Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 109C (2017) 529–536

Procedia Computer Science

www.elsevier.com/locate/procedia

The 8th International Conference on Ambient Systems, Networks and Technologies (ANT 2017)

Adaptive Goal Selection for improving Situation Awareness: the Fleet Management case study

Giuseppe D'Aniello[a], Vincenzo Loia[b], Francesco Orciuoli[b]

[a]*Dipartimento di Ingegneria dell'Informazione, Ingegneria Elettrica e Matematica Applicata, University of Salerno, Fisciano (SA) 84084, Italy*
[b]*Dipartimento di Scienze Aziendali, Management & Innovation Systems, University of Salerno, Fisciano (SA) 84084, Italy*

Abstract

Lack of Situation Awareness (SA) when dealing with complex dynamic environments is recognized as one of the main causes of human errors, leading to serious and critical incidents. One of the main issues is the attentional tunneling manifested, for instance, by human operators (in Decision Support Systems) focusing their attention on a single goal and loosing the awareness of the global picture of the monitored environments. A further issue is represented by stimuli, coming from such environments, which may divert the attention of the operators from the most important aspects and cause erroneous decisions. Thus, the need to define systems helping human operators to improve SA with respect to the two aforementioned drawbacks emerges. These systems should help operators in focusing their attention on active goals and, when really needed, switching it on new goals, in a sort of continuous adaptation. In this work an adaptive goal selection approach exploiting both goal-driven and data-driven information processing is proposed. The approach has been defined and injected in an existing multi-agent framework for Situation Awareness and applied in a Fleet Management System. The approach has been evaluated by means of the SAGAT methodology.

Peer-review under responsibility of the Conference Program Chairs.

Keywords: Situation Awareness, Intelligent Transportation System, Reinforcement Learning

1. Introduction

Most of the critical incidents happened in the last twenty years in large-scale technological systems and control rooms (e.g., chemical process facilities, energy production and transmission systems, logistic operations control, etc.) which had serious consequences, have been considered just as the result of human errors. Actually, subsequent investigations showed that the human errors are just a contributing cause of such events[1]. What clearly emerges is that the ability of the operator to understand what is happening in the environment represents the most critical element for the prevention and the management of complex situations. Such cognitive capability is defined as Situation Awareness (SA)[2,3]. SA can be considered as the level of awareness that a person has with respect to the task he/she is performing and with respect to the surrounding environmental conditions, as well as the ability of making informed decisions and predicting the plausible changes of the situations in the near future[1]. Lack of SA often appears as the root of

E-mail address: gidaniello@unisa.it; loia@unisa.it; forciuoli@unisa.it

Peer-review under responsibility of the Conference Program Chairs.
10.1016/j.procs.2017.05.332

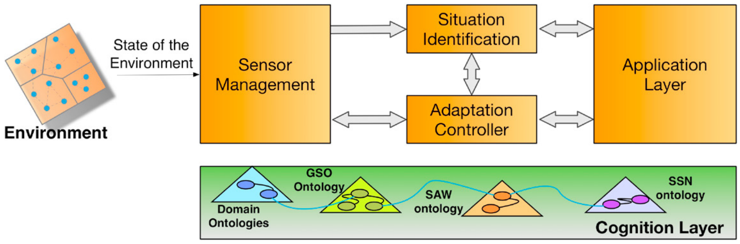


Fig. 1. Framework for Situation Awareness: architectural sketch

many incidents and errors, especially when operators have to consider multiple goals and multiple tasks require their attention. In such circumstances, users usually process data following two opposite approaches. The first one, namely the goal-driven information processing, is a very effective way to process information where data is elaborated with respect to a specific goal. In the second approach, i.e. the data-driven information processing, data is processed as soon as it is perceived by the users, without considering a specific goal. Both these two approaches suffer of some drawbacks with respect to the users' Situation Awareness. Indeed, although the goal-driven information processing is very effective as the users focus their attention on a specific goal without considering useless details, it may cause the so-called *attentional tunneling* problem[2,4]: the users remain overly fixed on certain data sources to the exclusion of others that do not relate with the current goal but may be just as relevant. On the other hand, the prevalent adoption of data-driven approaches could evoke another enemy of situation awareness: *data overload*. In this case, the rapid rate at which data changes quickly outpaces the ability of a person's sensory and cognitive system to supply that need[2]. The alternation among these two ways of processing information is critical for maintaining high level of situation awareness.

