Game Theoretic Fuzzy Multi-Entity Bayesian Networks for Collision Avoidance in VANETs

Keyvan Golestan, Ridha Soua, Fakhri Karray, and Mohamed S. Kamel

Abstract— **Situation prediction is a crucial part of active Advanced Driver Assistance Systems (ADAS) to prevent rear, lateral and other collisions. Majority of road crashes can be prevented if the ADAS issue a warning about a potential threat at least one-half second prior to the prominent accident. To take the suitable maneuver, active safety systems should assess succinctly the danger caused by other errant drivers and analyse surrounding drivers intent. This study presents a game theory impact assessment and decision making model that allows drivers to assess threat level caused during different road scenarios. Our model is based on Fuzzy Multi-Entity Bayesian Network (Fuzzy-MEBN) enriched by a game theory component. Illustrative scenarios are provided to show the merit of our model.**

I. Introduction

Vehicular Adhoc Networks (known as VANETs) are a cornerstone of the envisioned Intelligent Transportation Systems [1]. In these Adhoc networks, vehicles are equipped with wireless radio interfaces that enable them to communicate with each other via Inter-Vehicle Communication (V2V communication) as well as with a set of stationary units along the road called road infrastructure [2]. These stationary units can be traffic lights, street signs, and roadside sensors. The communication with stationary units is called Vehicle-to-Road infrastructure (V2R). Moreover, smart vehicles can communicate also with Internet (V2I). In VANETs, vehicle nodes continuously exchange messages with other moving cars in their proximity, and hence collect and share pieces of information about their surrounding environment. Therefore, these Adhoc cooperative networks contribute to safer trips by providing timely information to drivers. The target is to provide drivers with larger telematic horizon so potential accidents or crashes can be detected in earlier stages.

Road accidents cause a great deal of loss of lives worldwide. Conducted studies in [3] have highlighted that 60% of accidents can be mitigated if the driver was informed by the prominent accident at least one-half second prior to the crash. This situation has urged the need to have active Advanced Driver Assistance Systems (ADAS). The car acts in more proactive fashion to detect errant surrounding drivers and determine if a collision is imminent. If a threat is imminent, the vehicle applies the suitable maneuver to stop the car or slow it down to mitigate the crash. This is the focus of Impact assessment (IA): How to estimate likelihood and cost measures associated with the potential outcomes of a agent's planned actions [4]. IA is the third level of the JDL model. IA is composed of prediction and risk analysis. Based on previously assessed situations and their threats, IA computes the likelihood of future hypothesized situations. Then, the driver can take the proper maneuver. Hence, IA is important to provide cars with tactical level reasoning and Decision Making (DM) in the streets. Particularly, IA in the context of VANETs raises many challenges. Indeed, the spectacular increase of vehicles number coupled with the diversity of drivers behaviours make driving in the road a complex task. Predicting future situation and assess their impact can be difficult.

Approaches proposed to tackle IA in the context of VANET's can be broadly classified into two categories: Probabilistic Graphical Models (PGMs) and Game Theory (GT) [5]. On the basis of [6], we propose in this paper, an innovative data fusion framework for impact assessment and decision making based on GT. Particularly, threats are detected and their intents are predicted by a normal form game in the level three of JDL model. The remaining of the paper is organized as follows. In Section II, we review some existing work for IA in VANETs. Section III will provide a brief review of essential GM and Fuzzy Multi Entity Bayesian Networks (Fuzzy-MEBN) theoretic notions. Then, we will highlight in Section IV the problem of IA and DM in Fuzzy-MEBN and propose our new model for IA enriched with GT. Sections V and VI contain examples to illustrate the proposed methodology and the merit of our approach. Finally, the concluding remarks appear in Section VII.

II. Related Works

Situations in streets are developed by actions performed by drivers, pedestrians and cars which are the main players of situation evolution. By successfully assessing possible future threats from these involved entities, drivers (decision makers) can make more effective targeted decisions and mitigate the impact of unexpected surrounding entities actions. Game Theory (GT) is an efficient method to provide this information by modeling the behavior of different players. We focus in this section on studies that have used GT as a tool to tackle IA. The authors in [7] introduced a game-theoretic information fusion approach to tackle threat and impact assessment in military domain applications. The core of their proposed framework is based on Markov (stochastic) game theory. Crucial segments of the Markov game, namely, Players, State Space, Decision, Transition Rule, and Payoff

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Functions, along with different Strategies (Pure Nash, Mixed Nash, and Correlated Equilibria) are studied.

Tang *et al.* in [8] proposed a model for threat and situation assessment in cyber insider scenarios. They used dynamic Bayesian Networks (BN) as their information fusion module, and then coupled it with a game module that uses Quantal Response Equilibrium (QRE) as its strategy method. The main intuition behind choosing QRE is its capability in modeling rationality of players. However, authors made a strong assumption when they assume that all insiders and administrators are considered as single. Hence, the game is a two-person game only.

