ, objects of interest have a different degree of risk according to different criteria such as the distance between an object of interest and an AV.

In conventional methods, the classical definition of "membership" puts an object either inside our outside a zone. The approach proposed in this paper tries to evaluate the degree of severity of an object within the DZ by classifying this object based on several criteria. One criterion would be for example, the closeness of an object of interest to the AV, which could be interpreted as close, very close, far, very far. As such, the effort of this paper describes a DZ by applying multi-dimension fuzzy sets to model gradual changes in collision severity. The concept of fuzzy space (FS) is used to present the spatial consideration fuzzy sets in two dimensions.

4.1.1 Fuzzy Space

The concept of FS is based on fuzzy logic and fuzzy sets. Fuzzy logic is a superset of conventional (Boolean) logic that has been extended to handle the concept of partial truth. In 1965, Zadeh introduced fuzzy sets as an extension of the classical notion of a set to represent uncertain and imprecise knowledge [23]. Fuzzy sets and fuzzy logic are used to heuristically quantify the meaning of linguistic variables, linguistic terms, and linguistic rules that are specified by the expert.

Fuzzy logic uses graded statements rather than ones that are strictly true or false. Fuzzy logic attempts to incorporate the "rule of thumb"[2] approach generally used by human beings for decision making. Thus, fuzzy logic provides an approximate but effective way of describing the behavior of systems that are not easy to describe precisely.

Definitions.

To define a FS, the universe of discourse is in the form of $\mathbb{R}^2$. The work proposed in this paper considers the longitudinal distance x and the lateral distance y as linguistic variables from the relative coordinates of the AV. A typical linguistic variable is expressed as:

Linguistic Variable(*term 1, term 2,..., term n*)

where n is the number of terms in the linguistic variable.

To define a FS, let $X \subset \mathbb{R}$, and $x, y \in X$. A_x and A_y are the fuzzy sets for the degree of risk as defined below:

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[2]A method of procedure based on experience and common sense.

$$A_x = (x, \mu_{A_x}) | x \in X, X \to [0, 1]$$
$$A_y = (y, \mu_{A_y}) | y \in X, X \to [0, 1]$$

Figure 2 depicts a trapezoidal membership function for the longitudinal direction as defined by Equation 1.

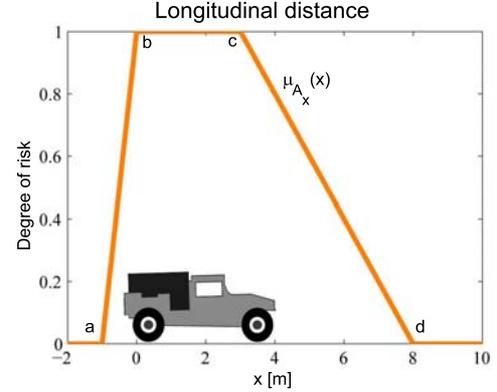$$\mu_{A_x}(x) = \max(\min(\frac{x - a}{b - a}, 1, \frac{d - x}{d - c}), 0) \qquad (1)$$

Figure 2: Longitudinal dangerous zone.

The parameters a and d correspond to the "feet" of the function $\mu_{A_x}(x)$. The parameter d represents the safe distance headway of the AV. This headway is typically defined in terms of time rather than distance, and a commonly recommended minimum safe headway is 2 s. That way, if a lead driver initiates a braking action, the following driver has 2 s to initiate a braking response to the slowing down of the vehicle ahead. Using several parameters (e.g., current velocity of an AV, aggressivity, and weather), PRIDE converts the safe time headway into the corresponding distance headway.

Being able to modify the headway is an interesting point for the LT prediction algorithm. The LT algorithm computes the future location of moving objects at n seconds in the future [16]. So far, the time of prediction was established before running the simulation and could not be changed thereafter. With the ability to change the headway regarding the situation of the AV and the environment, the time of prediction is also modified in real-time. This subjects is further discussed in the rest of this paper.

The parameters b and c represent the range of the membership function for which the degree of risk is the highest, i.e., where the x values are closest to the AV. It is reasonable to use the length of the AV (information from USARSim) to define b and c.

For an object far from the AV, the risk of collision is low. Conversely, for an object closer to the AV, the risk of collision increases to its maximum. The function increases faster in the rear of the AV, thus describing a greater danger for a vehicle too close to the leading AV.

