A Driving Situation Inference for Autopilot Agent Transparency in Collaborative Driving Context

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***Abstract*—Overly trust in the autopilot agent has been identified as the primary factor of road incidents involving autonomous cars. As this agent is considered a human driver counterpart in the collaborative driving context, many researchers suggest its transparency to mitigate such overly trust mental model. Hence, this paper aims to develop a driving situation inference method as a transparency provider explaining the types of situations the autopilot agent encounters leading to its certain decision. The proposed method is verified using an autonomous driving simulator called Carla. The findings show that the proposed method can generate situations which enable the human driver to calibrate their trust in the autopilot agent.**

***Index Terms*—transparency, situation inference, collaborative driving, human-agent interaction**

I. Introduction

An intelligent agent's role in smart cars is shifting from a supporting agent into a human counterpart [1], [2]. With this role, the agent can replace the human driver to perform driving tasks when the autopilot mode is activated. In manual mode, this agent helps to avoid hazardous events having a high risk of an accident. Such a collaboration between the intelligent agent and the human driver is called collaborative driving, which can be classified as level 4 of six levels (0-5) of autonomous driving according to the Society of Automotive Engineering [3]. Furthermore, the interaction between the human and an intelligent agent in collaborative driving can be an example of human-autonomy teaming (HAT) [4].

Even though collaborative driving in autopilot mode requires human driver involvement to monitor surrounding driving situations, the overly trust mental model makes them willing to take risky secondary tasks, for example, watching videos and sleeping [5], [6]. As a result, we have witnessed many road incidents involving automatic driving around the globe, and some of them caused fatalities [5]. Several researchers identified that one causal problem of such a mental model is the lack of mechanisms to compare the human driver's situational awareness with ones from the autopilot agent [7]. According to [8], [9], an intelligent agent can hold a certain degree of situational awareness. As consequences, this agent has its own perception states, reasoning, and designated action for given situations [10].

For humans, situational awareness can be defined as the comprehension of situations by relating the statuses of relevant surrounding objects at a certain time-length [11]. For example, the tailing situations in driving situations are formed based on the status of another moving car in front within the same lane located at a certain distance. In this regard, 'moving car', 'in front', 'same lane', and 'a certain distance' are considered the status of several surrounding objects such as cars and roads.

For an intelligent agent, the definition of its situational awareness can be borrowed from one for humans. This agent obtains relevant surrounding object statuses by using its sensory tools, including recognition models. For example, the camera-based sensors and distance sensors are used to recognize whether there is another vehicle in the same lane in front. Thus, this agent can artificially describe a tailing situation.

In the last few years, extracting the intelligent agent's situational awareness for transparency purposes has attracted a great attention from researchers, particularly to enhance HAT performance in i.e., collaborative driving and to communicate among intelligent agents such as connected vehicles. In this regard, they proposed various methods for situation inference. For example, [12], [13] proposed a rule-based approach to reveal driving situations recognized by the intelligent agent as a part of connected vehicles technologies using the IoT platform. Some researchers applied graph-based behavioral representation such as logic tree [14], belief-desire-intention (BDI) graph [15], and goal hierarchy [16] to infer what the agent is currently doing and the situations behind.

As million instruction codes may involve driving an intelligent agent's behaviors to respond given situations like in the autopilot agent, the development of such graphs and

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rules to infer situations become impractical. When the logic changed for an update, those graphs should be updated as well. Moreover, in the HAT context, the situation inference proposed in the previous studies do not consider time-length of situations that become a constraint factor for human to absorb situation description generated by the intelligent agent. This paper proposes a fuzzy-based situation inference with time-constrained transparency model to address these problems.

The proposed method was verified in a collaborative driving context using the autopilot agent as the intelligent agent. The implementation was conducted in an autonomous driving simulator called Carla using two common driving situation scenarios, namely traffic light (TL) scenario and overtaking scenario. The results indicate that the proposed method can provide a transparency mechanism by generating situation descriptions encountered by the autopilot agent to help the human driver comparing their situational awareness with those from the autopilot agent. This way, the human driver's trust in the autopilot agent can be calibrated.