In order to face the aforementioned problems, this work proposes a computational approach for *adaptive goal selection* that is able to sustain human operators in switching coherently between different goals. The approach adopts *desirability* measures for goals in order to evaluate their relevance without the users' intervention and it is able to balance goal-driven and data-driven information processing in order to maintain high level of SA. Furthermore, the approach is adaptive, as it adapts the process for evaluating the desirability according to the users' feedback and, thus, it is able to learn from its positive or negative results. This is realized by means of a reinforcement learning technique.

2. Overall Picture

In this Section the proposed approach to *adaptive goal selection* (AGS) is described and integrated into an existing multi-agent framework for Situation Awareness, inspired by the well-known Endsley Model[5]. Such framework has been presented, in the various development phases, in previous works[6,7,8,9,10]. In this paper, the framework has been empowered by the proposed approach and subsequently instantiated for implementing a Fleet Management System (described in the case study provided in Section 5). Specifically, the framework provides methods, techniques and data models aimed at supporting the three levels of Situation Awareness described by the Endsley Model (perception, comprehension and projection) in order to implement Decision Support Systems in complex environments.

2.1. Framework for Situation Awareness

Figure 1 depicts the main modules of the existing framework. The framework consists of a set of agents asynchronously communicating by exchanging events via an event bus. The framework gathers data from the monitored environment via *Sensor Management*, whose aim is to handle lifecycle of the sensor devices, acquisition of raw data and representation/organization of such data. *Cognition Layer* handles a set of integrated ontologies for semantically representing sensor data (by means of the W3C Semantic Sensor Network Ontology SSNO[1]) as well as the goals (represented by means of the Goal-Service Ontology GSO[11]) and all the information the agents need in order

[1] https://www.w3.org/2005/Incubator/ssn/ssnx/ssn

to cooperate and execute their tasks. *Situation Identification* provides algorithms and techniques for identifying the current situation, occurring in the monitored environment, by processing sensor data and exploiting prior and domain knowledge represented and stored within the Cognition Layer. Situations are modeled by using an extension of the Situation-aware Core Ontology (SAW)[12]. The *Application Layer* is responsible for presenting the information to the user coherently with his/her current goals and with the identified situation (as well as by exploiting data-driven events and alarms coming from the environment). This layer includes also components to handle situation projection. In brief, the described architecture provides a sort of incremental processing where raw data coming from sensing devices are transformed into context features, situations and projections along with a set of consecutive abstraction operations supported by the Cognition layer. The whole information processing is contextualized to the current goals of the human operators who interact with the Application Layer.

2.2. *Significance of active goals for SA*

According to the Endsley model for Situation Awareness, usually users process information by having a particular goal to achieve. They continue to process information by changing their current goals. The *active* goal (i.e., the goal user is considering) determines which are the elements of the environment to which pay attention. The active goal influences Level 2 SA[2], because it has impact on the way by which users perceive and interpret information and understand current situations (the mental model[2] of the users depends on the current goal). At the same time, being aware of the current situation helps users to determine which goal(s) should be considered afterwards for processing information. During goal-driven information processing, some information of the environment not related to goal may capture user's attention. For instance, alarms, flashing icons on the screen, interruptions, represent cues that may lead people to change their focus. When this happen, the user starts processing information from the bottom, without considering the current goals, in order to understand what is happening in the environment. This process drives the users' SA formation: when the users have identified what is happened they have the ability to perform the task that are needed for dealing with the situation. This allows users to re-prioritize their goals so to switch again to the goal-driven information processing (a more efficient way to process information). Such processes have to be supported by the systems in order to increase users' Situation Awareness. Thus, the *Adaptation Controller* (Fig. 1) has been introduced in the architecture in order to handle *goal selection*. In this paper a novel approach to goal selection, based on a hybridization of both goal-driven and data-driven information processing approaches, is proposed and is inserted in the existing framework as an enhancement of the Adaptation Controller.