Figure 3 shows the bell shape membership function for the lateral distance as defined by Equation 2.

$$\mu_{A_y}(y) = \frac{1}{1 + |\frac{x - c}{a}|^{2b}} \qquad (2)$$

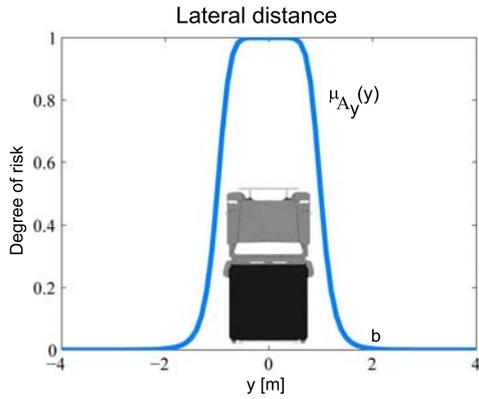The parameter b is linked to the width of the lane and is defined using the RND. The risk of collision grows for any

Figure 3: Lateral dangerous zone.

Figure 4: Fuzzy space A_{xy}.

point approaching the AV on its sides. The parameter c locates the center of the curve (0 in this case). The value of a determines the membership values of the extreme points (0,1) of the universe when the crisp value, c, coincides with the center of the universe (0 in this case). The membership function $\mu_{A_y}(y)$ shows an increasing risk of danger for any object coming closer to the sides of the AV. Similar to the definition of the longitudinal distance, the membership function for the lateral distance has the ability to include the dimension of the AV. In this case, the width of the lane is taken into account, and thus the width of the AV within the lane.

Construction of the Fuzzy Space.

Different methods exist for the construction of FSs to describe DZs, such as the minimum intersection, the multiplication intersection, the rotational extension, and the cylindrical extension (see [9] for an exhaustive list).

In this paper, the construction of the FS A_{xy} is performed with the multiplication intersection method. The algebra multiplication $\mu_{A_x}(x)\,\mu_{A_y}(y)$ is preferred to the fuzzy logic multiplication $\min(\mu_{A_x}(x), \mu_{A_y}(y))$. As pointed out by Shahrokhi and Bernard [18], the minimum intersection fuzzy space is not sufficient to demonstrate all DZs. Furthermore, the algebra multiplication is more efficient for risk detection. The multiplication intersection fuzzy space A_{xy} for the longitudinal and lateral distances is defined by Equation 3 and is depicted in Figure 4.

$$A_{xy} = \mu_{A_x}\mu_{A_y} \qquad (3)$$

It is important to understand that the fuzzy sets defined previously are not a standard for all road structures. The fuzzy sets are tuned according to the type of the road. The membership functions defined by Equations 1 and 2 are appropriate for a straight road. For a AV approaching an intersection for example, the fuzzy space can be spread over a larger area and can be represented by a semi-spherical shape incorporating some parts of the intersection.

4.2 Fuzzy Expert System

As discussed previously, the membership functions depend on different parameters, e.g., the aggressivity of the driver to compute the safe distance headway d in Equation 1 (Figure 2). The designer has to intelligently choose relevant parameters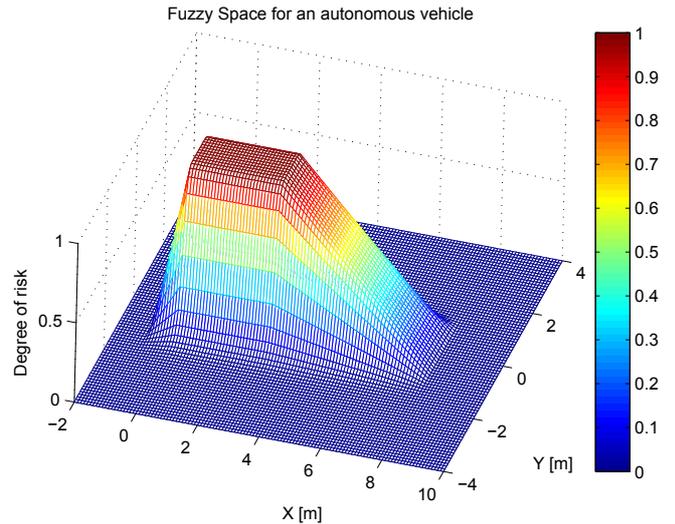 so that the FS could adapt to different situa-tions. A fuzzy expert system is used with these parameters to compute the appropriate FS.

Fuzzy expert systems are rule based controllers where the inference mechanism is grounded on fuzzy logic. The general architecture of a fuzzy expert system is depicted in Figure 5.
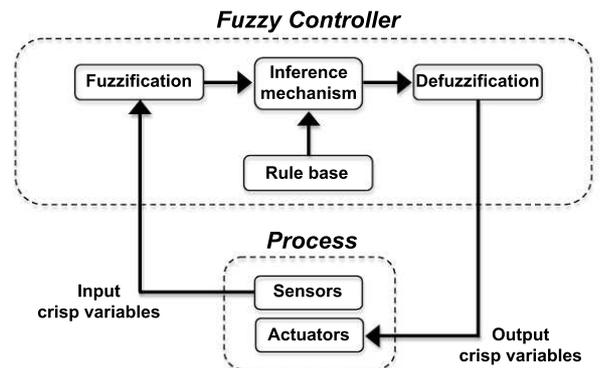

Figure 5: Architecture of a fuzzy expert system.