A Threat Assessment (TA) model proposed by Aoude *et al.* [9] is based on a combination of game theory and Rapidly-exploring Random Trees (RRT). The authors tackled the problem of collision avoidance at intersections containing a host vehicle, and an erratic traffic vehicle which is similar to an adversary unit in a game model. Threat assessment is calculated based on the Time To Collision [10] metric for each expanded node in RRT. However, in this approach, computing all possible trajectories and pair-wise probabilities for intersections introduces a considerable computational cost.

A prediction and planning framework for collision avoidance is introduced in a technical report by Broadhurst *et al.* [11]. The authors determined the main entities involved in prediction, and the most important elements of planning. Furthermore, the main aspects of a game such as states, actions, strategies and payoff functions are formulated. In the experiments, sequential game playing is employed and it is assumed that the states are updated in turn-based manner.

Authors of [12] used an influence diagram, a natural extension to a BN, as basic data to develop a technique that models higher-level agent interaction. The proposed architecture is based on two criteria: 1) agent's decisions are based on their belief on the other agents' information. Authors ensure this criteria by playing a game with incomplete information, 2) well-established and realistic probabilistic model of the situation. This latter criteria is achieved by using an influence diagram for representing the model of the current situation awareness.

III. Technical Background

A. Normal Form Games

A game models a situation where two entities or more are competing for some resources or issues. Entities involved in the game are called players and could represent people, cars, military troupes, etc. The available actions to the players are referred to as options. A strategy is the set of options that can be used by a specific player. The games can be represented in two forms: 1) The normal (strategic) form and 2) The extensive form. In the following, we will formally define the strategic form since we will used it for IA. The strategic form game ensures the modeling of simultaneous, perfect-information interactions between a set of agents. Moreover, all other representations of finite games such as extensive form, Bayesian can be encoded in it.

Definition 1: A finite, n-player game $\langle$ N, $\mathcal{A}$, u $\rangle$, is defined by:

- N: a finite set of n players, indexed by i;
- $\mathcal{A}$: $\langle$ $\mathcal{A}_1$,.. $\mathcal{A}_n$ $\rangle$: a tuple of action sets for each player. We call each node $\mathcal{A}_i \in \mathcal{A}$ an action profile.
- u:$\langle$ u_1,..., u_n $\rangle$: a utility/payoff function for each player where: $u_i \rightarrow \mathcal{R}$ is player i's utility function.

It is worth noting that a player's utility depends not only on his own strategy but also on the strategies played by other players. Each player tries to maximize the expected value of u_i. The expected value is computed based on his own beliefs. A player i is called $rational$ iff he tries to maximize u_i given his beliefs.

A strategy str_i for a player i is any probability distribution over the actions A_i. Therefore, we differentiate two classes of strategies:

- Pure strategy: one action is played with positive probability by the player.
- Mixed strategy: multiple actions are played with positive probability.

Let str_{-i} denote the strategies taken by all other players $\neq i$. $str_{-i} = \langle str_1, ..., str_{i-1}, str_{i+1}, ...str_n\rangle$. Hence $str = (str_{-i}, str_i)$.

If a player knows what strategy that every other players will accomplish, the Best Response (BR) of the player i can be defined as:

Definition 2: $str_i^* \in$ BR(str_i) iff $u_i(str_i^*, str_{-i}) \geq u_i(str_i, str_{-i})$ for every strategy str_i available to player i.

B. Fuzzy Multi-Entity Bayesian Network

The concept of situation is very important for IA. Indeed, a situation is composed of a set of entities that are tightly related by causal or semantic relationships. In road safety applications, involved entities include drivers, cars and pedestrians. Consequently, a situation might be configured to monitor driver's distraction, while another one is set to monitor crossing a road intersection to identify potentially hazardous situations. Moreover, a set of situations, tightly related, can construct a super-situation that will be assessed. Figure 1 depicts a collision threat supers-situation that highlights the arrangement of involved component situations

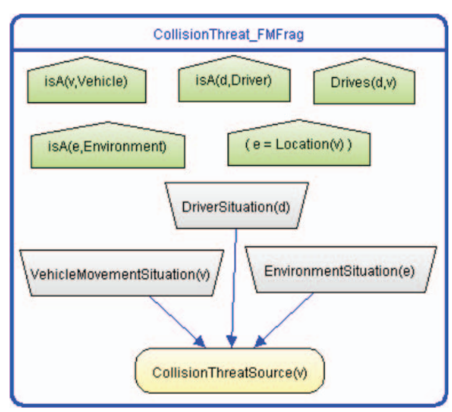

Fig. 1. Collision Threat super-situation

In the following, we briefly describe our model for situation and threat Assessment model proposed in [13]. It provides the fundamental concepts of a threat assessment system using Fuzzy-MEBN. The reader can refer to [14] and [13] for further details.

The fundamental component of our Situation and Impact Assessment are the component situations $s_i = (E_i; R_i)$ which are modeled in Fuzzy Multi-Entity Bayesian Network using Fuzzy MEBN Fragments (FMFrags). An FMFrag is defined as $\mathcal{F} = (\mathcal{C}; \mathcal{I}; \mathcal{R}; \mathcal{G}; \mathcal{D}; \mathcal{S})$ where:

- $\mathcal{C}$ denotes context nodes
- $\mathcal{I}$ denotes Input nodes
- $\mathcal{R}$ denotes resident nodes
- $\mathcal{G}$ represents a FMFrag graph
- $\mathcal{D}$ contains local distributions per each resident node
- $\mathcal{S}$ encompasses a set of fuzzy if-then rules.

