Fuzzy Cognitive Maps for Intelligent Agent's Artificial Situational Awareness in Collaborative Driving Context

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***Abstract*—Automation such as the autopilot car technology is considered to be a promising solution to reduce the number of accidents on the road. However, it is believed that to increase safety for such technologies, it is necessary for an intelligent agent (IA) and the human driver to share their situational awareness so that the same conclusions regarding driving situations can be reached. Hence, developing a reasoning engine to generate goal-driven explanations regarding IA's situational awareness is highly required. To address this challenge, this paper proposes a fuzzy-cognitive-map-based reasoning engine to disclose inferred situations behind IA's executed action. Carla simulator was used to conduct an experimental test in a collaborative driving context. As the results, goal-driven explanations can be generated with a better performance than the baseline method. This work is important to reduce road incidents involving autonomous cars.**

***Index Terms*—artificial situation awareness, intelligent agent, collaborative driving**

I. Introduction

Granting a higher level of autonomy to IA as a member of a human-IA team requires a mechanism to generate the explicit representation of IA's situational awareness (referred to as artificial situational awareness) that provides explanations about the situations behind IA's selected action (goal-based explanations) [1]. Such explanations are useful for human to understand IA's behaviors [2]. One example of human-IA team can be seen in the collaborative driving. In the collaborative driving, the on-board advanced driver assistance system (ADAS) provides cognitive supports when the human driver drives the car in a manual mode. Moreover, ADAS through its autopilot agent as IA has a certain level of autonomy for driving tasks when the autopilot mode is on. Hence, such driving collaboration between the human driver and the autopilot agent is considered at level 4 of 6 levels (0-5) car automation based on the Society of Automotive Engineering classification [3].

For humans, situational awareness is constructed by relating task-relevant surrounding objects statuses at a certain time-window to form comprehension of situations [4]. For example, a human driver concludes a tailing red light situations by connecting the color of traffic light and the existence of another car in front located at a certain distance within the same lane. In this regard, 'traffic light color' and 'the existence of a lead vehicle within the same lane at a certain distance' are considered to be the statuses of surrounding objects relevant to the driving task.

The construction of human's situational awareness can be adopted for IA that infers the statuses of surrounding objects from its sensory tools and a set of recognition models [5], [6]. For example, cameras and distance sensors can be used to collect the data to infer the statuses of traffic light and surrounding objects, respectively. By combining those statuses, the IA's situation understanding can be artificially developed. There are many approaches for IA developers to present the IA's comprehension of situations to its human counterpart. In the tailing red light situation case, a red traffic light icon and a car icon representing the lead vehicle can be provided. However, this approach requires a more cognitive effort from the human driver to conclude the meaning of such icon combinations.

As the recognition models may not perfectly accurate, IA can fail in detecting the statuses of surrounding task-relevant objects such as traffic light state [7]. Assuming that in the traffic light situation, red light is not recognized. By design, the IA's logic instructs the vehicle to keep moving in such a situation. This design is considered a trade-off between road safety and other road users' convenience [8]. But this trade-off might lead to road incidents as the red light can be violated. Presenting the traffic light icon may give cues to the human driver about IA's perception. However, the human driver might wonder how IA will react given unrecognized status of the traffic light [9], [10].

The simple illustration above highlights the necessity of a reasoning engine which can link the IA's action to the background situation so its human counterpart can have better understanding on IA's behaviors. Mostly, previous studies rely on graph-based behavioral representation to develop a reasoning engine, such as decision tree [11], provenance graph [12], belief-desire-intention (BDI) hierarchy [13], and goal hierarchy [14]. Moreover, researchers in [5] and [15] proposed knowledge graph system and rule-based system for the reasoning engine, respectively. However, the main weakness of such behavioral representation is their limitations to disclose the type of situations encountered by IA behind its selected action. We believe that a graph representing a situation model is more suitable to reveal IA's situational awareness. Hence, this paper aims to propose a reasoning engine using a graph-based situation model as the core part of IA's artificial situational awareness to generate goal-based explanations. In this regard, such a situation model is implemented using Fuzzy Cognitive Maps in our proposed approach.

