Artificial Situation Awareness for an Intelligent Agent

1st Rinta Kridalukmana
Department of Computer Engineering
Diponegoro University
Semarang, Indonesia
rintakrida@ce.undip.ac.id

2nd Dania Eridani
Department of Computer Engineering
Diponegoro University
Semarang, Indonesia
dania@ce.undip.ac.id

3rd Risma Septiana
Department of Computer Engineering
Diponegoro University
Semarang, Indonesia
rismaseptiana@live.undip.ac.id

4th Adian F. Rochim
Department of Computer Engineering
Diponegoro University
Semarang, Indonesia
adian@ce.undip.ac.id

5th Charisma T. Setyobudhi
Department of Computer Engineering
Diponegoro University
Semarang, Indonesia
charisma@ce.undip.ac.id

***Abstract*—A behavioural representation of an intelligent agent (IA) is considered an important part to generate explanations on its behaviours to understand what it is thinking. Previous studies have introduced various behavioural representations, such as decision tree, goal hierarchy, belief-desire-intention (BDI) hierarchy, and physical system network. However, they cannot optimally disclose IA's comprehension on given situations which is needed in certain cases of human-autonomy teaming like collaborative driving. To address this gap, this paper proposes a new behavioural representation based on artificial situational awareness to reveal situations encountered by the IA behind its executed action. The experimental implementation was conducted in collaborative driving context using the Carla simulator. The results show that the proposed behavioural representation has better performance in extracting IA's situational awareness compared to the baseline method. This work is significant to enhance human comprehension on IA so their trust in IA can be calibrated.**

***Index Terms*—artificial situation awareness, intelligent agent, behavioural representation**

I. Introduction

Promoting an intelligent agent (IA) to be a human counterpart in human-autonomy teaming (HAT) requires a mechanism to make IA understandable and predictable by explaining its behaviours [1], [2]. Thus, the human counterpart can enhance their situational awareness to monitor the IA adequately and to receive strong cues to calibrate their trust and expectations on IA [3]. Clarifying the rationale behind an executed action of IA is referred to as goal-driven explanations [4]–[6]. However, generating such explanations is highly dependent on how IA's behavioural representation is developed [7].

Previous studies have introduced various behavioural representation to generate goal-driven explanations. For example, researchers in [8], [9] developed decision tree as the behavioural representation for a logic-based IA whose behaviours are driven by a decision network representing its logic. In this regard, connected nodes in the decision tree are viewed as the goal model representation and the goal-execution plans. As illustrated in Fig. 1, the decision tree is used to trace the executed paths (indicated by the blue arrow) back to the source (S1 and D1) using algorithms like A* search and best-first-search. In this figure, M is considered as the main function, and both S and D are two subfunctions feeding M. Each executed path has a certain meaning describing the way IA thinking.

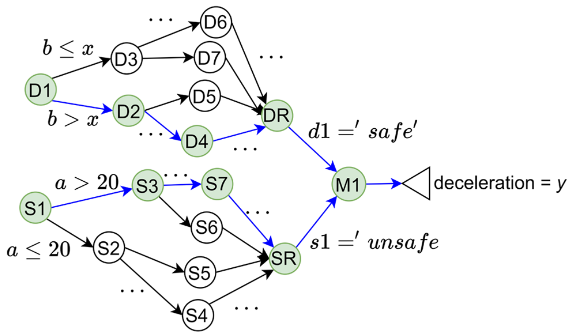

Fig. 1. Behavioural representation using a decision tree

Tracing methods becomes inefficient as it is also necessary to identify which paths are truly causing an action. For this regard, a temporary space can be allocated to store executed paths in a session [8]. Alternatively, a provenance graph can be applied to connect the data and IA's logic within a session [9]. The main weakness of applying the provenance graph is unable to address simultaneous function execution (i.e., S and D in Fig. 1) and inter-functional dependencies. As recent IA technologies often require software update to enhance IA's behaviours, the structure of behavioural representation can be affected. As a consequence, a new meaning for every possible path should be re-identified.