- The *fuzzification* module takes real input values (crisp values) and maps them to the terms by assigning a degree of membership. For continuous variable, the degree of membership is expressed by a membership function. There is a degree of membership for each linguistic term that applies to the linguistic input variable.

- The *rule base* holds the knowledge in the form of a set of rules, of how best to control the system. In general, fuzzy controllers are based on control rules of the type "IF `condition`" THEN "`control`" where `condition` and `control` are always fuzzy propositions (formula of fuzzy logic) of the type "x is A", where x is a linguistic variable and A is a linguistic term.

`condition` tells when the rules should be applied and `control` describes the action to apply.

- The *inference mechanism* is the kernel of the fuzzy controller. The inference mechanism evaluates which control rules are relevant at the current time and then decides the fuzzy commands to apply to the process.

- The *defuzzification* module is needed to translate the fuzzy output of a fuzzy controller to a numerical representation. Intuitively, defuzzification can be done using an averaging technique. The work described in this paper uses the center of gravity method [9], which is the same method employed to calculate the center of gravity of a mass.

4.2.1 Linguistic Variables

In this paper, PRIDE uses the aggressivity, the speed, the weather, and the acceleration as input linguistic variables and the safe distance headway as the output. The linguistic variables and the linguistic terms are presented in Table 1.

	Variables				
	Input				Output
	Speed	Aggressivity	Weather	Acceleration	Headway
Terms	Zero	Passive	Rainy	Zero	Very Low
	Small	Normal	Snowy	Small	Low
	Medium	Aggressive	Stormy	Medium	Medium
	Big		Sunny	Big	Big
					Very Big

Table 1: Linguistic variables used by the fuzzy expert system.

Once the linguistic variables are established, a set of rules for the inference mechanism has to be defined. Example of rules are shown below:

1. IF "`Speed is Small`" AND "`Aggressivity is Normal`" AND "`Weather is Sunny`" AND "`Acceleration is Zero`" THEN "`Headway is Low`".

2. IF "`Speed is Medium`" AND "`Aggressivity is Normal`" AND "`Weather is Snowy`" AND "`Acceleration is Small`" THEN "`Headway is Medium`".

4.3 Evaluation of Driving Risk Level

Any object of interest is likely to lead to a potential collision. To evaluate the driving risk level (DRL) of the AV, the distribution of the objects of interest within the DZ is taken into account. Each object of interest is represented by its position O_{x_i,y_i} in the environment. The DRL for each object of interest O_{x_i,y_i} is computed by maximizing the FS $A_{x_iy_i}$ as shown by Equation 4 [3].

$$DRL = \max(A_{x_iy_i}) \qquad (4)$$

Since the time of prediction coincides with the headway, the LT cost-based approach computes the cost for an AV to perform an action sequence. When an object of interest is identified in the DZ, the LT algorithm computes the cost of collision of the AV with the object of interest. At this point, this cost is modified by the value of the DRL computed using Equation 4.

5. PRELIMINARY RESULTS AND DISCUSSION

This section describes a traffic scenario and demonstrates the performance of the DZ for an AV. In the following scenario, the dimension of the AV is Length× Width=3.686 m×1.799 m (from USARSim). According to the RND, the width of the lane is 3.75 m. Finally, the weather is set to "snowy".

The chosen scenario is a lane-change maneuver over an obstacle. The AV and the static obstacle are in lane L1 as shown in Figure 6.
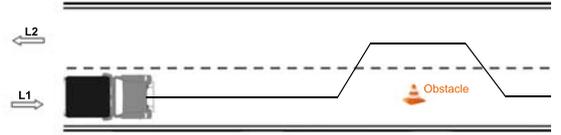

Figure 6: Vehicle avoiding a static obstacle.

Figure 7 shows the current positions of the AV and the static obstacle. The negative values for the Y coordinates are due to the coordinates of this particular road network in USARSim.