2.3. *Goal Representation and Management*

The way goals are represented and managed is a core concept of the framework, given that it is directly connected to the GDTA (Goal-Directed Task Analysis)[2]. GDTA is adopted as a methodology for the designer of a system supporting Situation Awareness in order to define what Situation Awareness means in a specific domain. GDTA focuses on the goals the operator (final user of the system to be designed) must accomplish in order to successfully perform the job, the decisions he/she must make to achieve the goals, and the information that is needed in order to make the appropriate decisions. Developing GDTA involves interviewing experienced (in the specific domain) operators and combining these results with other sources. The GDTA results are formatted in a hierarchical structure.

The resulting hierarchical structure is modelled, in the framework, by means of GSO and SAW in order to provide a shared interoperable machine-understandable knowledge, included in the Cognition Layer, useful for the agents to perform their tasks and co-operate to support Situation Awareness for the operators. In particular, a coordinator agent knows, from the Adaptation Controller, the active goals and is able to activate other agents that, following the above hierarchical structure, can perform their tasks and provide results useful for the operators to achieve the active goals. This mechanism is flexible and can be easily adapted if the Adaptation Controller, that receives operators' indications from the user interface, changes the active goals and notifies this change to the coordinator agent by means of a full top-down mechanism.

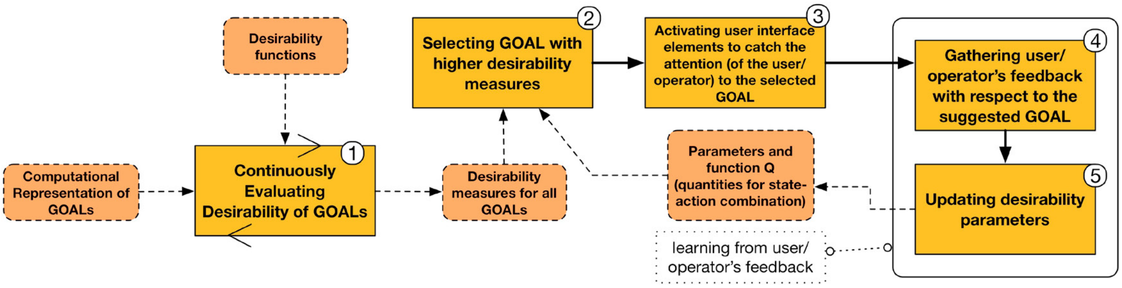


Fig. 2. Adaptive Goal Selection

2.4. Adaptive Goal Selection

In order to enhance the full top-down adaptation of goals in the existing framework, a hybrid approach to adaptive goal selection is proposed. The defined approach is able to combine top-down and bottom-up mechanisms. Fig. 2 depicts the approach by considering an iterative process including five steps. More in details, a set of agents continuously evaluate (first step) the *desirability* of any goal modelled in the knowledge base managed by the Cognition Layer. Desirability, which will be more formally described in Section 3, gives an expert-based measure (by means of specific desirability functions) of how much a goal is important, at a given time, to guide the user/operator's attention to the environmental elements that are significant to achieve high levels of Situation Awareness. These goals are defined by means of the GDTA design process and correspond to some specific visualizations provided by the user interface. An additional agent accesses the desirability measures of goals (this can be accomplished also by a push-based mechanism), selects one goal, by taking into account both the above measures and the users/operators' feedback, and suggests it to the Application Layer (second step). When the above suggestion arrives to the Application Layer, it is transformed into special cues (indeed a complete automatic reconfiguration of the user interface is not useful and it may be harmful[2], within the user interface, with the aim of catching the user/operator attention on the selected goal (third step). This step is executed only if the new selected goal is different from the active one. Once stimulated, the user/operator can decide to switch to the suggested goal (that, in turn, becomes the new active goal) or to continue to focus her/his attention to the aspects related to the active goal. The user/operator's behaviour represents a feedback regarding the suggested goal (fourth step). The above feedback is gathered and used to update the function Q that is used with the desirability measures to select the goal to suggest to the users/operators (fifth step). In brief, the system learns how to suggest goals by exploring how the users/operators react to suggested goals in specific states. Ultimately, the suggested goal, at each iteration, is calculated by the function $\Phi(D, Q)$, where Q is the function learnt from the user/operators' feedback and D is the ordered vector (in decreasing order) of all goals desirability measures plus the active goal. The iterative process (used to calculate Φ), which is executed at periodical intervals of time, combines the top-down mechanism proposing suitable goals by GDTA and user/operators' feedback, and the bottom-up mechanism that for each goal calculates a desirability measure taking into account contextual and environmental information coming from sensor data.