In different studies, other behavioural representations are proposed such as goal hierarchy [10] and belief-desire-intention (BDI) hierarchy [11]. Using such behavioural representations, IA's behaviours are explained using the relation descriptions between low-level nodes and higher-level nodes in the hierarchy. Then, other researchers in [12]–[14] proposed a physical system network as the behavioural representation to generate goal-driven explanations. For a machine-learning based IA, researchers in [15]–[17] generated behaviour explanations based on the relation among machine learning model states.

The major weakness in existing behavioural representations is due to their limitation to reveal the IA's comprehension on given situations (referred to as situational awareness) behind its executed behaviours. The extraction of IA's situational awareness is important in HAT, particularly for human team member to compare their situational awareness with ones from IA so the HAT performance can be enhanced. Moreover, previously introduced behavioural representations do not have abstraction of IA's action. Considering those weaknesses, a new behavioural representation is highly desired, particularly for a logic-based agent as most of IAs are logic-based agents. This new behavioural representation should be able to reflect IA's behaviours which relate executed actions with its situational awareness.

We view that behaviours of either human or IA, can be driven by their three-level situation awareness previously modeled by [18]. Unlike human, the IA's situational awareness needs to be explicitly defined. Hence, we define artificial situation awareness as an explicit representation of the three-levels situation awareness model comprising perception (Level 1), comprehension (Level 2), and action (Level 3). Using this perspective, this paper aims to propose the development of artificial situation awareness as a new behavioural representation for IA.

This paper conducted an experimental evaluation in the collaborative driving context to implement the proposed behavioural representation and exploit it to generate goal-based explanations. The collaborative driving context refers to partially automated driving, which is at level 4 of six levels (0-5) autonomous vehicle categories according to the Society of Automotive Engineering. In this regard, the autopilot agent is considered as the human driver counterpart. The results indicate that the proposed behavioural representation can be used to reflect IA's behaviours. Moreover, it has better capability to reveal IA's situational awareness compared to the baseline method that uses goal hierarchy as behavioural representation.

The key contributions of this work are as follows:

- This paper proposes artificial situation awareness as behavioural representation for IA
- This paper provides a mechanism to exploit the proposed artificial SA to generate goal-driven explanations

The remainder of this paper is structured as described below. Section 2 presents the theoretical background, and Section 3 proposes artificial situation awareness architecture. An experimental implementation of the proposed behavioural representation is presented in Section 4. Finally, the conclusions are drawn in Section 5.

II. Background

A. Situation Awareness

Situation awareness (SA) can be described 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" [18]. Thus, there are three levels of information processing stages to form human SA including perception (SA Level 1), comprehension (SA Level 2), and projection (SA Level 3).

IA can hold a certain degree of SA [19], which is referred to as artificial SA according to [20]. For this regard, the three-level SA model can also be adopted for IA to form its own artificial SA. Even though IA can provide support to human to enhance their SA, there are some limitations due to i.e., imperfect recognition models, system boundaries, and sensor failures. Those weaknesses can lead IA to have incorrect SA, and thus, misbehaves. Therefore, understanding IA's behaviour from its SA can be one way to enhance human-IA collaboration.

B. Case-based Reasoning

Case-based reasoning (CBR) is considered a commonly used technique to develop knowledge-based system. The fundamental of CBR system is the case concept, and each case is characterized by a set of features or attributes. CBR is formed by four sequential stages [21]:

1) RETRIEVE the most relevant and similar case
2) REUSE the information in the retrieved case to solve given problems
3) REVISE the proposed solution if necessary
4) RETAIN the revised version for future problem solving

There are four main factors affecting the case retrieval stage [22]: 1) the cases presentation in the base, 2) the case indexes (when applicable), 3) search methods, and 4) similarity functions. A well-known similarity function is Levenstein Distance ($lev()$) which can be formulated as follows:

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

where x and y are two strings to be compared. The similarity ratio (R) is calculated by

$$R = (len(x) + len(y) - lev(x,y))/(len(x) + len(y)) \tag{2}$$

R is ranging from 0 to 1, the highest value represents complete similarity between two strings.