During its trajectory, the AV starts to switch to the left lane L2 at X=103.6 m and Y=-220 m. At this time, the distance between the AV and the static obstacle is approximately 5.5 m. The average speed of the AV on this track was 4 m/s. Since the weather is snowy for this scenario, the headway is greater (about 6.6 m) than it would be for a sunny weather.
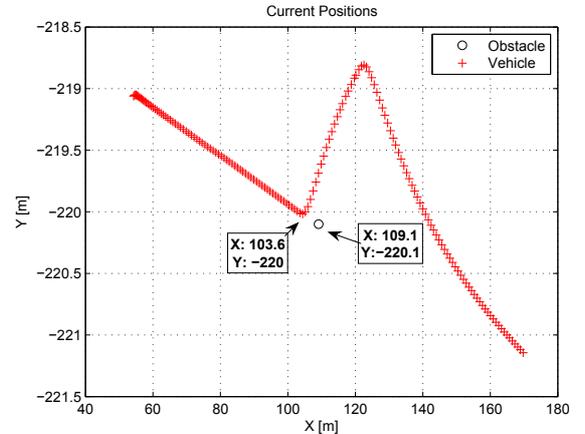

Figure 7: Current positions of the autonomous vehicle and the static obstacle.

Figure 8 depicts the variation of the DRL computed using Equation 4 with the static obstacle as object of interest. The negative values refer to the distance while the AV drives toward the obstacle (before reaching the obstacle), and the positive values indicate the distance when the AV drives away from the obstacle.

It can be seen that the DRL is null while the AV is far away from the obstacle, before and after passing the obstacle. During this time period, no object of interest is detected
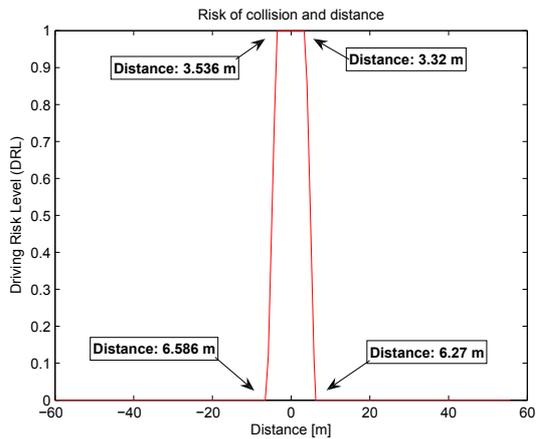
Figure 8: Driving risk level compared to the distance from the obstacle.

by the AV. However, at a distance of 6.586 m from the obstacle, the DRL starts to increase when the object of interest is identified within the DZ of the AV. The closer the AV is to the obstacle, the faster the DRL increases, meaning the higher is the risk of collision. The AV starts to gradually move to L2 as soon as the value of the DRL is high enough for a possible danger of collision. The DRL starts to increase at a distance of 6.5 m from the obstacle, however, the AV starts to switch to L2 only at a distance of 5.5 m from the obstacle, i.e., when the DRL is in [0.6 - 0.7] (Figure 8). The DRL value within this range modifies the cost associated to the straight path of the AV and thus the LT algorithm chooses a less expensive action, i.e., swerving to L2 in that case.

The DRL reaches its highest level (0.9982) for the AV being at around 3.5 m from the obstacle. While the AV is moving to L2, the value of the DRL decreases and reaches 0 at 6.27 m away from the obstacle. At this point, since no object of interest is identified within the DZ, the LT algorithm modifies the cost associated to the AV driving in lane L2. A penalty is given to the AV for not being in the right-most lane, hence the lane switching to L1 at X=120 m and Y=-218.7 m as depicted in Figure 7.

6. CONCLUSION

The work presented in this paper enhances situation awareness within the PRIDE framework by identifying objects of interest in the environment. Autonomous driving requires human-like situation awareness capabilities. Consequently, autonomous vehicles (AVs) must consider objects of interest in the environment in order to plan a collision-free trajectory. Identifying objects of interest can be assimilated to a driver who only focuses on some objects that most constrain his available actions.

The identification of objects of interest is performed by a dangerous zones (DZs). In this context, a DZ is a fuzzy space which represents a hazard area for an AV. The DZ is built by first assembling relevant parameters, which are then processed through a fuzzy expert system to adapt the fuzzy space to different situations. Any object that falls inside the DZ is identified as object of interest. Once the objects of interest are identified, the risk of collision of the AV is

evaluated.

The fuzzy space has the advantages in considering the dimension of the AVs, thus improving collision avoidance. Another advantage is the modifications of the time of prediction for the LT prediction algorithm in real-time. This second point is useful to emulate driving tasks taking into account the current forecast and the variation of the aggressivity for example. Lastly, by first identifying objects of interest, and only then evaluating the danger pertinent to these objects, the time of computation of the LT algorithm is theoretically reduced, as compared with the former version of the LT algorithm.

The concept of DZ has demonstrated reasonable results with a new way to identify any danger in the environment. However, the preliminary results were obtained for a single AV on a simple straight road with a static obstacle. Identifying objects of interest in more complex traffic situations is a challenge and should be developed in the near future. Since the concept of DZ was first introduced in industrial systems, PRIDE already has the capacity of considering DZs before moving towards simulation in industrial facilities.

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