We define an FMTheory as a set of FMFrag instances whose consistency constraints are satisfied. In other words, an FMTheory implicitly models a super-situation such the collision threat super-situation depicted in Figure 1. Threat entities are grouped based on their context and then are imported to the super-situation.

Fuzzy Extension to Multi-Entity Bayesian Networks was introduced in our Attention Assist Framework (AAF) [6] as depicted in Figure 2. The data is originated from the vehicle,

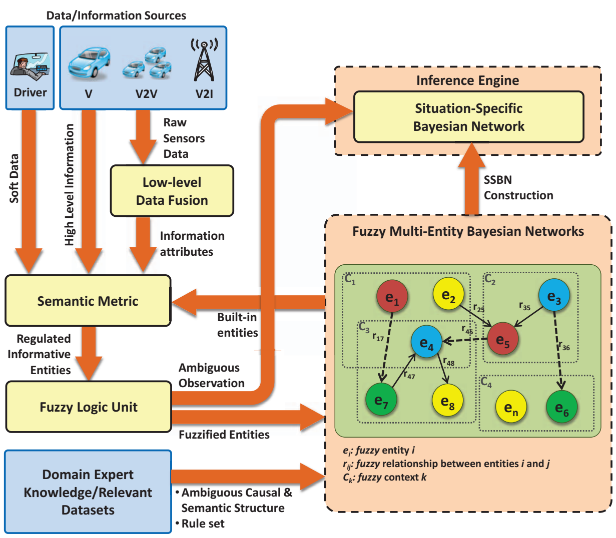

Fig. 2. Incorporation of Fuzzy MEBN in AAF

surrounding cars, infrastructure, or the driver with various levels of abstraction. Upon having their information attributes set, interpretation of input entities are compared with the built-in entities (predefined by domain experts within Fuzzy MEBN structures) using semantic similarity methods. Next, the input entities are annotated and are represented by fuzzy singletons. Finally, a Situation Specific Fuzzy Bayesian Network is constructed based on the imprecise contextual information. However, a limitation of MEBN (and our Fuzzy extension) is its incapability of performing IA and DM. Therefore, this paper proposes a game theory approach to enrich the current model with projection of the current situation into the future to accomplish DM.

IV. Game Theoretic Fuzzy Multi-entity Bayesian Networks

As our cities suffer from the overwhelming increase in the number of vehicles on the roads, the question of IA and safe behavior of drivers becomes challenging. GT may provide useful insights into the way road users, that share a critical space, should take actions under different situations.

A. Problem Statement

The original MEBN [15] model is not able to model the inherent ambiguity in human language. Therefore, we have introduced the fuzziness in [13] to handle ambiguous data, and perform inference on vague information. Despite this new extension, our model is not able to perform IA and DM.

To overcome this drawback, we propose a new version of Fuzzy-MEBN called AcTive Fuzzy-MEBN (ATFY-MEBN). It is enriched with action and game nodes that models different interactions between different entities in VANETs. The new version is able to assess hazardous situations and predict incoming threats. In the following, different aspects of this new version are defined, and its main components are introduced.

B. Game Theoretic Fuzzy MEBN

The focus of this paper is IA and DM therefore we will tackle the Traffic Impact Assessment Unit and DM. These two units are crucial components of our impact model depicted in Figure 3. These units will be modeled by GT to succinctly handle the large number of actions of normal and errant vehicles.

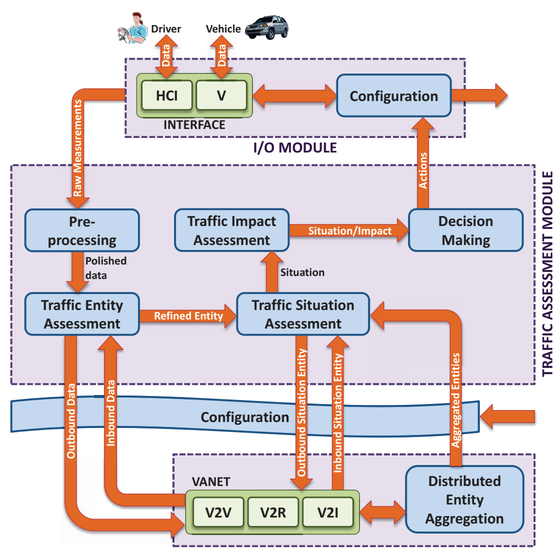

Fig. 3. Blocks diagram of Threat/Impact Framework

We define here the new structure of MFrags that incorporate the game/actions aspect. We denote it by MFrag*.

