A Framework for Proactive Assistance: Summary

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***Abstract*— Advanced Driving Assistance Systems usually provide assistance to drivers only once a high risk situation has been detected. Indeed, it is difficult for an embedded system to understand driving situations, and to predict early enough that it is to become uncomfortable or dangerous. Most of ADAS work assume that interactions between road entities do not exist (or are limited), and that all drivers react in the same manner in similar conditions. We propose a framework that enables to fill these gaps. On one hand, an ontology which is a conceptual description of entities present in driving spaces is used to understand how all the perceived entities interact together with the subject vehicle, and govern its behavior. On the other hand, a dynamic Bayesian Network enables to estimate the driver situation awareness with regard to the perceived objects, based on the ontology inferences, map information, driver actuation and driving style.**

I. Proposed Approach

A. Motivations

The aim of the framework is not to generate alerts when the situation is already dangerous, but rather to provide advice as a human copilot could do. For example, a passenger who feels that it is likely that the driver did not understand the situation or did not perceive a very important road entity will not wait for the last moment to warn the driver. It will make sure that the driver has the situation under control by asking "Did you see … ?".

If the assistance is pertinent and comes early enough, it is perceived as a comfortable advice by the driver, and not as an uncomfortable warning. To do so, it is of importance for the copilot to know how the driver is used to drive in the given situation in order to evaluate the pertinence of the assistance. If the copilot judges the situation to be dangerous whereas the driver behaviour is similar as usual, the driver might consider any assistance as not pertinent. His confidence in the copilot would be deteriorated.

B. Framework

The proposed framework needs different types of information from different sources, as illustrated in Fig. 1:

- Environment: The vehicle has to be able to perceive the environment in order to be aware of the nearby road entities (vehicles, pedestrians, road infrastructures, etc.). It can be perceived by embedded perception sensors, such as cameras, radars or lidars, but also by using digital maps storing *a priori* information about the road network.
- Vehicle State: The position, speed and other parameters related to the subject vehicle are provided by localization devices (GNSS, etc.) and the vehicle CAN bus.
- Driver: Actuation of the driver (throttle, brakes, etc) can be directly provided by messages in the vehicle CAN bus. Driver patterns (habits, in other words) have to be previously learned.

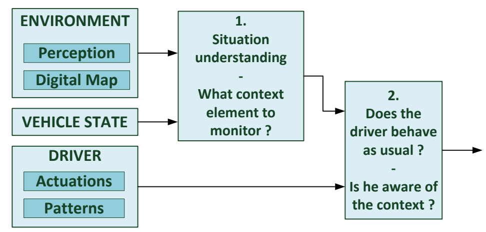

Fig. 1: Block diagram of the proposed framework.

The first step aims at interpreting the data related to the environment in which the vehicle is navigating. The challenge is to understand how all the perceived entities (dynamic and static) govern/will govern the subject vehicle state and behaviour. The second step consists in estimating if the driver is aware of its interaction with the other road entities and if an advice would be relevant for the driver to keep the situation safe and comfortable. This paper gathers and summarizes work presented in former papers [1], [2], [3].

II. Driving space situation understanding

Within a driving space, different entities (vehicles, vulnerable road users) are in constant interaction. Modern vehicles can be equipped by smart sensors which provide information about the state of the perceived objects. However, considering the spatio-temporal relationships and the interactions between these objects is a difficult task. It is proposed to address this problem by using contextual information to infer how perceived entities are expected to behave, and thus what are the consequences of these behaviours on the subject vehicle. For this purpose, an ontology is formulated about the vehicle, perceived entities and context. This provides a conceptual description of all road entities evolving in the driving space.

A. Ontologies

An ontology is a semantic tool, understandable by humans and computers that consists of a formalized representation of

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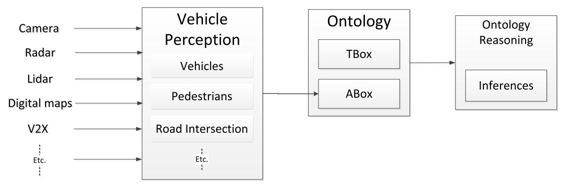


Fig. 2: Block diagram of the ontology framework.

knowledge about a field of discourse. The literature defines it as a knowledge-base [4], composed by:

- A Terminological Box (TBox) which consists of the definition of the concepts. This is *a priori* knowledge about the concepts described by the ontology.
- An Assertional Box (ABox) in which instances of concepts are described. In practice, real world data is stored in the ontology through the ABox.

B. Proposed ontology

The proposed ontology is defined for 1D scenarios, in addition it is assumed that vehicles navigating in the driving space comply with the traffic rules. Fig. 2 describes how the ontology is used.