In summary, the key contributions of this work are as follows:

- A fuzzy-theory-based situation inference is proposed to generate a situation description encountered by an intelligent agent
- A time-constrained transparency model to regulate transparency presentation based-on the situation timespan

The remainder of this paper is structured as described below. Section 2 presents related studies, and Section 3 presents the proposed situation inference. The implementation and results of the transparency requirements are presented in Section 4. Finally, the conclusions are drawn in Section 5.

II. Related Studies

Many researchers have studied the methods for situation recognition for various purposes. Related to driving situations, [17] proposed an approach to identify hazardous driving situations for automated driving. [18], [19] developed a rule-based system situation inference, particularly to help recognize the human driver's driving maneuvers. Similarly, [20] also built rule-based driving inference approach for connected vehicles. Furthermore, [21] applied generic probabilistic for situation recognition.

Other approaches of situation inference are conducted by exploiting behavioral representation of an intelligent agent. These approaches are built for transparency purposes. The basic idea of using the behavioral representation is to provide a situation context based on the development purpose of an intelligent agent. There are many forms of behavioral representation such as a logic tree, goal hierarchy, and BDI hierarchy. Such representations, then, are used to generate situation descriptions describing the rationale behind the intelligent agent's actions.

Using logic tree, [14] situations are inferred by searching the executed paths to examine which paths that are truly causing the intelligent agent's actions. As this approach is too costly, [22] proposed the implementation of a provenance graph during execution runtime. But its main weakness is when dealing with inter-functions dependencies. Similar to, [14], the proposed graph-based methods for situation inference from [15], [16] also struggle from the tracing back mechanism, particularly in a complex intelligent agent like an autopilot agent. Hence, a more reliable approach for situation inference is needed.

III. The Proposed Situation Inference Approach

This section presents a situation inference approach. As illustrated in Fig. 1, the first stage of this approach is collecting situation data, followed by identifying the situation of concern. The identification process requires a situation model. A time-constrained transparency model is used to regulate transparency presentation on the user interface. The fuzzy theory is used in this approach. The detail of this approach is presented in detail in the following sub-sections.

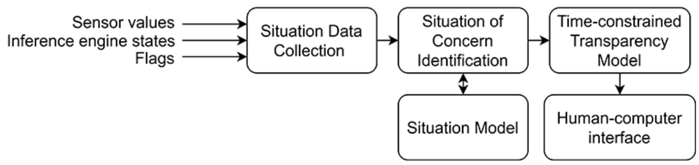

Fig. 1: The proposed situation inference approach

A. Constructing Situation Model

This part presents some definitions used to construct a situation model.

Definition 1 (Situation attribute). A situation attribute is a set of surrounding object statuses, and those objects are related to each other within a context. An object can be in a conceptual or physical form.

Definition 2 (Situation attribute representation). A situation attribute is represented by binary values. The *true* state (1) indicates the presence of the situation attribute, and the *false* state (0) indicates otherwise.

Definition 3 (Situation of concern). A situation of concern is a collection of situation attribute representation and characterized by combination values of situation attribute representations. This collection is discrete and ordered.

Definition 4 (Situation context). A situation context is a generic subset of situations associated with the current task.

Definition 5 (Situation description). A situation description is textual information describing the situation.

Definition 6 (Situation assets). Situation assets are the collection of cues that graphically represents surrounding objects of concern and their statuses.

Definition 7 (Situation model). A situation model contains situation context, situation description, situation attribute representation, and situation assets.

Definition 8 (Situation library). A situation library is a collection of situation models.