In this research, we conducted an experimental implementation in a collaborative driving context. We used Carla simulator for the experiments. Carla simulator is an open-source software to simulate autonomous driving [16], and the autopilot is considered to be IA. There are two scenarios for simulations, namely traffic light and overtaking scenarios. The result shows that the proposed method is applicable and has better performance in generating goal-based explanations than the baseline method.

The key contributions of this work are as follows:

- This paper proposes a reasoning engine with the Fuzzy Cognitive Maps as the situation model
- This paper provides a mechanism to exploit the proposed representation of situation model to generate goal-based explanations.

The remainder of this paper is structured as described below. Section 2 presents the theoretical background, and Section 3 proposes the reasoning engine. An experimental implementation and evaluation are presented in Section 4. Finally, the conclusions are drawn in Section 5.

II. Background

A. Fuzzy Cognitive Maps

The Fuzzy Cognitive Map (FCM) is firstly introduced by Kosko [17], and it is a graph-based knowledge representation. Its nodes denote concepts in the domain of problem while the edges represent causal relationships among concepts. FCM offers fuzziness in each relation by using fuzzy binaries of causal influences. Suppose C_i and C_j are the FCM's nodes (see Fig. 1); the strength of the edge connecting those two concepts will be weighted where the value of the weight w_{ij} is ranging from -1 to 1. There are three types of edge strength that indicate possible causalities between C_i and C_j [18]:

- $w_{ij} > 0$ represents a positive causality. If C_i occurs (or not), C_j will also occur (or not)
- $w_{ij} < 0$ represents a negative causality. If C_i occurs (or not), C_j will not occur (or occur)
- $w_{ij} = 0$ represents no causality. Both C_i and C_j do not have influence each other.

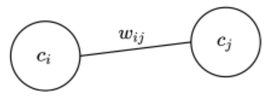

Fig. 1. Relation between two concepts in FCM

FCM comprising n factors is mathematically represented by a $n \times n$ matrix (W), and w_{ij} becomes the element of W. Hence, based on Fig. 1, the mathematical representation of FCM is as follow:

$$W = \begin{bmatrix} 0 & w_{ij} \\ w_{ji} & 0 \end{bmatrix}$$

FCM gets the input from a state vector given time t $(X^{(t)})$ which can model the changes of a scenario in a certain time-window by letting its nodes interact to each other.

B. Situation Awareness

Endsley [19] described situation awareness (SA) as "the 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". Hence, situation awareness is formed through three steps of information processing: perception (SA Level 1), comprehension (SA Level 2), and 3) projection (SA Level 3).

According to [20], a certain degree of SA can be hold by IA. As it is owned by IA, such SA is called artificial situational awareness as it needs to be explicitly defined [5], [6]. However, as IA's behaviors are created by design, we define artificial situational awareness as an explicit representation of the three-levels situation awareness model comprising perception (Level 1), comprehension (Level 2), and action (Level 3).

The development of artificial SA may have many problems due to i.e., system boundaries, imperfect recognition models, and sensor failures. As a result, IA might misbehave as it has incorrect SA. Hence, exposing IA's artificial SA can be one way to comprehend IA's behaviors and to improve human-IA collaboration.

III. The Proposed Reasoning Engine

This section presents the proposed FCM-based reasoning engine that can generate goal-based explanations to clarify situations encountered by IA behind its selected action or decision. Fig. 2 depicts the diagram block illustrating the architecture of the proposed engine. There are two main parts in the architecture, IA system (drawn in the yellow block) and the reasoning engine (drawn in the green block). The details about each part will be explained in the following sub-sections.

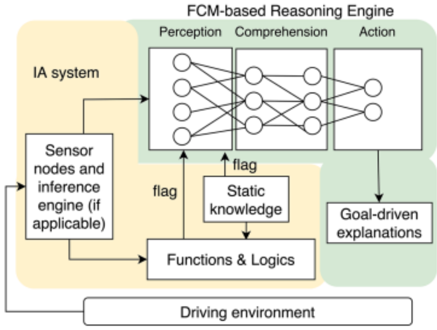

Fig. 2. FCM-based reasoning engine

A. IA System

In this paper, we only focus on the core components of IA system which becomes the inputs for the reasoning engine. The first group of IA system's components is a set of sensory tools and inference engines. Sensors generate the input data with various data type. Some of them can produce measurement values, and these values can be directly used without an inference engine to interpret them. For example, distance sensors and temperature sensors. However, the other types of sensors, such as cameras, need an inference engine to recognize the state of concerns, such as the red light.