3. Goal Desirability

According to the approach described in section 2.4, the information coming from the environment via the sensors is processed in order to evaluate the desirability of each goal. The desirability of a goal can be influenced by: users' actions, data-driven events (e.g., alarms), behaviors of agents and results of their tasks, users' feedback about suggested goals. The proposed approach foresees the expert-based definition of a desirability function[13] for each goal by using the peculiar parameters of the considered problem and environment. In order to better explain the way by which the desirability is computed, let us consider the set of goals of Figure 3, which shows a subset of the goals identified by applying the GDTA approach to a sample scenario regarding the fleet management (this is the domain of the case study described in Section 5). In this scenario, logistic operators manage a fleet of vehicles in order to optimize their routes, increment their efficiency, reduce the environmental pollutions, and they communicate with the

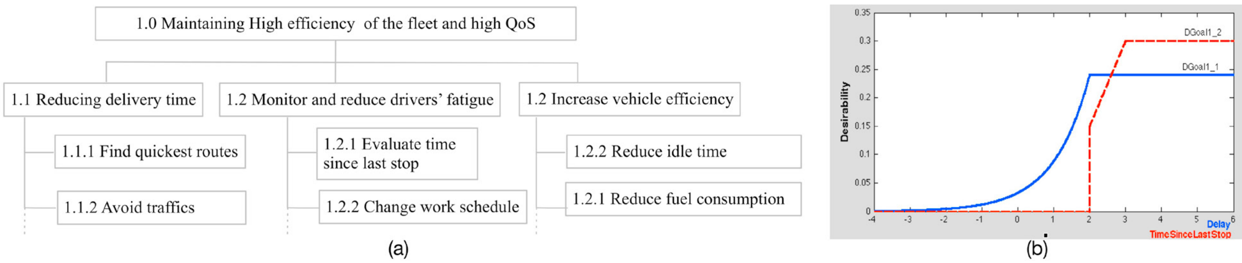


Fig. 3. Sample GDTA and Goal Desirability for Fleet Management System

drivers in order to complete the shipments and satisfy the customers' orders. In Figure 3(a), there is one high level goal and three competitive operational goals. Consider, for instance, that in order to reduce the delivery time is not always possible to reduce the fatigue of the drivers or to increase the vehicles' efficiency. In these cases, the operator generally adopts one strategy according to the boundary conditions and to the customers' requests. But, during the shipping, some conditions may change, thus making a different task more useful for optimizing the fleet; nonetheless, the operator may continue to maintain his/her current strategy and follow his/her current goal.