B. Situation Data Collection

This part provides a mechanism to collect current statuses of observable surrounding objects and transform them into situation attribute representation. Assume that a Fuzzy set *A* is used to represent a situation attribute, so that

$$A = \{(a_k, \mu_{a_k}), \ldots, (a_n, \mu_{a_n})\} \tag{1}$$

where *a* is the statuses of an object relevant to the situation attribute, and *k = 1,2,...,n* is an infinite number. The value of μ for each *a* can be manually determined or assigned from the result of a recognition model in term of i.e., accuracy. For example, consider the status of a traffic light is obtained by a recognition model which detects 95% of current traffic light color is red. Now, assume that a_k represents the status of red light, and, thus, the value of μ_{a_k} is 0.95.

Now, consider that *R* is the binary representation of *A*, and *R* can be obtained from a [0,1] mapping function as follows:

$$R = \begin{cases} 1 & if \ \frac{\sum_{k=1}^{n} \mu_{a_k}}{n} \geq \alpha - cut \\ 0 & otherwise \end{cases} \tag{2}$$

In this regard, the $\alpha - cut$ indicates an acceptable value of the membership degree average to confidently determine the presence of a certain situation attribute. Thus, we can now define a situation (*S*) as follows:

$$S = \{R_k, \ldots, R_n\} \tag{3}$$

Furthermore, the situation context *SC* is a subset of *S*, *SC* $\subset$ *S*. While *S* is considered a situation explained in detail, *SC* is its generic form. For example, a TL situation is a generic situation, and a red-light situation is a more specific form of a TL situation.

C. Situation Model and Situation Library Development

Fig. 2 illustrates the structure of situation model. The content of situation context and situation attribute representations are obtained from pre-determined of set *SC* and *S*, respectively. Situation description is a textual presentation describing the situation of concern in the form of words or sentences. Furthermore, the situation assets provide any graphical cue to support user interface presentation to visually explain the situation of concern.

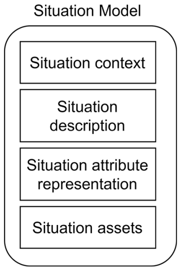

Fig. 2: The structure of the situation model.

The situation library is a critical part of the proposed approach. This library consists of a set of situation models. This library is managed as an XML file. This way, the computation cost to access this library can be significantly reduced.

D. Situation of Concern Identification

This part explains the mechanism to identify the current situation of concern by comparing the set *S* as the situation attribute representation obtained from sensory tools with each member of *S'* as the collection of situation attribute representation in the situation library. For this regard, another fuzzy theory called fuzzy matching is applied. The core of fuzzy matching is based on the Levenshtein distance which calculates the distance between two strings i.e., string *a* and string *b*. Now, consider the elements of *S* as string *x* and the elements of each member in *S'* as string *y*. The Levenshtein distance can be written as follows:

$$lev(x,y) = \begin{cases} |x| & if|y| = 0, \\ |y| & if|x| = 0, \\ lev(tail(x), tail(y)) & if x|0| = y[0] \\ 1 + min \begin{cases} lev(tail(x), y) \\ lev(x, tail(y)) \\ lev(tail(x), tail(y)) \end{cases} & otherwise \end{cases} \tag{4}$$

The similarity between *S* and *S'* is obtained by calculating similarity ratio (Sim_{ratio}) which can be done by the following equation:

$$Sim_{ratio} = \frac{(|x| + |y|) - lev(x,y)}{|x| + |y|} \tag{5}$$

where $|x|$ and $|y|$ are the lengths of string *x* and string *y*, respectively. Then, the similarity ratio calculation results are stored in a set called *results*. The situation of concern ($S_{concern}$) is determined by selecting the highest value of the similarity ratio as follows:

$$S_{concern} = max(results) \tag{6}$$

Based on this result, the other related information from situation model can be obtained, such as situation description, situation context, and situation assets.

E. Time-constrained Transparency Model

Providing transparency needs to consider the human ability to absorb the information presented on a user interface. In fact, humans need a few seconds to estimate the basic situation topology by themselves, but a longer time is required to compare their situational awareness with ones from the intelligent agent by reading presented information on the provided user interface.