Definition 3: An $MFrag^*$ $\mathcal{F} = (\mathcal{R}, \mathcal{C}, \mathcal{I}, \mathcal{A}, \mathcal{M}, \mathcal{G}_{0,1}, \mathcal{D}_{0,1}, \mathcal{S})$ is a 2-tier 8-tuple wherein $\mathcal{R}$, $\mathcal{C}$, and $\mathcal{I}$, are respectively the conventional sets of resident, context, and input nodes that reside on traffic entity and situation assessment units (see figure 3). Furthermore, $\mathcal{A}$ and $\mathcal{M}$ are action nodes and game nodes sets, which bring the active feature to MFrag and are laid on Traffic Impact Assessment and DM units. Moreover, $\mathcal{G}_{0,1}$ and $\mathcal{D}_{0,1}$ are respectively the graph representation of $\mathcal{F}$ and the probability distributions defined for $\mathcal{R}$ and $\mathcal{A}$. [1] The fuzzy rules are also defined in the fuzzy rule-set $\mathcal{S}$.

A number of important characteristics of $\mathcal{F}$ are as follows:

- $\mathcal{C}$, $\mathcal{R}$, and $\mathcal{I}$ are pairwise disjoint sets
- Context value assignment terms in $\mathcal{C}$ are used for enforcing constraints under which the local distributions apply.

The result of this stage is a situation-specific game whose players along with their actions are determined based on the current situation. The whole process produces a situation-specific Fuzzy BN that is capable of assessing the impact of situations by playing games.

1) Players: In VANETs, players (or agents) may differ from an application or environment to another. In intersection safety application, the aggressor vehicle along with other victim vehicles and pedestrians can be all assumed to be the players of the intersection safety game. The purpose of all these road users will be avoiding car-to-car and car-to-pedestrian crash. Meanwhile, in highway safety application, vehicles are the only involved players. Their intent is to mitigate the risk of rear, frontal and lateral collision. In the following, we will assume that drivers (or vehicles) are the players of the safety game.

We denote the aggressor vehicle player (ego vehicle) with v_e while all the other vehicle players (opponents) with v_i. The neighboring vehicles of v_e at instant t is denoted by $N_e(t)$. Thus, in the game there are $|N_e(t)+1|$ players. Since, the neighboring vehicles of v_e may change over time, N_e is annotated with the time variable t.

2) Actions: The class of each player defines the possible actions that can be undertaken. Inspired by the study of Klauer [16], the actions taken by the vehicle and the Driver are the main factors that can alter the situations states. Therefore, the actions set is broadly classified into two classes: 1) Vehicle actions and 2) Driver actions (see Table IV-B.2). The former class includes the operating level actions of a car such that steering left, steering right, accelerating, decelerating, take exit, merge braking, etc. These actions are situation specific. Indeed, some high-level actions allowed in urban areas cannot be realized in highways (e.g steering left). The second class includes driver's actions such that looking forward and back, turning on/off lights, signaling right/left, etc.

3) Transition Rules: The transitions rules are the changes in the states estimation of involved players triggered by selected actions. Thus, the state space will be a network of situations that are connected with lateral or temporal links as illustrated by Figure 4. Two situations S_1 and S_2 are temporally connected if taking the action a_1 at S_1 leads to S_2, where S_2 has the same topology as S_1. Furthermore, if taking the action a_1 causes S_1 to change topologically and create S_2, then the two situations are connected with a lateral link.

[1]The sub-scripts in $\mathcal{G}_{0,1}$ and $\mathcal{D}_{0,1}$ show the tier index

TABLE I

LIST OF OPERATING-LEVEL ACTIONS OF THE VEHICLE AND DRIVER CLASSES

Vehicle
Accelerate, Decelerate, Steer Right, Steer Left, Shift Gear Up, Shift Gear Down, Stop, Toggle Reverse Gear
Driver
Look Forward, Look Back, Shoulder Check Right, Shoulder Check Left, Turn on/off Lights, Turn on/off Wiper, Signal Right, Signal Left, Take the Cell Phone, Put Down the Cell Phone, Keep Driving, Take a Rest,

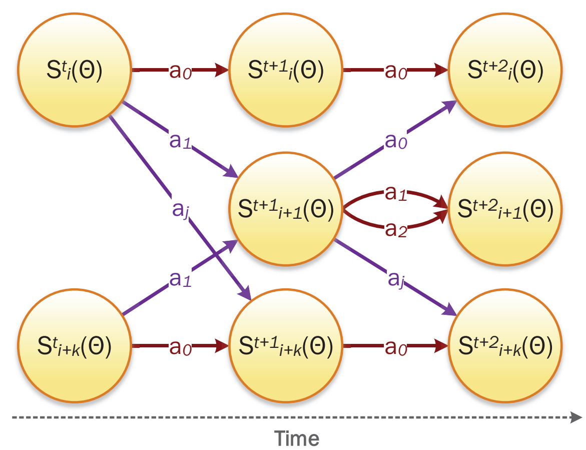

Fig. 4. A sample network of interconnected situations

4) Payoff calculation: The payoff function expresses how the actions of the opponent players influence the decision of the main player. Our situation prediction algorithm assumes that each car has a local information which is shared between its surrounding cars via V2V or V2I wireless communications. Indeed, VANETs has the flexibility in seamlessly supporting both single-hop and multi-hop communications. Thus, exchanging messages ensures for each player (ego and normal vehicles), the knowledge of the action profiles of its opponents and their corresponding payoffs (see Figure 5).