Before using the ontology to reason on real data, knowledge about concepts have to be stored in the TBox. For our problem, the ontology has to know what types of entities usually evolve in a driving space, and how these entities usually interact with each other. The TBox is defined as follows and described in Fig. 3:

- Classes represent the entities which can be met in a driving space. These entities can be separated into 2 categories: mobile entities (such as vehicles, pedestrians observable by embedded sensors) and static entities (such as pedestrian crossings, intersections, for which existence can be stored in a digital map).
- Object properties enable to define relationships and interactions between classes. These properties describe the state of mobile entities (*goes toward, etc*.), their future behaviour (*is to reach, etc*) and what behaviour they must have to keep the situation safe (*has to stop,* etc.).
- Data properties enable to assign properties to instances of classes (in the ABox), such as their position, or speed.
- Rules enable to define axioms to reason and infer new knowledge about data stored in the ABox. For example, a rule defines that a vehicle that is about to reach a stop intersection has to stop at the intersection.

To reason on an environment perceived by a vehicle, every entity perceived has to be stored in the ABox as a instance of class, with properties. It is therefore possible to reason on all these instances of classes, using a reasoner. The later interprets all the data stored in the ontology (ABox and TBox), takes chain reactions into consideration to understand how the whole context interacts with the

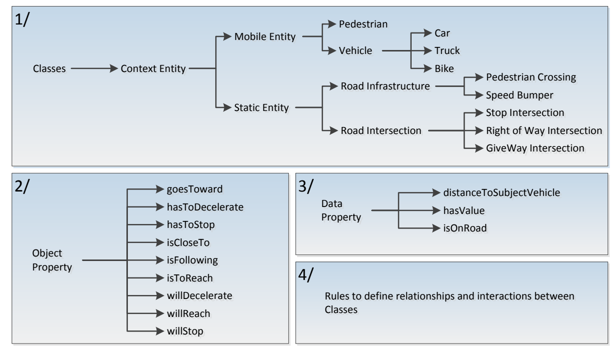


Fig. 3: Classes, objects and data properties defined in the ontology.

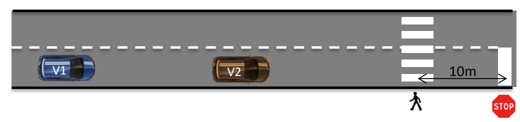


Fig. 4: Scenario chosen for the evaluation of the ontology used in real time (subject vehicle V1 in blue).

subject vehicle, and what to monitor to keep the situation safe.

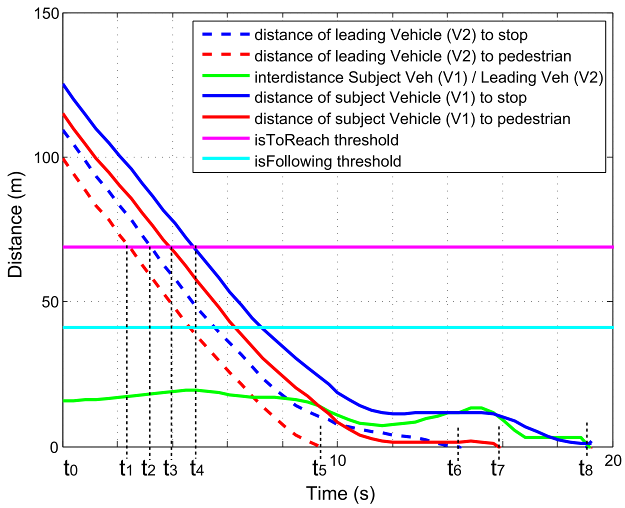
C. Experimental evaluation

The ontology has been tested in the scenario presented in Fig. 4. In most conventional ADAS, V2 the lead vehicle only would be taken into consideration, ignoring the pedestrian, the pedestrian crossing and the stop. However, taking all entities at the same time enables to infer that the lead vehicle is likely to decelerate or stop to let the pedestrian cross the road, and also that it will stop at the intersection.

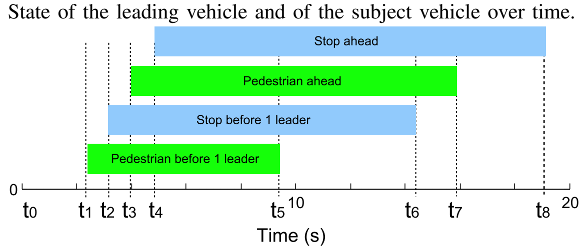
A passenger vehicle was used for the experimentation. A set of perception sensors is installed on the vehicle, and enables to measure the position of a lead vehicle and of pedestrians. The positions of the stop intersection and of the pedestrian crossing are stored in a digital map.