III. Artificial Situation Awareness Architecture

This section presents an artificial situation awareness architecture as the proposed behavioural representation for IA. As illustrated in Fig. 2, boxes in the yellow block represent the generic core components of IA system, the artificial situation awareness architecture is in the grey block, and the module to generate goal-driven explanations is in the green block. The details of each block will be explained in the following subsections.

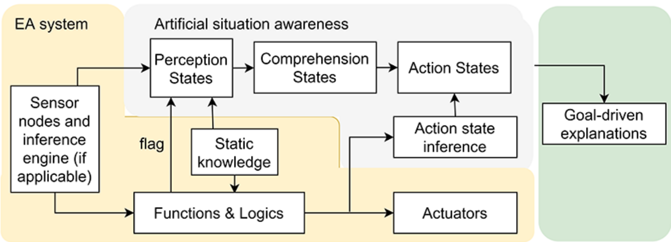

Fig. 2. The intelligent agent and its artificial situation awareness

A. IA System

IA system comprises an array of sensors, functions and logics, static knowledge (i.e., rules, system/user-defined settings), and actuators. Some sensors, such as distance sensors, can directly generate measurement values. However, other sensors, such as camera-based sensors, need inference engines for recognition purposes. Functions and logics will further process the values generated by the sensing tools to provide actuators parameter values that drive the IA's behaviours. In this context, a function can be described as a self-contained programming module to accomplish a certain IA's task. Besides receiving inputs from sensors and inference engine, functions and logic also get their inputs from static knowledge which can be i.e., values from system settings or user-defined variables.

B. Artificial Situation Awareness

We were inspired by the three-level human SA model from [18] to develop artificial SA for IA, which is intended to link IA's perception (SA Level 1), IA's situation comprehension (SA Level 2), and IA's selected action given a certain situation (SA Level 3). In the original three-level SA model, the third level is projection level. We argue that as IA's logic strictly drives its behaviours, so it does not have projection level that make it possible to choose the best action among the worst like human. Hence, our three-level SA model is constructed from perception states, comprehension states, and action states to represent IA's behaviours.

Perception states (PS) obtain inputs from a set of sensors values (S), a set of inference engines states (E), and a set of both flags and static knowledge (F). Flags are generated by IA's logic. Hence, PS can be formally described by:

$$PS = S \cup E \cup F \tag{3}$$

where S = $\{s_j \rightarrow val_{s_j}, \ldots, s_n \rightarrow val_{s_n}\}$, *j=1, 2, …, n*. In this regard, s_j is the index key representing a node of sensor, and val_{s_j} denotes the value generated by this sensor node. The key-value structure is also applied for E and F. It should be noted that each element of the set *PS* is considered attributes which form a situation of concern. Encoding rules such as discretization are applied to transform the value of each element in PS into binary form, where one (1) indicates the presence of a situation attribute is recognized, and zero (0) indicates otherwise. Hence, situation A, for example, which has ten attributes might be presented as '0101111011' where each character in the encoded string is the attribute of situation A.

Furthermore, CBR is applied to form the comprehension state. As illustrated in Fig. 3, the encoded string of perception state is used as the retrieval key to be compared to the situation index of each situation in a situation collection. Each character in situation index follows the order of situation attributes. Hence, the encoded string should be in the same order with the situation index. Fuzzy matching method based on Lavenstein Distance is selected as the similarity function in the comparison process. In this regard, completely matching situation will be reused. Otherwise, the encoded string will be written in the log file to be reviewed and considered as a new situation. When IA receives software updates, the new situation will be retained in the new version of situation collection. The situation description from the selected solution is considered the IA's comprehension state.