Continuing with the example of Figure 3(a), Eq. (1) shows the way by which the desirability of goal 1.1. "Reducing delivery time" is computed:

$$d(g_{1.1}) = \begin{cases} \frac{DeliveryPriority \cdot e^{Delay}}{e^{\alpha}} & \text{if } Delay < \alpha \\ DeliveryPriority & \text{if } Delay \geq \alpha \end{cases} \tag{1}$$

where $d(g_{1.1})$ is the desirability of goal 1.1; $DeliveryPriority$ is an index ($0 \leq DeliveryPriority \leq 1$) of the priority of the delivery as arranged with the customer who commissioned the shipping, $Delay = EstimatedArrivalTime - ExpectedDeliveryTime$ is the delay between the estimated arrival time of the shipping and the expected delivery time by the client (when it is negative, it means that the truck is in advance with respect to the delivery time). α represents a threshold of the delay after which the desirability of the goal is at its maximum value.

Another example of a desirability function is shown in Eq. (2) that refers to the desirability of goal 1.2 "Monitor and reduce drivers' fatigue":

$$d(g_{1.2}) = k \begin{cases} 0 & \text{if } timeSinceLastStop \leq \beta \\ \frac{timeSinceLastStop}{\beta} - 0.5 & \text{if } \beta \leq timeSinceLastStop \geq 1.5\beta \\ 1 & \text{if } timeSinceLastStop \geq 1.5\beta \end{cases} \tag{2}$$

where $d(goal_{1.2})$ is the desirability of goal 1.2, k is a normalization factor, set by the experts who defined the hierarchy of goal with the GDTA and it depends on the relative importance of this goal with respect to the other goals; $timeSinceLastStop = CurrentTime - LastStopTime$ represents the time passed since the last stop of the driver; β represents the estimated next stop time and can be set by the operator (e.g., according to the applicable law and regulations). In order to clarify the evaluation of the desirability of the goal, let us consider the following example that refers to the two above mentioned desirability functions. Figure 3(b) shows the two functions with the following parameters: $DeliveryPriority = 0.24$, $\alpha = 2$, $\beta = 2$, $k = 0.3$. The x axis represents the time, which for the $d(g_{1.1})$ function it is the $Delay$, while for the $d(g_{1.2})$ function it represents the $TimeSinceLastStop$. In this example, the active goal $\overline{g}$ is goal $g_{1.1}$. Over the time, when $timeSinceLastStop$ is equal to 2.8, $d(g_{1.2}) > d(g_{1.1})$ and so goal 1.2 is more desirable than the active one. In this case, the system suggests to the user to change the active goal, as described in the next section.

4. A Reinforcement Learning approach to define Φ

In Section 2 the selection function Φ is introduced to choose, at each iteration, the goal that will be recommended to the user/operator by considering both some environmental features and the user/operator's preferences with respect

Table 1. Evaluation scenarios

Id	# of vehicles	# of routes	Conditions at the frozen point	Events supplied for suggesting a goal change (in the case of Adaptive Goal Selection)
1	3	5	Driver of truck n. 2 exhibits a bad driving behavior	Notifications on the guiding styles of the drivers; Icon of truck blinking
2	3	5	Heavy traffic on the route n.1 which is followed by truck 2. Truck 2 exhibits a poor eco-friendly driving behavior. Alternative routes are congested.	Info on the traffic situation of the possible routes
3	6	3	The route of truck n. 4 is traffic congested. Driver of truck 4 exhibit a bad driving behavior. One alternative route is traffic congested. Other routes are longer.	Alarm on the guiding styles of the drivers; Info on the traffic situation of the possible routes; Info on the pollution level of the areas.

to other plausible goals in a given state of affairs. In order to define Φ it is possible to employ a *reinforcement learning* algorithm. The idea is to gather users/operators' feedback regarding past goal suggestion operations in order to understand how much a goal, selected and recommended in a given context (state), has been accepted by the user/operator and used for the task to execute. Reinforcement learning is learning how to map contexts to actions in order to maximize a numerical reward signal. The learning problem is modelled as follows. The environment is the combination of the user/operator with all plausible goals coming from GDTA. The learning agent continually senses the state of the environment and selects/executes an action on the environment that concretely consists in recommending a goal to the user/operator. In turn, the user/operator provides the learning agent with a reward that corresponds to a feedback on the aforementioned suggested goal. The reward is positive if the feedback is positive. The agent tries to maximize the received reward over time.