Assume that t_1 and t_2 are pre-determined values representing time sensitive of a situation. These values are used to determine whether the time-length of a situation ($t_{situation}$)

has a strong time constraint or not. The time constraint (*TC*) of situations is determined as follows:

$$TC = \begin{cases} strong & if\ t_{situation} \leq t_1, \\ medium & if\ t_1 > t_{situation} < t_2, \\ low & if\ t_{situation} \geq t_2 \end{cases} \quad (7)$$

Based on the characteristic of *TC*, the rule-based time-constrained transparency model is developed, such that:

- If *TC* is strong, then the transparency presentation only displays situation context and situation assets
- If *TC* is medium, then the transparency presentation displays situation context, situation assets, and medium size of situation description
- If *TC* is low, then the transparency presentation displays situation context, situation assets, and situation description

IV. Experimental Evaluation

This section presents two driving situation cases, TL situations and overtaking situations. These two cases are simulated using Carla [23], open-source software for autonomous driving. In this experiment, the values of t_1 and t_2 are three seconds and five seconds, respectively.

The TL situation scenario is illustrated in Fig. 3. Assume that ego vehicle (our vehicle) is just entering a traffic light situation with a lead vehicle ahead. This situation is recognized by the existence of TL ahead in a certain distance *d*. TL situation is divided into two segments. For human drivers, they react on TL state after *D* unit distance away from TL. This segment is called Segment 1. While in Segment 2, they keep their maneuver. This behavior is implemented in our autopilot agent simulation. Hence, Segment 2 of TL situation is considered a situation with a *low* TC, while Segment 1 has a *medium* TC.

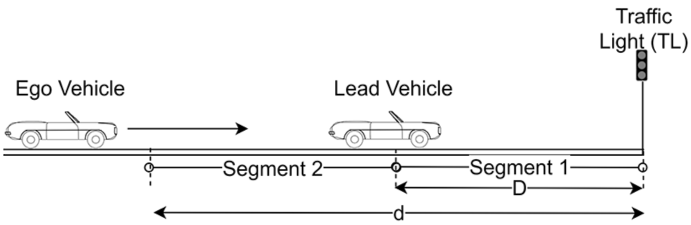

Fig. 3: Traffic light situation scenario

Fig. 4 shows the user interface to present transparency of the autopilot agent's situational awareness in Segment 1 of TL situations. As this segment has a *medium* TC, the situation context, short situation descriptions, and situation assets are displayed. The text 'Tailing in traffic light situations' on the left area is the situation context. The text on the top is the short situation descriptions. Finally, the traffic light icon and the car icon are the situation assets representing ego and lead vehicle, respectively.

Furthermore, Fig. 5 shows the overtaking scenario. In this scenario, the ego vehicle overtakes the lead vehicle. For such

Fig. 4: The user interface for autopilot agent transparency based on TL situation scenario

overtaking, the ego vehicle has v_{OT} indicating overtaking speed and a_{OT} indicating its acceleration. During overtaking, the ego vehicle is in overtaking lane already, but the lead vehicle increases its speed. The autopilot agent predicts that the road speed limit will be violated if the overtaking maneuver continues.