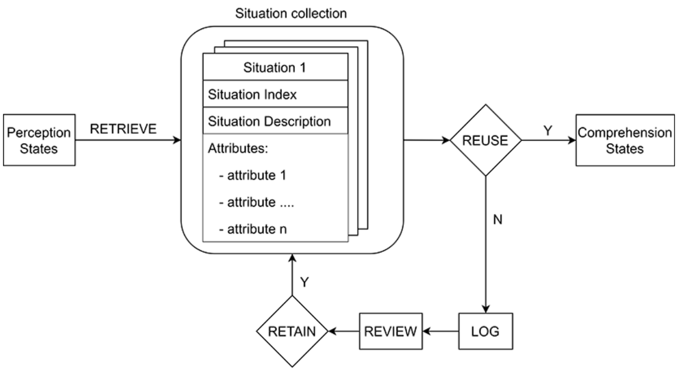

Fig. 3. Case-based reasoning to obtain IA's comprehension state

The last part of artificial SA is the action state. In a logic-based agent, the logic generates values for actuator parameters (i.e., acceleration, steering wheel angle, and braking pressure) which drive the behaviours of EA. If we present such parameters, it might be difficult for human to understand. Hence, an approach is needed to translate the meaning of actuator parameter values into a natural language that is easier for human to absorb, such as stopping, keep going, or maintaining speed. In this regard, some rules can be applied in action state inference for such translations.

C. Goal-driven Explanations

The main purpose of goal-driven explanation module is to reveal the IA's comprehension on the given situation by exploiting its artificial SA. The perception state, comprehension state, and action state are linked to generate goal-driven explanations. However, the process of generating explanations is triggered when a certain situation of concern is recognized, and it is ended when this certain situation is passed. While comprehension and action states are presented mostly in form of text-based information, perceptions state can be presented through indicators i.e., traffic light icon.

The critical problem in generating explanations is due to synchronizing both explanations and associated situation timespan. Hence, we use a variable called $t_{explanation}$ to regulate the timing to update explanations. Ideally, $t_{explanation}$ should have a lower value than the situation timespan ($t_{situation}$), particularly to prevent missing situations or obsolete explanations. However, it is difficult to define $t_{situation}$ in practice as a situation can have different timespan. We recommend using sensor reading cycle as $t_{explanation}$ to mitigate the synchronization problem. Even though the update seems very fast, it will generate the same explanations when the situation does not change. This way, we can optimize explanation timespan to be equal to situation timespan.

IV. Experimental Evaluation

A. Testing Scenario

A showcase in collaborative driving context is presented following an overtaking scenario in a one-way road. In the middle of overtaking manoeuvre (the ego vehicle is already in the overtaking lane), the overtaken vehicle increases its speed. If the autopilot agent continues its manoeuvre, the road speed limit will be overridden. According to the autopilot agent's logic, the autopilot agent will cancel the overtaking manoeuvre and continue driving in the overtaking lane. Without explanations, the human driver might wonder why their vehicle stopped performing overtaking task and stayed in the overtaking lane. By revealing the autopilot agent's situational awareness behind its action cancelling the overtaking task, human driver's comprehension on this agent's behaviours can be enhanced and their trust can be calibrated.

B. Testing Environment

The experiment used Carla simulator [23] which is an open-source software to simulate autonomous driving. Built-in virtual sensors of the simulator are used including semantic and depth camera, LIDAR, lane invasion sensors, and the navigation system. The camera is functioning for surrounding objects recognition and identification. LIDAR and lane invasion sensors are used to measure the distance to surrounding objects and to recognize the road line type, respectively. Additionally, lane invasion sensors help the ego vehicle (our vehicle) to maintain its position within the lane. Finally, the navigation system provides geo-location and position in the virtual map.

Furthermore, $t_{explanation}$ is set to 0.25 second, which is equal to sensor reading cycle in the system setting. We adopted the logic from a patent which drives the autopilot agent overtaking behaviours proposed by [24]. We selected the approach from [10] using goal hierarchy as the baseline method. However, as their IA is not designed for collaborative driving context, we adopted goal hierarchy from [25] suitable for this context.