In our case, the payoff function, g, maps a situation with an estimated state to a real number that depicts how much the current situation is desired. We define g as: $g\ : S_i(\theta_i) \longrightarrow \mathcal{R}$ where:

- $S_i(\theta i)$: an arbitrary state-space situation of interest
- θi: is the ordinary variables vector of S_i.

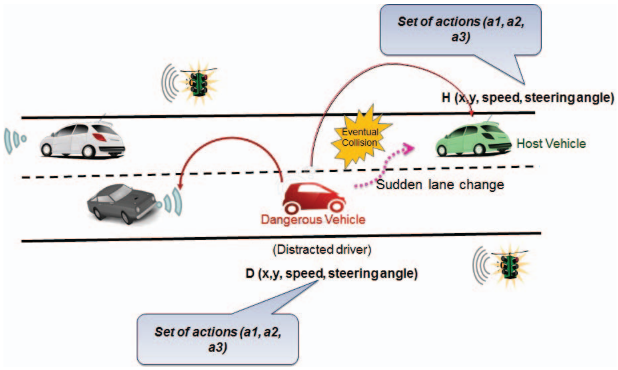

Fig. 5. Local information shared between neighbors cars using V2V

In our ATFY-MEBN, a situation S_i is accessed through its representing fuzzy resident node R_i, which has a set of possible values defined using fuzzy sets [13], [17]. We define the payoff of S_i as the real value of R_i that is yield by defuzzifing its final fuzzy state after performing the fuzzy inference. The defuzzification technique used in this process is the center of gravity method [18].

5) Equilibrium Calculation: A game is ready be solved when the game table is generated, and all of the players payoffs for each action profile are calculated. Different game solution algorithms such as Nash equilibrium can be used to output the optimal strategy of the main player as well as his/her estimated payoff. This is the last stage of the IA whose results can be used to decide on the next action to be taken.

V. Case Study

In this section, we propose a case study that makes use of ATFY-MEBN to perform impact assessment and decision making in VANETs. The designed scenarios are pertinent to safety applications in which the vehicles aim to keep staying far from collisions. Most parts of the underlying situation assessment task is similar to what we have previously presented in our previous work [13], [6], [14]. In fact, major situations and their building blocks still reside on Traffic Entity and Situation units (see figure 3), and can be used directly for situation assessment. What is extra in our new setting is the involvement of relevant game components that are used to predict the future situations. Accordingly, we use our novel ATFY-MEBN model and its underlying components to re-design our previously constructed Collision Warning System (CWS), and to enable IA and DM.

The first version of CWS is instantiated from our general High-Level Information Fusion model for VANET called Attention Assist Framework (AAF) [6], which is fundamentally modeled based on the conventional Fuzzy-MEBN [13]. As it is also mentioned earlier, AAF is only able to perform situation assessment on the road, and lacks the capabilities of traffic IA and DM. This is mainly due to the inability of Fuzzy-MEBN in predicting future situations, and taking rational actions accordingly. To overcome these issues, we use AAF-II that is enriched with ATFY-MEBN.

The following explains the main components of our new CWS model, called (CWS-II). First of all, game ingredients such as players, state space, decisions, transition rules, and payoff functions are specified. Moreover, respective ATFY-MEBN game components, *i.e.*, actions, action nodes, game nodes, *etc.*, are defined and used to build the Traffic Impact Assessment and DM units of the new ATFY-MTheory. Finally, two different scenarios of driving in a highway, and at an intersection are outlined to demonstrate the applicability of CWS-II in different situations.

A. Game Components Specifications

- Players: The players classes vary in the two separate scenarios we will investigate. In the intersection safety scenario, the ego vehicle along with other traffic vehicles, and the pedestrians can all be assumed to be the game players. In such scenarios, the players (no matter of which type they are) intend to avoid vehicle-to-vehicle and vehicle-to-pedestrian collisions. Moreover, vehicles are the only type of players participating in the highway safety scenario. To make our simulations simpler, we assume that the only type of players in our scenarios are vehicles. As we mentioned before, the main player is shown with v_e, and its opponents v_i, where $e \neq i$, at time t are in the neighboring set $N_e(t)$.
- States Space: The states are selected based on the underlying ATFY-MTheory constructed for our domain. The main situation that can be uses to measure the threat of the current driving situation is $\mathrm{CollisionThreatLevel}(v_e, t)$, which reflects the degree of how much a vehicle is close to an accident. Another possible situations of interest can be $\mathrm{ManeuveringLevel}(v_e, t)$, $\mathrm{DistanceDangerLevel}(v_e, t)$, and so on.
- Decisions (Actions): The list of the operating-level actions that vehicles usually take are presented in Table IV-B.2. For instance, a vehicle should *accelerate* (upto a safe speed) and *steer left* at the same time to merge onto the passing vehicles in the highway. Moreover, acceleration, and steering wheel requires changing throttle pedal angle (and possibly gears), and the wheels angle, respectively.
- Transition Rule: The situations of interest set in our case study contains only the $\mathrm{CollisionThreatLevel}(v_e)$ situation that is composed of four main sub-level situations on Vehicle, Driver, Environment, and VANET, and therefore, reflects a comprehensive look of all the crucial situations. A fragment of state space along with the transition links is illustrated in Figure 6. In the simple example shown in Figure 6, the vehicle V_e is estimated to be in unstable situation with 80% certainty. The movement situation of the vehicle changes at the next time step upon taking the "steer left", or the "accelerate" actions. Accordingly, if the "steer left" action is taken (considering the actions that the neighboring vehicles will take), and assuming that this action gets the maximum payoff to V_e, then the collision threat level