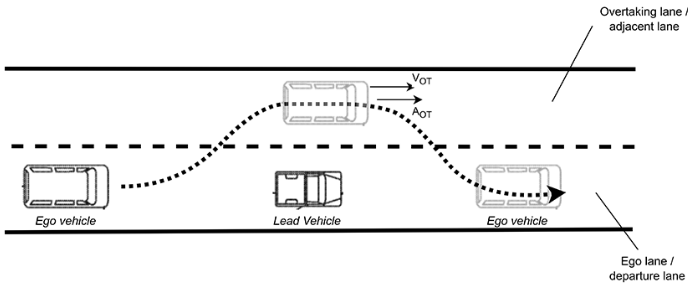

Fig. 5: Overtaking scenario

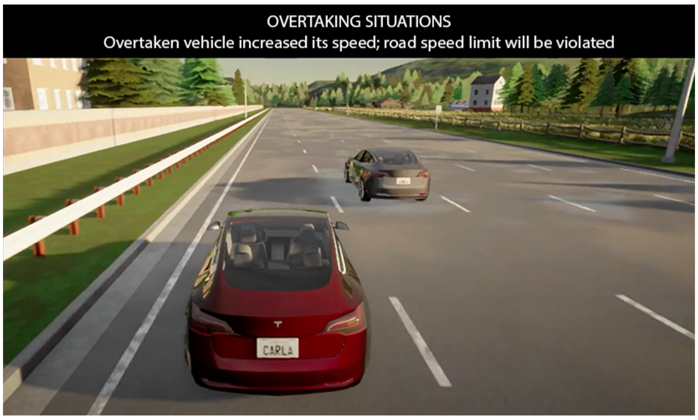

Fig. 6: The user interface for autopilot agent transparency based on the overtaking scenario

The overtaking situation is considered as a situation with medium time constraints. The situation context and situation descriptions are displayed as the text on the top area. In the meantime, the situation asset provides the car icons indicating the ego and lead vehicle, including their visual positions.

V. Conclusions

This paper introduces a situation inference approach to provide the autopilot agent transparency. Such transparency helps compare the human driver's situational awareness and the autopilot agent's situational awareness. The proposed approach used the Fuzzy theories including Fuzzy set and Fuzzy matching methods. An experimental evaluation is conducted using Carla, an autonomous driving simulator. The results show that the proposed approach is applicable and can help the human driver to calibrate their trust on the autopilot agent.

References

[1] S. Lin and N. F. Maxemchuk, "An architecture for collaborative driving systems," in 2012 20th IEEE International Conference on Network Protocols (ICNP), 2012, pp. 1–2.

[2] Y. Xing, C. Lv, D. Cao, and P. Hang, "Toward human-vehicle collaboration: Review and perspectives on human-centered collaborative automated driving," Transportation research part C: emerging technologies, vol. 128, p. 103199, 2021.

[3] W. Li, F. Duan, and C. Xu, "Design and performance evaluation of a simple semi-physical human-vehicle collaborative driving simulation system," IEEE Access, vol. 7, pp. 31971–31983, 2019.

[4] M. R. Endsley, "From here to autonomy: Lessons learned from human–automation research," Human Factors, vol. 59, no. 1, pp. 5–27, 2017.

[5] V. A. Banks, A. Eriksson, J. O'Donoghue, and N. A. Stanton, "Is partially automated driving a bad idea? Observations from an on-road study," Applied Ergonomics, vol. 68, pp. 138–145, 2018, doi: https://doi.org/10.1016/j.apergo.2017.11.010.

[6] M. Korber, E. Baseler, and K. Bengler, "Introduction matters: Manipulating trust in automation and reliance in automated driving," Applied Ergonomics, vol. 66, pp. 18–31, 2018, doi: https://doi.org/10.1016/j.apergo.2017.07.006.

[7] M. Freiman, M. Caisse, J. Ball, T. Halverson, and C. Myers, "Empirically Identified Gaps in a Situation Awareness Model for Human-Machine Coordination," in 2018 IEEE Conference on Cognitive and Computational Aspects of Situation Management (CogSIMA), 2018, pp. 110–116. doi: 10.1109/COGSIMA.2018.8423980.

[8] N. A. Stanton, P. M. Salmon, G. H. Walker, E. Salas, and P. A. Hancock, "State-of-science: Situation awareness in individuals, teams and systems," Ergonomics, vol. 60, no. 4, pp. 449–466, 2017, doi: 10.1080/00140139.2017.1278796.