More specifically, the agent interacts with the environment along a sequence of discrete time steps, $t = 0, 1, 2, 3, ...$ At each time step, the agent receives some representation of the environment state, $S_t \in S$, where S is the set of possible states. $S_t = \langle \overline{g}, g_1, g_2, \ldots, g_k \rangle$ is the state of the environment at time t, where $\overline{g}$ is the active goal for the user/operator, $g_1, g_2, \ldots, g_k$ is the sequence of all plausible goals such that $d(g_i) \geq d(g_{i+1}), \forall i = 1, \ldots, k-1$. Function $d(g)$ returns the current desirability measure of goal g by using the correct (for g) desirability function (see Section 3). On the basis of S_t, the agent selects an action $A_t \in A(S_t), A(S_t) = \{a \in A | a = suggest(g), (g = \overline{g}) \vee (d(g) > \rho)\}$, where $a = suggest(g)$ means that the action a consists in recommending the goal g to the user/operator. One time step later, in part as a consequence of its action, the agent receives a numerical reward, $R_{t+1} \in R$, and finds itself in a new state, S_{t+1}. The reward R_{t+1} is calculated by considering in which extent the user/operator has accepted the system suggestion. For this first work a simple reward function has been defined: 1 if the suggestion has been accepted, otherwise 0. At each time step, the agent implements a mapping from states to probabilities of selecting each possible action. This mapping is called the agents policy and is denoted π_t, where $\pi_t(a|s)$ is the probability that $A_t = a$ if $S_t = s$. In order to specify how the agent changes its policy as a result of its experience it is possible to adopt the Sarsa algorithm[14] essentially based on the following update rule:

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha \left[R_{t+1} + \gamma Q(S_{t+1}, A_{t+1}) - Q(S_t, A_t)\right] \tag{3}$$

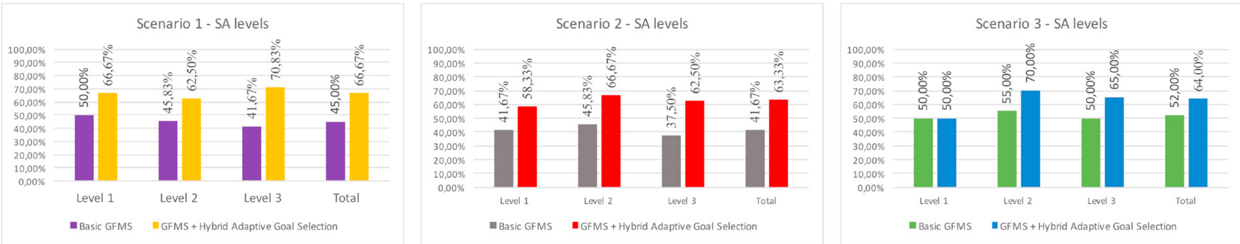
In Eq. 3, $Q(S_t, A_t)$ is the action-value function, γ is the discount factor and α is is a constant stepsize parameter. The used algorithm trades off exploration (suggesting a random goal selected by the vector of goals with high desirability values) and exploitation (suggesting the goal with max Q value in the given state) by executing ϵ-greedy selection[14] on the set $A(S_t)$. The idea is to run the Sarsa algorithm during the system execution and provide its results as suggestions for the users/operators. Thus, the selection function Φ is the execution of the Sarsa algorithm, whose ability to give suggestions improves along the timeline.