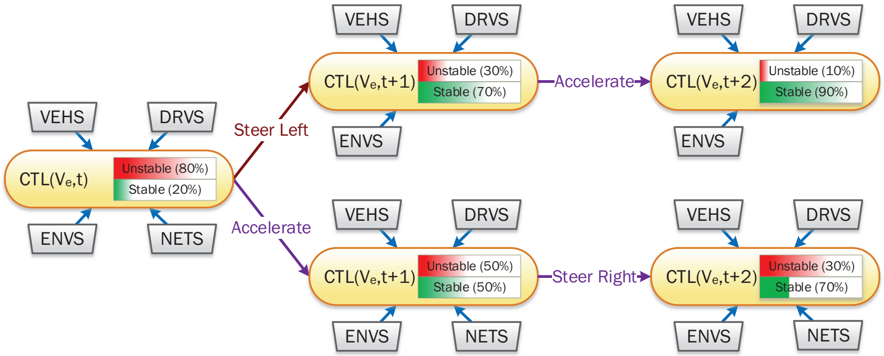

Fig. 6. The state space of the $\mathrm{CollisionThreatLevel}(v_e)$ situation

is estimated to be at *Stable* state with 70% of certainty. If we assume that V_e is a rational agent and he will take the "accelerate" action, then future situations can be predicted based on the same strategy.

- Payoff Function: the possible values of the $\mathrm{CollisionThreatLevel}(v_e)$ situation along with their fuzzy sets are used to calculate the payoff. As seen in Figure 7, the fuzzy sets are defined using triangular membership functions on a universe of discourse in the range of $[0..100]$.

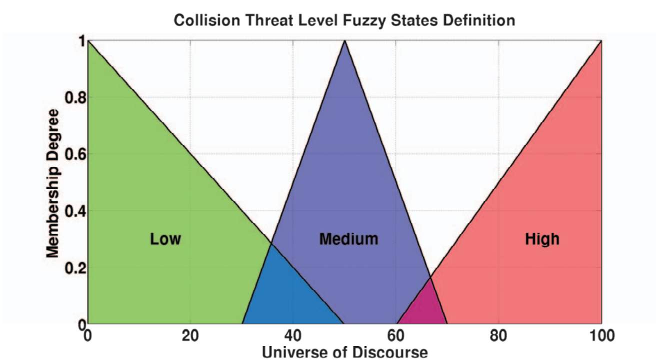

Fig. 7. The fuzzy sets definitions of the possible values of $\mathrm{CollisionThreatLevel}(v_e)$ situation

Moreover, the likelihood of each state is estimated, and consequently, the fuzzy state is calculated using Equation 1.

$$\sum_{v \in V(s)} \mu_v(x) p(s = v) \tag{1}$$

The center of gravity of the resulting function, which is presented in Figure 8, is used to find the payoff value. Centroid and Bisector methods for calculating the center of gravity are employed in this paper.

VI. Simulation Results

In this section, we study the performances of the proposed ATFY-MEBN that is used to implement a CWS. Two separate scenarios are defined to demonstrated the applicability of the ATFY-MEBN in multi-car settings. It is assumed that all the vehicles in the scenarios run an instance of CWS for

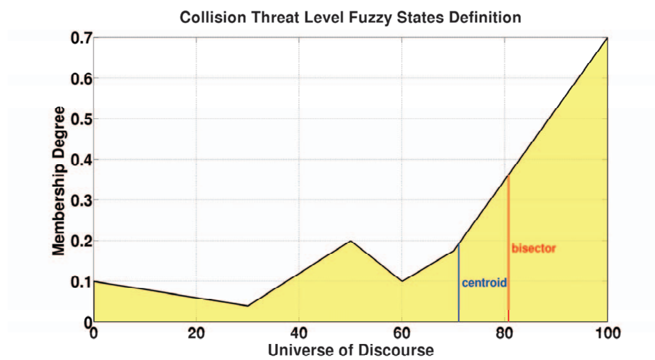

Fig. 8. The fuzzy sets definitions of the possible values of $\mathrm{CollisionThreatLevel}(v_e)$ situation

100 seconds. In both scenarios, the only player entities are those derived from the vehicle class, and their actions are limited to: Accelerate, Brake, Steer Left, and Steer Right. These entities are V_e, which is the ego vehicle, and V_i for $i = 2 \cdots n$, which are the neighboring vehicles. The payoff function is composed of the $\mathrm{VehicleMotionSituation}(V_e)$, whose host FMFrag is shown in Figure 9.