[9] N. A. Stanton et al., "Distributed situation awareness in dynamic systems: Theoretical development and application of an ergonomics methodology," Ergonomics, vol. 49, no. 12–13, pp. 1288–1311, 2006, doi: 10.1080/00140130600612762.

[10] O. McAree and W.-H. Chen, "Artificial situation awareness for increased autonomy of unmanned aerial systems in the terminal area," Journal of Intelligent & Robotic Systems, vol. 70, no. 1–4, pp. 545–555, 2013.

[11] G. Underwood, A. Ngai, and J. Underwood, "Driving experience and situation awareness in hazard detection," Safety Science, vol. 56, pp. 29–35, 2013, doi: http://doi.org/10.1016/j.ssci.2012.05.025.

[12] M. Abe, G. Yamamoto, and T. Miyahira, "Rule-Based Situation Inference for Connected Vehicles," in 2017 IEEE International Congress on Internet of Things (ICIOT), 2017, pp. 159–161. doi: 10.1109/IEEE.ICIOT.2017.28.

[13] M. Abe, G. Yamamoto, and S. Furuichi, "(WIP) IoT Context Descriptor: Situation Detection and Action Invocation Model for Real-Time High-Volume Transactions," in 2018 IEEE International Congress on Internet of Things (ICIOT), 2018, pp. 130–133.

[14] A. Al-Ajlan, "The comparison between forward and backward chaining," International Journal of Machine Learning and Computing, vol. 5, no. 2, p. 106, 2015.

[15] M. Harbers, K. van den Bosch, and J. J. Meyer, "Design and evaluation of explainable BDI agents," 2010. doi: 10.1109/WI-IAT.2010.115.

[16] F. Kaptein, J. Broekens, K. Hindriks, and M. Neerincx, "Personalised self-explanation by robots: The role of goals versus beliefs in robot-action explanation for children and adults," 2017. doi: 10.1109/RO-MAN.2017.8172376.

[17] G. Hagele and A. Sarkheyli-Hägele, "Situational hazard recognition and risk assessment within safety-driven behavior management in the context of automated driving," in 2020 IEEE Conference on Cognitive and Computational Aspects of Situation Management (CogSIMA), 2020, pp. 188–194.

[18] J.-M. Nigro, S. Loriette-Rougegrez, and M. Rombaut, "Driving situation recognition with uncertainty management and rule-based systems," Engineering Applications of Artificial Intelligence, vol. 15, no. 3, pp. 217–228, 2002, doi: https://doi.org/10.1016/S0952-1976(02)00070-2.

[19] J. M. Nigro and M. Rombaut, "IDRES: A rule-based system for driving situation recognition with uncertainty management," Information Fusion, vol. 4, no. 4, pp. 309–317, 2003, doi:https://doi.org/10.1016/S1566-2535(03)00042-3.

[20] G. Lu, L. Li, Y. Wang, R. Zhang, Z. Bao, and H. Chen, "A rule based control algorithm of connected vehicles in uncontrolled intersection," in 17th international IEEE conference on intelligent transportation systems (itsc), 2014, pp. 115–120.

[21] J. Li, H. Ma, W. Zhan, and M. Tomizuka, "Generic probabilistic interactive situation recognition and prediction: From virtual to real," in 2018 21st international conference on intelligent transportation systems (ITSC), 2018, pp. 3218–3224.

[22] O. Reynolds, "Towards Model-Driven Self-Explanation for Autonomous Decision-Making Systems," in 2019 ACM/IEEE 22nd International Conference on Model Driven Engineering Languages and Systems Companion (MODELS-C), 2019, pp. 624–628. doi: 10.1109/MODELS-C.2019.00095.

[23] A. Dosovitskiy, G. Ros, F. Codevilla, A. Lopez, and V. Koltun, "CARLA: An Open Urban Driving Simulator," in Proceedings of the 1st Annual Conference on Robot Learning, 2017, pp. 1–16.