The components in the second group are functions and logics. In a logic-based agent, functions and logics can be viewed as the representation of goal model and goal-execution plans, respectively. Functions and logics generate flags to feed the FCM. A flag is a variable providing a signal regarding a certain state of programming or logic. Hence, it can also be used to indicate the IA's selected action state.

The last group is IA's static knowledge, which can be described as a set of default values or user-custom values stored in the system settings. From the static knowledge, a flag can also be generated and sent to FCM for the reasoning process. Before feeding the FCM, the values from static knowledge may undergo a discretization process, particularly when these values are continuous.

From the inputs above, a time-dependent state vector A is constructed and denoted as follows:

$$A^t = [a_0^t, \ldots, a_k^t] \tag{1}$$

where a represents the state of an input (e.g., a sensor, an inference engine, or a flag) with $k = 0, 1, 2, \ldots, n$ is the infinite number of inputs, and A^0 is considered to be the initial state vector.

B. The Reasoning Engine

The reasoning engine consists of two parts, namely the FCM graph representing a situation model and a goal-driven explanation generator. We divided the FCM graph into three groups of nodes, namely root, intermediate, and leaf nodes that represent IA's perception, comprehension, and action, respectively. Root nodes gather their inputs from sensors, inference engine states, and flags. Intermediate nodes directly connected to the root nodes without linked to leaf nodes are referred to as IA's lower-level comprehension of situations. Meanwhile, intermediate nodes directly connected to action nodes are referred to as IA's higher-level comprehension of situations.

The connections among concepts and their weight values are defined by the expert. The state vector denoted in Eq. 1 becomes the initial points for FCM, and the concept state at A^{t+1} can be calculated according to following equation:

$$A_i^{t+1} = f\left(\sum_{j=1, j\neq i}^{n} w_{ij} \times X_j^t\right) \tag{2}$$

where X_j^t is the value of C_j in the simulation at time t, and f is a sigmoid function denoted by:

$$f(x) = \frac{1}{1+e^{-\lambda x}} \tag{3}$$

where $\lambda > 0$, and x is the value of X_j^t for the given t. Once the concept states A_i^{t+1} are obtained, goal-driven explanations can be inferred from the state of concepts representing IA's action and the higher-level comprehension.

Now, let $\delta = \{o_1, \ldots, o_q\}$ be the set of concepts' states for higher-level comprehension, where q is the number of concepts in this part. The following equation is used to determine which concept representing current IA's situational awareness at the given time t:

$$\sigma = max(\delta) \tag{4}$$

Similarly, by assuming that $\gamma = \{p_1, \ldots, p_w\}$ is the set of leaf nodes' states where w is the number of leaf nodes, current IA's action given time t can be determined by the following equation:

$$\varsigma = max(\gamma) \tag{5}$$

The goal-driven explanations, then, are obtained by linking ς (as the IA's selected action) to σ (as the situation behind IA's selected action).

IV. Experimental Evaluation

A. Testing Environment

Carla simulator [16] was used in the experiment, and the autopilot agent which drives the autonomous car in the simulator is considered IA. Built-in Carla's virtual sensors are used, such as depth and semantic cameras, navigation system, lane invasion sensors, and LIDAR. The cameras are used to recognize and identify surrounding objects in the driving environment. Geo-location of the simulated autonomous cars in the Carla's virtual map is provided by the navigation system. Furthermore, lane invasions sensors and LIDAR provides the recognition of road line types and distance measurement to surrounding objects, respectively. Moreover, the lane invasion sensors provide a support to keep the ego car (our car) within the lane.

B. Scenarios

There are two showcases in the experiment, namely traffic light (TL) and overtaking scenarios. As illustrated in Fig. 3, the ego vehicle just entered a tailing TL situation. Two segments are determined for the TL situation, namely Segment 1 and Segment 2. For the human drivers, they respond to TL state after D unit of distance away from the TL location. From D to the TL location is called Segment 1. Before entering Segment (Segment 2), the drivers tend to keep their current maneuver. Such behaviors, then, are implemented in our autopilot agent. The scenario for TL situations can be described as follows: the ego vehicle enters TL situation without recognizing TL state, but a lead vehicle exists.