The results of the experiment are presented in Fig. 5. Fig 5a presents the situation of the lead and subject vehicles. Fig. 5b presents the ontology inferences about the subject vehicle individual over time. From the point of view of the subject vehicle, the situation evolves through 8 main events (from t_0 to t_8). It is noticeable that the ontology inferences evolve as the subject vehicle and the lead vehicle move towards the other entities and interact with them. A conventional system (which would have taken into consideration only the closest entity), would have ignored the pedestrian until the lead vehicle passes him (at t_5), whereas it is necessary to know that the lead vehicle may decelerate or brake. The use of the ontology enables to consider the pedestrian at any time, even if an other entity is between him and the subject vehicle.

The ontology inferences are used by the Box 2 in Fig. 1 to decide what algorithm to run to make sure that the situation



(a) State of the leading vehicle and of the subject vehicle over time.



(b) Class equivalences of the subject vehicle after ontology reasoning.

Fig. 5: Results of the experimental evaluation. State of the contextual entities over time and ontology inferences.

is, and will remain safe and comfortable.

III. Estimation of driver awareness

Most conventional ADAS assume that all drivers are the same, and react in the same manner in similar situations. However, this is not the case as drivers react as a function of their own driving style. For example, it is unlikely that a driver used to decelerate smoothly intentionally decides to decelerate much harder than usual. It is proposed to use learned driver profiles with regard to road situations to detect unexpected behaviours which might be a sign that the driver is not fully aware of the situation. A Bayesian Network is used for this estimation.

A. Bayesian Network

The proposed Bayesian Network is presented in Fig. 6 and its corresponding joint distribution is given by (1) :

$$P(P_t, N_t, A_t, R_t) = P(N_t) \times P(R_t) \times P(P_t|N_t) \times P(A_t|R_t, N_t, A_{t-1}) \quad (1)$$

The variables of the Bayesian Network are separated into two categories, depending whether or not they are observable through sensors. The meaning of these variables is briefly described in the following paragraphs, and the conditional probabilities related to them can be found in [2]

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Observable variables:

- $P_t \in \mathbb{R}$, the parameter to be monitored, with regard to the contextual object considered by Section II. It may be the vehicle speed, the interdistance with the lead vehicle, the lateral position on the lane, etc.
- $R_t \in \{0, 1\}$, the reaction of the driver. The driver can give an indication that he finally perceived/ took into consideration the most relevant contextual object. This variable is considered as a way to reduce the risk of non-relevant assistance. It is related to the parameter to monitor, and may be an action on the brake pedal, or for instance an information provided by a camera observing the driver.

Hidden variables: These variables cannot be directly measured. However the DBN enables to estimate their values.

- $N_t \in \{0, 1\}$, the estimation of the "Normality" of the driver's behaviour. By "Normal behaviour", it is understood a behaviour that can be expected for the driver, in other words the behaviour the driver usually has in similar contexts.
- $A_t \in \{0, 1\}$, the estimation of the awareness of the driver with regard to the contextual object taken into consideration according to the ontology inferences (c.f. Section II).

The relationships between all the nodes have to be understood as follows:

- A behaviour considered as Normal means that the observed Parameter matches with the driver's patterns, and that the driver seems Aware of the most relevant contextual object.
- The Awareness of the driver (with regard to the main contextual object) is inferred by the estimation of the Normality of the driver's behaviour, and also by a Reaction of the driver.

We estimate the relevance to provide assistance to the driver by computing the probability $P_{assistance} = P([N_t = 0], [A_t = 0]|P_t, R_t, A_{t-1})$.

B. Application to a simple use case

The use case chosen for the application of the DBN is the arrival of the subject vehicle to a stop intersection. It

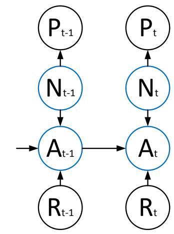


Fig. 6: Graphical representation of the Bayesian network.

is assumed here that the ontology presented in Section II already inferred that the intersection is the most relevant context entity of the situation, and therefore that the vehicle has to stop.

The DBN has to be adapted to the given situation, that is measurements have to be affected to the variables P_t and R_t.

Since the vehicle is expected to stop at the intersection, the parameter P_t which has to be monitored is the vehicle velocity with respect to the distance to the stop intersection. It is considered that a driver has an unusual behaviour when he does not decelerate at the intersection as early as he usually does, that is the vehicle velocity stays rather constant. Therefore, the manner the driver usually decelerates at the approach to a stop intersection has to be learned to customize the system. Gaussian processes were chosen to learn the driver velocity profiles as described in [1].