5. The Fleet Management Case Study

The proposed *adaptive goal selection* (AGS) approach has been implemented and evaluated by means of a prototypical system, namely Green Fleet Management System (GFMS)[10,15]. This system supports logistic operators (which are responsible of planning shipments and managing the vehicles in a company) to optimize the deliveries while reducing pollution emission. The complete description of the GFMS can be found in[10], where we have conducted an experimentation of the system in order to demonstrate that it effectively helps logistic operators in being aware of what is happening to the fleet of vehicles and thus to make coherent decisions. In the present work, instead, we have

SA Level 1	SA Level 2	SA Level 3
Q1) The current distance to the destination is	Q2) The behavior of the driver is	Q3) It is suitable to change the current route of the vehicles? Explain why.
- small (<20km)	- green-friendly	- yes
- medium (>20 km < 50 km)	- normal	- no
- long (<50km)	- not green-friendly	- I don't know
- I don't know	- I don't know	

Fig. 4. Examples of questions extracted from the questionnaire.



(a) (b) (c)

Fig. 5. Evaluation results. Each graph refers to a scenario and shows the percentage of correct answers given by the users, grouped according to the level of SA to which the questions refer to. For each level of SA, we compare the two modalities of execution of the scenario.

focused our attention on the evaluation of the AGS approach that enhances the already existing GFMS. We have used the SAGAT methodology [16] to assess the improvement in terms of levels of SA achieved by the human operators [5] when they interact with the GFMS integrating the proposed approach. In such a way, it is possible to quantify the benefits deriving from the introduction of the proposed approach with respect to the previous version of GFMS [10].

5.1. Experiment

The experiment has been conducted by involving 15 stakeholders of the Italian funded research project MAR.TE[2]. According to the SAGAT methodology, such users interact with the GFMS in order to execute some scenarios. In our experiment we have defined three scenarios, described in Table 1. Each scenario provides an increasing level of difficulty with respect to the elements of the environment that the users should perceive and understand and to the decisions they have to make. During each scenario, we have submitted to the users a questionnaire (consisting of 10 items) which allows us to measure the three levels of SA gained by the users. An excerpt from the questionnaire is shown in Figure 4. In order to compare the improvements related to the introduction of the proposed AGS approach, each scenario has been executed in two different modalities. In the first modality, the users have not received any suggestions about changing the active goal while, in the second modality, the users have received such suggestions according to the AGS approach described in Section 2.4. With respect to the three levels of SA, the elements the users have to perceive at level 1 (Perception) are related to the identification of the vehicles that can increase the level of pollution. At level 2 (Comprehension), the users have to answer questions about the traffic situation that involves the vehicles identified at level 1 and about the driving style of their drivers. Lastly, at level 3 of the SA (Projection), users are asked to decide if the drivers have to change their current routes or their driving styles. We have also asked the users for the motivations of their choices.

5.2. Evaluation

Figures 5.a-c show, respectively for each scenario, the average of correct answers grouped together according to the level of Situation Awareness to which the questions refer to. For each level of SA, the graph compares the percentage of correct answers with respect to the two modalities of execution of GFMS. All the three levels of SA are improved thanks to the AGS approach, with an average percentage increase of 18.44% of correct answers. Specifically, in the

[2] http://mar-te.com and http://www.corisa.it/project/martem/

first two scenarios we obtain a clear improvement for all the three levels of SA, while in the third scenario (Figure 5.(c)) we observe just a slight increase in correct answers at SA level 2 (Comprehension) but we do not observe a substantial improvement at SA level 1 and SA level 3. This is mainly due to the difficulty of the third scenario (in which the users have to control many trucks in a situation in which many roads are congested). If we analyze the specific users' answers, we observe that the suggestion to change the active goal (although correct) has confused the users, leading them to to make a wrong decision. This is due to the lack of correct mental models and lack of experience of the operator, which make a difference in being able to project the situation in the near future for making correct decisions. This means that a fundamental role is still played by the user experience confirming that SA training is crucial to the success of any system for SA[17]. In conclusion, the AGS approach provides good results in the improvement of the SA gained by logistic operators in different scenarios.

6. Final Remarks

In this work a novel adaptive goal selection approach has been described. Such approach has been defined by taking care of both goal-driven and data-driven information processing mechanisms. The hybridization of the two aforementioned mechanisms provides efficacy to the systems for Situation Awareness. Moreover, the proposed approach adopts a reinforcement learning algorithm in order to learn from users/operators' feedback the ability to suggest alternate goals. The proposed approach has been implemented and injected in an existing multi-agent framework for Situation Awareness and, subsequently, applied in a Fleet Management System evaluated by means of the SAGAT methodology. Further experimentations in different domains are planned for the next months.