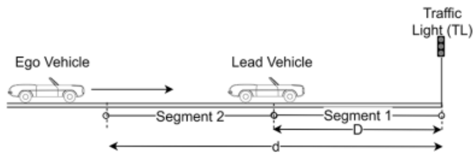

Fig. 3. Traffic light situation

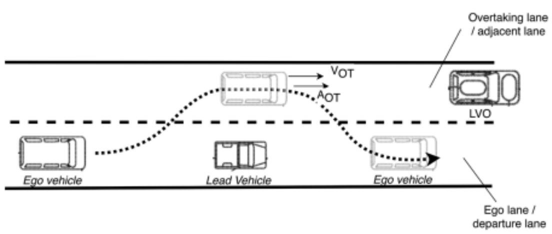

Fig. 4. Overtaking situation

Overtaking situation is illustrated in Fig. 4. The lead vehicle will be overtaken, and the existence of other vehicles in the overtaking lane is called LVO. In the overtaking scenario, two main risks are considered, namely the risk to violate road speed limit during overtaking maneuver and the risks associated with LVO including the distance to LVO and the space to go back departure lane after overtaking. Furthermore, the scenario for overtaking situation can be described as follows: while next to overtaken vehicle in the overtaking lane, the overtaken vehicle increases its speed so the road speed limit will be violated if the overtaking maneuver is insisted.

C. FCM Settings

The list of concepts for the two scenarios can be seen in Table I and Table II. The weighted connections among concepts are presented in Fig. 5 and Fig. 6. The state vector feeding the root nodes in TL scenario consists of five elements indicating the three states of traffic light (red, green, unknown; denoted by TLR, TLG, and TLU, respectively), the existence of lead vehicle with respect to TL location, and TL segment (see Table I).

There are also five elements in the state vector as the inputs of FCM's root nodes for overtaking scenario. Those elements

TABLE I
LIST OF CONCEPTS IN TRAFFIC LIGHT SCENARIO

Symbol	Descriptions
Root Nodes	
TLR	Red light
TLG	Green light
TLU	Unknown light
LVTL	The existence of a lead vehicle with respect to the TL location
Segment2	The ego vehicle position with respect to TL Segment (Segment 1 or 2)
Intermediate Nodes	
T	Tailing situations
FR	Free ride situations
TS2	Tailing situations in Segment 2
FRS2	Free ride in Segment 2
TRLS1	Tailing under red light situations in Segment 1
TGLS1	Tailing under green light situations in Segment 1
TULS1	Tailing under unknown light situations in Segment 1
FRRLS1	Free ride under red light situations in Segment 1
FRGLS1	Free ride under green light situations in Segment 1
FRULS1	Free ride under unknown light situations in Segment 1
Leaf Nodes	
KG	Keep going
AS	Keeping safe distance with lead vehicle
ST	Stopping vehicle

TABLE II
LIST OF CONCEPTS IN OVERTAKING SCENARIO

Symbol	Descriptions
Root Nodes	
RS	Risk of overtaking speed
OL	Overtaking lane
BOV	The ego vehicle position is still behind the overtaken vehicle
NOV	The ego vehicle position is next to the overtaken vehicle
RLVO	Risk to other vehicles in the overtaking lane
Intermediate Nodes	
C1	Overtaken vehicle is increased its speed; road speed limit will be violated
C2	Risk to vehicles in overtaking lane is detected; it is not safe to return to the departure lane
C3	It is still behind overtaken vehicle, unsafe speed to overtake
C4	It is still behind overtaken vehicle, unsafe risk to vehicles in overtaking lane
C5	No overtaking risk detected
Leaf Nodes	
COT-1	Overtaking cancelled and go back to departure lane behind overtaken vehicle
COT-2	Overtaking cancelled and stay in the overtaking lane
KP	Keep processing overtaking

represent risk of overtaking speed (denoted by RS), overtaking lane (denoted by OL), the ego vehicle position whether behind (denoted by BOV) or next to (denoted by NOV) the overtaken vehicle, and risk to LVO (denoted by RLVO) (see Table II).