C. Results

Table I shows situation attributes related to overtaking scenario in which their presence is inferred from perception states. Based on Table I, there are 12 situation attributes, and therefore, there are 12 characters in encoded string of perception states PS. The situation attributes at index 0 and 9 are the member of set F in Equation 3. Moreover, indices 8, 10, 11 are the member of S, and the remaining are the member of E. When all situation attributes are presence, the encoded string will be '111111111111'. The combination of situation attribute values has its own meaning which is written in situation description. For example, '110010011011' means 'overtaking task confirmed by the driver'. This encoded string will be evaluated against the situation index in the case collection. Furthermore, there are three action states identified for the overtaking scenario: 1) proceed lane changing, 2) keep going, 3) overtaking cancelled and stay in the overtaking lane.

TABLE I
Situation attributes related to overtaking scenario and their indices

Index	Situation attributes
0	Lead vehicle exists
1	Current position behind lead vehicle
2	Current position after lead vehicle
3	There are conjunctions ahead affecting the overtaking task
4	Current position in ego lane
5	Current position in departure lane
6	Current position in overtaking lane
7	Driver approval for overtaking task detected
8	Safe prediction of overtaking speed
9	A vehicle in front in overtaking lane exists
10	Safe distance to the vehicle in front in overtaking lane
11	Safe space to go back to departure lane

Fig. 4. Explanations for starting overtaking

The screenshot of the overtaking scenario in the Carla simulator is presented in Fig. 4 and Fig. 5. The overtaking situation is started after the human driver sends his/her approval on overtaking recommendation by the autopilot agent. Hence, the process to generate goal-driven explanations is initiated and generate explanations as illustrated in Fig. 4. Furthermore, Fig. 5 shows generated explanations when the overtaken vehicle increased its speed, so the overtaking task is cancelled. After receiving a flag representing the status of overtaking task, i.e., completed or cancelled, the overtaking situation is ended.

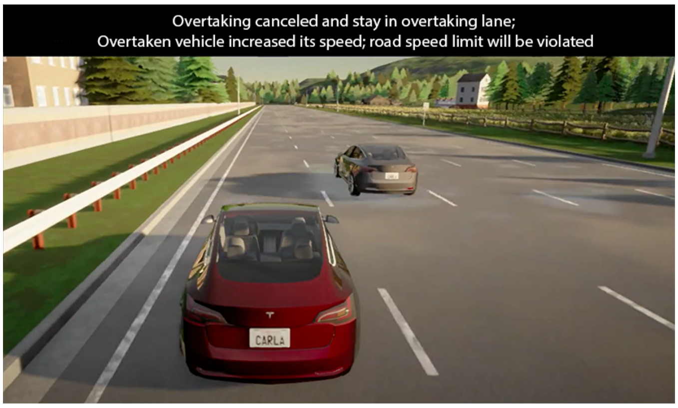

Fig. 5. Explanations for cancelling overtaking

TABLE II
COMPARISON OF EXTRACTION KEY INFORMATION USING THE BASELINE AND PROPOSED BEHAVIOURAL REPRESENTATIONS

Key information	Goal hierarchy	Artificial SA
Cancel overtaking	○	✓
Stay in overtaking lane	×	✓
Overtaken vehicle increased its speed	○	✓
Road speed limit will be violated	×	✓

Notes:
✓ = extracted ○ = mixed with irrelevant information
× = not extracted

Table II presents the comparison of key information points generated by goal-driven explanations using behavioural representation provided by the baseline (goal hierarchy) and our proposed (artificial SA) methods. As the goal hierarchy in the baseline method is structured based on IA's functions, their simultaneous executions raised some problems. While the function of cancelling overtaking is executed, the others like 'assess rear risk' and 'assess front risk' are also executed. Hence, the extraction of overtaking cancelation decision from IA's behaviour resulted in mixed information. The similar problem occurred when extracting the IA's situational awareness regarding 'the overtaken vehicle increased its speed'. Furthermore, the key information about 'stay in the overtaking lane' and 'road speed limit will be violated' cannot be extracted by exploiting the goal-hierarchy as behavioural representation.