When a driver understands that he has to stop at the coming intersection, his behaviour and actuation change before the vehicle velocity starts decreasing. This reflects, at first, a reaction and his intention to decelerate. This intention to decelerate can be estimated by observing the gas pedal and the brake pedal. For the proposed use-case, the state of the brake pedal (0 or 1) is used as the parameter R_t. As soon as the driver touches the pedal, the signal turns from 0 to 1.

C. Experimental evaluation

A passenger vehicle was used for the experimentation. The position of the stop intersection was stored in a digital map.

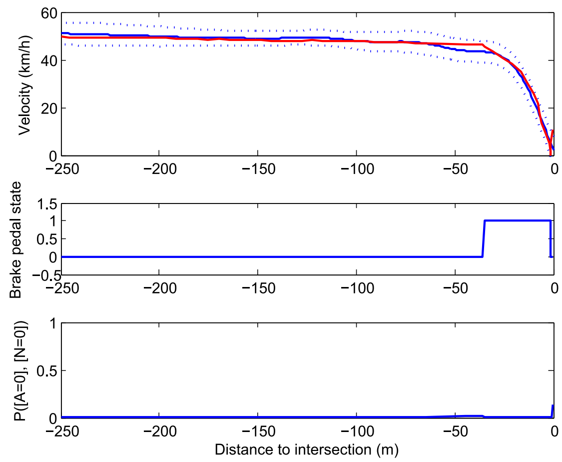
Results are presented in Fig. 7 for two scenarios, but other results can be found in [2]:

- Scenario 1 (Fig. 7a): The driver is aware of the intersection and stops as expected. The vehicle velocity remains inside the individual velocity envelope defined by the customized driver pattern. Since the velocity matches with the expected velocity, the reaction of the driver does not affect the DBN inference. The probability $P_{assistance}$ remains close to 0.
- Scenario 2 (Fig. 7b): The driver is not aware of the intersection and does not even decelerate. The velocity leaves the individual velocity envelope about 35m before the intersection. As soon as it happens, the probability $P_{assistance}$ increases up to 0.9. Since the driver does not touch the brake pedal, the probability remains very high until the arrival to the intersection.

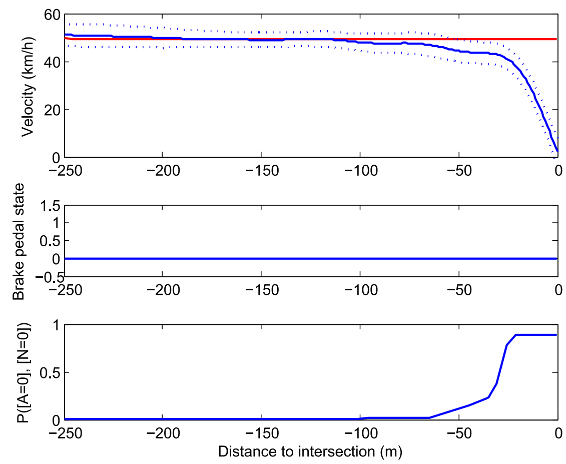
According to this use-case driven evaluation, the Bayesian Network provides a coherent estimation of the risk that the driver is not aware of the stop intersection. The use of customized driver patterns enables to enhance the integrity of the information generated by such systems.

IV. Conclusion

A framework for proactive assistance, composed by two main subsystems was presented. On one hand, an ontology allows for the interpretation of the perception data to understand how the driver and his vehicle are expected to behave. On the other hand, a Dynamic Bayesian Network which takes advantage of personal driver patterns enables to estimate the driver situation awareness. These two systems were tested separately. Ongoing work consists in combining these two subsystems to estimate the performance of the proposed framework.



(a) Scenario 1 : Normal situation.



(b) Scenario 2 : Abnormal situation.

Fig. 7: Results of the Bayesian Network inferences for the 2 situations.

References

[1] A. Armand, D. Filliat, and J. Ibañez-Guzmán. Modelling stop intersection approaches using gaussian processes. In *Proceedings of the 16th International IEEE Conference on Intelligent Transportation Systems-ITSC*, 2013.

[2] A. Armand, D Filliat, and J Ibanez-Guzman. Detection of unusual behaviours for estimation of context awareness at road intersections. In *in Proceedings of the 5th Planning, Perception and Navigation for Intelligent Vehicles Workshop (IROS 2013)*, 2013.

[3] A. Armand, David Filliat, Javier Ibañez-Guzman, et al. Ontology-based context awareness for driving assistance systems. In *Proc. of the IEEE Intelligent Vehicles Symposium*, pages 1–6, 2014.

[4] R. Studer, V R. Benjamins, and D. Fensel. Knowledge engineering: principles and methods. *Data & knowledge engineering*, 25(1):161–197, 1998.