In the simulation, each FCM graph will be called when a certain situation is recognized. For example, in TL scenario, TL situation begins when the ego vehicle is within d distance from TL location. Furthermore, overtaking scenario starts when an overtaking recommendation is suggested by the ADAS and the human driver send a signal to ADAS to execute the maneuver.

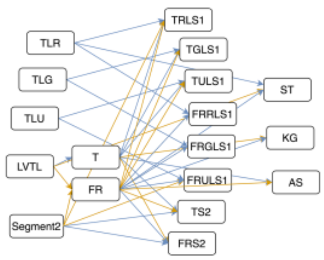

Fig. 5. The weighted relation of concepts in traffic light scenario (the weight of yellow line = -1 and blue line = 1)

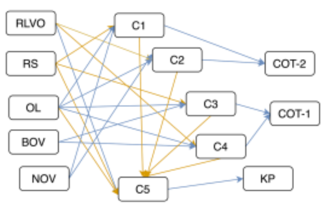

Fig. 6. The weighted relation of concepts in overtaking scenario (the weight of yellow line = -1 and blue line = 1)

D. Results and Discussion

The final states of concepts in the TL scenario can be seen in Fig. 7. It can be seen that the leaf node having the maximum value is AS (0.05). Hence, it can be inferred that currently, the ego vehicle is keeping safe distance with the lead vehicle. Furthermore, the maximum value of intermediate nodes representing higher-level comprehension is hold by $TULS1$(0.36) which represents tailing situation with unrecognized traffic light. Carla simulation of generated explanations based on FHM state in TL scenario can be seen in Fig. 8.

Similarly, the final states of concepts in the overtaking scenario are presented in Fig. 9. $COT-2$ is the leaf node having the maximum value which indicates that current autopilot action's is 'overtaking cancelled and stay in overtaking lane'. Based on Fig. 7, the reason behind such an action can be inferred from $C1$ indicating 'Overtaken vehicle increased its speed; road speed limit will be violated'. The generated explanations by Carla simulator for overtaking scenario can be seen in Fig. 10.

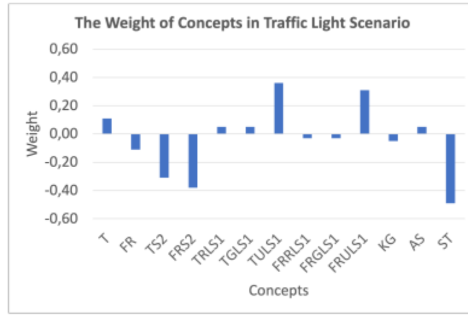

Fig. 7. The weight of concepts in TL scenario

Fig. 8. Generated explanations in traffic light scenario using the Carla simulator

For evaluation, we selected a baseline method from [13] because this method provides the relation between IA's executed action and the rationale through BDI hierarchy. The results show that the proposed method can extract critical key information for explanations such as 'cancel overtaking and stay in overtaking lane', and 'overtaken vehicle increased its speed'. Such extractions cannot be accomplished by the baseline method. Furthermore, there are some limitations in our proposed method, particularly when two concepts hold the same weight which are recognized as the maximum values in Eq. 4 and Eq. 5. Under such conditions, the generated

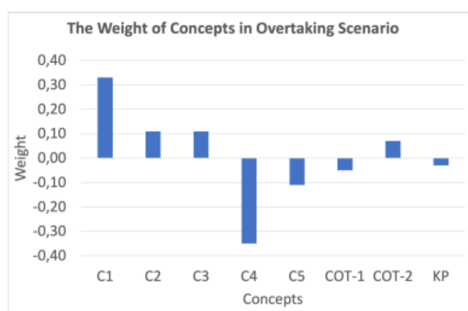

Fig. 9. The weight of concepts in overtaking scenario

Fig. 10. Generated explanations in overtaking scenario using the Carla simulator

goal-driven expanations may fail to indicate actual situations. However, carefully designing and verifying the FCM can minimize those problems.

V. Conclusions

This research proposes a new FCM-based reasoning engine which can generate goal-driven explanations. This proposal is useful to disclose IA's situational awareness behind its executed actions. The proposed method is implemented in the autonomous driving simulator software called Carla, and the results show its applicability and capability to generate explanations on IA's behaviors.

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