V. CONCLUSIONS

This research proposes a new behavioural representation for IA which is useful to reveal IA's comprehension on given situations causing a certain behaviour from this agent. The artificial situation awareness of IA is formulated using its perception states, comprehension states, and actions states. Several techniques are used to generate explanations from those three states, including case-based reasoning and similarity metrics. The proposed method is simulated using the Carla simulator, and the experimental evaluation shows that the proposed approach is applicable. Additionally, generated explanations for transparency can help human to understand and predict their non-human counterpart's behaviours.

ACKNOWLEDGMENT

This research was financially supported by The Faculty of Engineering, Diponegoro University, Indonesia, through Strategic Research Grant 2022.

REFERENCES

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

[2] C. P. Janssen, S. F. Donker, D. P. Brumby, and A. L. Kun, "History and future of human-automation interaction," International Journal of Human Computer Studies, vol. 131, pp. 99–107, 2019, doi: 10.1016/j.ijhcs.2019.05.006

[3] J. Lundberg, "Situation awareness systems, states and processes: a holistic framework," Theoretical Issues in Ergonomics Science, vol. 16, no. 5, pp. 447–473, 2015.

[4] N. J. McNeese, M. Demir, N. J. Cooke, and C. Myers, "Teaming with a synthetic teammate: insights into human-autonomy teaming," Human Factors, vol. 60, no. 2, pp. 262–273, 2018.

[5] N. Bencomo, K. Welsh, P. Sawyer, and J. Whittle, 'Self-explanation in adaptive systems," in 2012 IEEE 17th International Conference on Engineering of Complex Computer Systems, 2012, doi: 10.1109/ICECCS.2012.34.

[6] J. Zhu, A. Liapis, S. Risi, R. Bidarra, and G. M. Youngblood, "Explainable AI for Designers: A Human-Centered Perspective on Mixed-Initiative Co-Creation," in 2018 IEEE Conference on Computatonal Intelligence and Games, 2018, doi: 10.1109/CIG.2018.8490433.

[7] S. Anjomshoae, A. Najjar, D. Calvaresi, and K. Främling, "Explainable agents and robots: Results from a systematic literature review," in Proceedings of the 18th International Conference on Autonomous Agents and MultiAgent Systems, 2019, pp. 1078–1088.

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

[9] 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.

[10] M. Harbers, K. van den Bosch, and J. J. Meyer, "Design and evaluation of explainable BDI agents," in Proceedings - 2010 IEEE/WIC/ACM International Conference on Intelligent Agent Technology, IAT 2010, doi: 10.1109/WI-IAT.2010.115.

[11] A. Abdulrahman, D. Richards, H. Ranjbartar, and S. Mascarenhas, "Belief-based Agent Explanations to Encourage Behaviour Change," 2019. doi: 10.1145/3308532.3329444

[12] R. Kridalukmana, H. Lu, and M. Naderpour, "Component-Based Transparency to Comprehend Intelligent Agent Behaviour for Human-Autonomy Teaming," in 2019 IEEE 14th International Conference on Intelligent Systems and Knowledge Engineering (ISKE), 2019, pp. 771–777.

[13] C. D. Le, ”System transparency through self-explanation,” AAAI Technical Report FS-02-03. The Association for The Advancement Of Artificial Intelligence (AAAI), 2002. [Online]. Available: http://www.aaai.org/Papers/Symposia/Fall/2002/FS-02-03/FS02-03-006.pdf

[14] P. J. F. Lucas, ”Bayesian model-based diagnosis,” International Journal of Approximate Reasoning, vol. 27, no. 2, pp. 99–119, 2001, doi: https://doi.org/10.1016/S0888-613X(01)00036-6.

[15] F. Elizalde, L. E. Sucar, M. Luque, F. J. Díez, and A. Reyes, ”Policy explanation in factored Markov decision processes,” Proceedings of the 4th European Workshop on Probabilistic Graphical Models, PGM 2008, pp. 97–104, 2008.