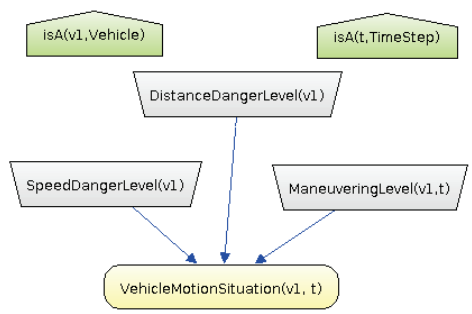

Fig. 9. The $\mathrm{VehicleMotionSituation}(V_e)$ FMFrag

1) Scenario 1: Highway: It is assumed that the ego vehicle is driven in a highway with randomly positioned and controlled normal vehicles, which are able to communicate with each other through V2V communication. The games are generated for the maximum of 5 players (maximum 4 neighbors), and the hopping threshold is set to 2. We repeat the scenario for 33 iterations and calculate the collisions ratio occurred with and without the game nodes deployed. As

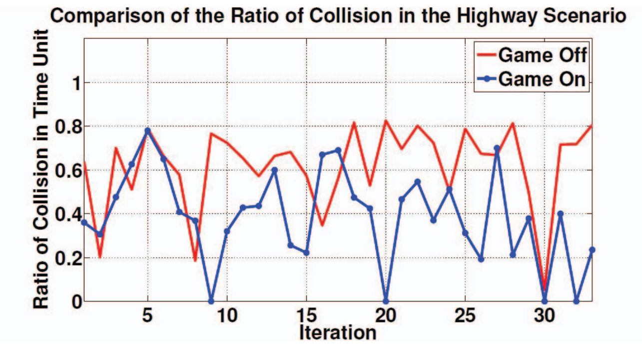

Fig. 10. The ratio of collisions for turned on and off impact assessment unit.

depicted in Figure 10, the collisions ratio is decreased when the IA is done and its resulting actions are performed by the vehicle. The averages of the collisions ratio for turned off and on IA unit are 61.95% and 38.84%, respectively. Another interesting aspect about this experiment is that in about 12% of iterations the ratio of collision is zero (iterations 9, 20, 30, and 32), when the IA unit is turned on. This is a significant improvement when compared to 80% collision rate with the turned off IA unit. Finally, non-zero collision rates, when games are played, are attributed to the situation-invariant method when actions are taken. In other words, the optimal actions proposed by the IA unit are high-level (Keep safe speed, keep safe distance, merge, take exit, etc), and lack the detailed information about how it should be taken. For example, when the optimal action is to steer left, it does not deliver how much the vehicle needs to go to its left. This may result in translating to an unforeseen situation that leads to a collision. However, this can be improved by providing lower-level information about the actions as well, and let the driver know how an action need to be take.

The $\mathrm{VehicleMotionSituation}(V_e, t_1)$ for both cases of turned on and off IA unit shows that the game components are successful in keeping the vehicle motion situation in stable state. Figures 11 and 12 demonstrate the state estimation of the $\mathrm{VehicleMotionSituation}(V_e, t_1)$ for these two cases at the iteration with highest collision ratio.

Clearly, with the IA unit turned on, the vehicle motion situation of V_e is more stable during the simulation.

Finally, the evolution of the calculated payoffs for the lowest and highest collision ratios when the IA unit is turned on are shown in Figures 13 and 14. It is obvious that in both best and worst cases, the IA unit is able to keep the payoff of the vehicle at high values in longer periods of time.

2) Scenario 2: Intersection: We assume that the ego vehicle along with the normal vehicles approach an intersection as depicted in Figure 15. The intersection scenario is studied in 7 separate sub-scenarios created with 2 to 8 cars. In each sub-scenario, the vehicles are initialized with random roads and with random speeds, and have their CWS deployed and

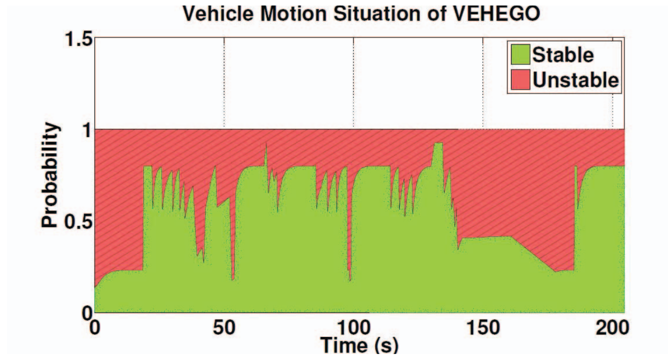

Fig. 11. The $\mathrm{VehicleMotionSituation}(V_e, t_1)$ for the highest ratio iteration when the IA unit is turned on.