[16] N. Wang, D. v Pynadath, and S. G. Hill, ”The impact of pomdp-generated explanations on trust and performance in human-robot teams,” in Proceedings of the 2016 international conference on autonomous agents & multiagent systems, 2016, pp. 997–1005.

[17] D. v. Pynadath, M. J. Barnes, N. Wang, and J. Y. C. Chen, ”Transparency Communication for Machine Learning in Human-Automation Interaction,” 2018. doi: 10.1007/978-3-319-90403-0-5.

[18] M. R. Endsley, ”Toward a theory of situation awareness in dynamic systems,” Human Factors, vol. 37, no. 1, pp. 32–64, 1995, doi: doi:10.1518/001872095779049543.

[19] 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.

[20] 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.

[21] C. K. Riesbeck and R. C. Schank, Inside case-based reasoning. Psychology Press, 2013.

[22] G. C. Silva, E. E. O. Carvalho, and W. M. Caminhas, “An artificial immune systems approach to Case-based Reasoning applied to fault detection and diagnosis,” Expert Systems with Applications, vol. 140, p. 112906, 2020.

[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.

[24] U. P. Mudalige and M. Losh, “Efficient data flow algorithms for autonomous lane changing, passing and overtaking behaviours.” Google Patents, 2015.

[25] R. Kridalukmana, H. Y. Lu, and M. Naderpour, ”A supportive situation awareness model for human-autonomy teaming in collaborative driving,” Theoretical Issues in Ergonomics Science, vol. 21, no. 6, pp. 658–683, 2020, doi: 10.1080/1463922X.2020.1729443.

Rinta Kridalukmana He earned his title as Computer Bachelor from Stikubank University (2003), and Master Degree Bandung Institute of Technology (2007), Indonesia. He got PhD degree in the University of Technology Sydney (UTS). The research fields are in situation awareness support systems, fuzzy and probabilistic inference for intelligent systems, and data integration. He is an IEEE’s member.

Dania Eridani Dania Eridani pursued Bachelor’s Degree in Electrical Engineering from Diponegoro University and a Master’s Degree in Electrical Engineering from Gadjah Mada University. She is currently working as Lecturer at the Department of Computer Engineering Diponegoro University. Her main research focuses on Computer Engineering, Embedded Systems, IoT implementation, and Human-Computer Interaction. She has 6 years of teaching and research experience.

Risma Septiana Risma Septiana is a Junior Lecturer at the Department of Computer Engineering at Diponegoro University. Her research specializes in Wireless Sensor Network Topology and Computer Vision Technology. She graduated from Diponegoro University in 2012 with a Bachelor’s Degree in Electrical Engineering and completed a Master’s Degree in Electrical Engineering and Information Technology from Gadjah Mada University in 2016. Until now, she has had 7 years of teaching experience in the field of information technology.

Adian F. Rochim Adian Fatchur Rochim - Dr. Adian Fatchur Rochim, SMIEEE is an associate Professor of Computer Engineering, Diponegoro University. He received his Ph.D. from Department of Electrical Engineering, Computer Engineering, Faculty of Engineering, Universitas Indonesia. He received Bachelor degree at Electrical Engineering Diponegoro University and Master degree at Computer Engineering, Bandung Institute of Technology. He research interest are Computer Networks, Computer Security, Scientometrics, and H-index variants. He is working on several researchs i.e. ‘impact of researcher using quantity on the number of publication and citation’, Network automation based on API and IEEE 802.11 wireless protocols

Charisma T. Setyobudhi He studied computer science degree at Nanyang Technological University in Singapore for 4 years and earned Bachelor Degree of engineering (Computer science) in 2010. He then studied master programme in electrical engineering focusing in media digital and game technology in 2012. In 1 and half year he completed his master degree and earned Magister teknologi degree in electrical engineering(2013). His master degree almamater was institute technology of Bandung (ITB). He specialized in game programming and computer graphics. Another research interest is artificial intelligence streams.