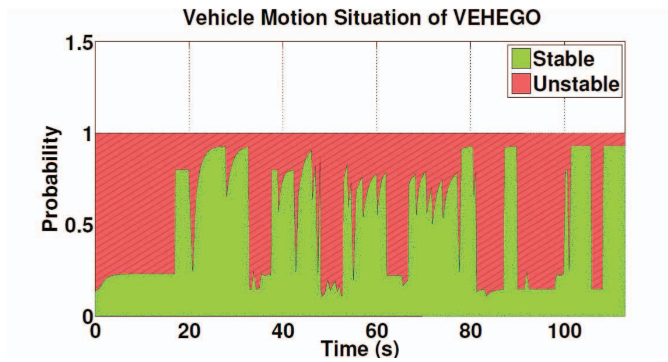

Fig. 12. The $\mathrm{VehicleMotionSituation}(V_e, t_1)$ for the highest ratio iteration when the IA unit is turned off.

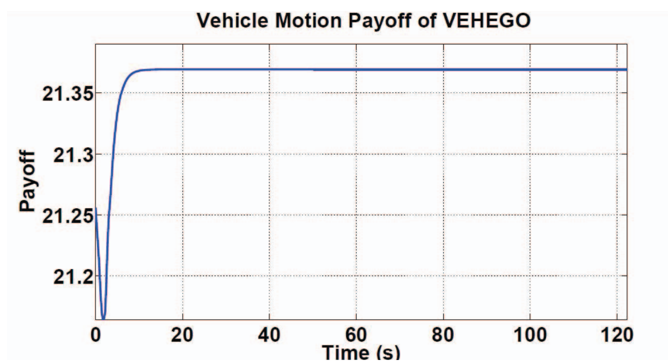

Fig. 13. The payoff of V_e for the lowest collision ratio with the IA unit is turned on.

running. We study the effect of IA and DM by turning on and off the IA units, running the simulation for 22 iterations, and finally, counting the number of times the vehicles collide at the intersection.

Table II briefly presents the ratio of collisions in each sub-scenario. As it is shown in Table II, the IA unit remarkably decreases the collision ratio by projecting the status of the current driving situation into the future, assessing its impact, and taking an appropriate action accordingly. Besides, the applicability and the performance of generating situation specific games is clear when facing various situations with different number of players at an intersection.

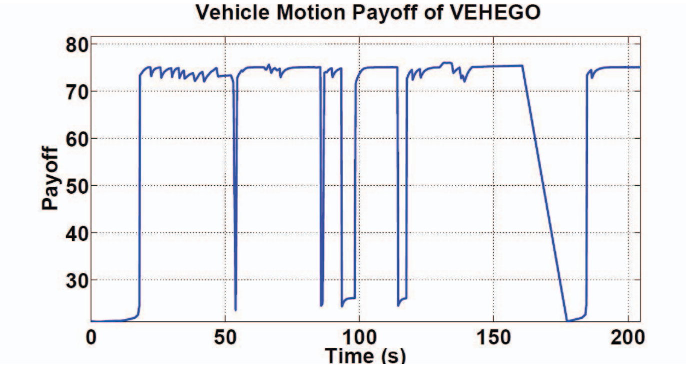

Fig. 14. The payoff of V_e for the highest collision ratio with the IA unit is turned on.

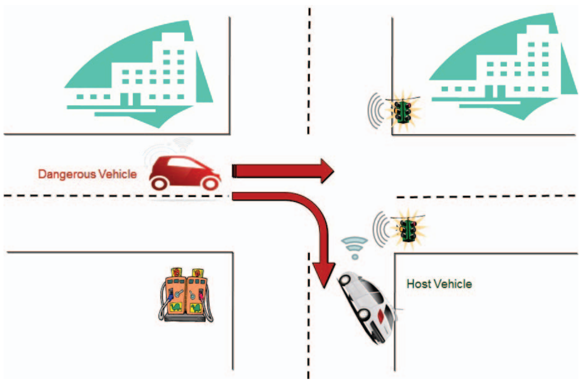

Fig. 15. Errant Vehicle vs Normal Vehicle: Intersection Scenario

TABLE II
THE RATIO OF COLLISION IN THE 2 TO 8 CARS INTERSECTION SCENARIOS WITH THE IA UNIT ON AND OFF

	Game Off	**Game On**
2-Cars	85.2%	11.4%
3-Cars	91.7%	29.8%
4-Cars	83.1%	23.5%
5-Cars	93.6%	26.5%
6-Cars	94.5%	29.6%
7-Cars	88%	33.2%
8-Cars	89.8%	49.1%

VII. CONCLUSION

Cities are known high-risk areas where drivers must monitor the traffic succinctly for sudden events such as errant vehicles changing lanes, slowing vehicles and entering and exiting high speed roads. Assessing such hazardous situations while driving is challenging. Therefore, in this paper, we propose a game theoretical approach based on Fuzzy Multi-Entity Bayesian Networks (Fuzzy-MEBN) to simulate the strategic interactions between different entities involved in a highway and intersection driving scenario. We enrich our previous Attention Assist Framework with a game theory component that ensures impact assessment conditioned on the current situation and appropriate maneuvers making to mitigate hazardous crashes. Our simulation results in Vehicular Ad-hoc Networks show how our Game-Theoretic Attention Assist Framework helps in assessing the coming threats and avoid imminent crashes properly.

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