References

1. M. Naderpour, S. Nazir, J. Lu, The role of situation awareness in accidents of large-scale technological systems, Process Safety and Environmental Protection 97 (2015) 13 – 24, ISSN 0957-5820.
2. M. R. Endsley, Designing for Situation Awareness: An Approach to User-Centered Design, Second Edition, CRC Press, Inc., Boca Raton, FL, USA, 2nd edn., ISBN 1420063553, 9781420063554, 2011.
3. L. Chen, P. Rashidi, Situation, activity and goal awareness in ubiquitous computing, International Journal of Pervasive Computing and Communications 8 (3) (2012) 216–224, ISSN 1742-7371.
4. T. C. Stratmann, S. Boll, Demon Hunt - The Role of Endsley's Demons of Situation Awareness in Maritime Accidents, in: Human-Centered and Error-Resilient Systems Development: IFIP WG 13.2/13.5, 203–212, 2016.
5. M. R. Endsley, Toward a theory of situation awareness in dynamic systems: Situation awareness, Human factors 37 (1) (1995) 32–64.
6. G. Benincasa, G. D'Aniello, C. De Maio, V. Loia, F. Orciuoli, Towards perception-oriented situation awareness systems, Advances in Intelligent Systems and Computing 322 (2014) 813–824.
7. G. D'Aniello, A. Gaeta, V. Loia, F. Orciuoli, A granular computing framework for approximate reasoning in situation awareness, Granular Computing (2016) 1–18.
8. G. D'Aniello, V. Loia, F. Orciuoli, A multi-agent fuzzy consensus model in a Situation Awareness framework, Applied Soft Computing Journal 30 (2015) 430–440.
9. G. D'Aniello, A. Gaeta, M. Gaeta, M. Lepore, F. Orciuoli, O. Troisi, A new DSS based on situation awareness for smart commerce environments, Journal of Ambient Intelligence and Humanized Computing 7 (1) (2016) 47–61.
10. G. D'Aniello, A. Gaeta, V. Loia, F. Orciuoli, Integrating GSO and SAW ontologies to enable Situation Awareness in Green Fleet Management, in: 2016 IEEE Int. Multi-Disciplinary Conference on Cognitive Methods in Situation Awareness and Decision Support (CogSIMA 2016), 138–144, 2016.
11. L. O. Bonino da Silva Santos, G. Guizzardi, R. Guizzardi-Silva Souza, E. Goncalves da Silva, L. Ferreira Pires, M. van Sinderen, GSO: Designing a Well-Founded Service Ontology to Support Dynamic Service Discovery and Composition, in: Proceedings of the 13th Enterprise Distributed Object Computing Conference Workshops, EDOCW 2009, IEEE Computer Society Press, Los Alamitos, 35–44, 2009.
12. C. J. Matheus, M. M. Kokar, K. Baclawski, A core ontology for situation awareness, in: Proceedings of the Sixth International Conference on Information Fusion, vol. 1, 545–552, 2003.
13. A. Khatami, P. Huibers, J. J. Roessingh, Architecture for goal-driven behavior of virtual opponents in fighter pilot combat training, in: Proceedings of the 22nd Annual Conference on Behavior Representation in Modeling and Simulation, 2013.
14. R. S. Sutton, Generalization in reinforcement learning: Successful examples using sparse coarse coding, Advances in neural information processing systems (1996) 1038–1044.
15. H. Billhardt, A. Fernandez, L. Lemus, M. Lujak, N. Osman, S. Ossowski, C. Sierra, Dynamic Coordination in Fleet Management Systems: Toward Smart Cyber Fleets, Intelligent Systems, IEEE 29 (3) (2014) 70–76.
16. M. Endsley, Situation awareness global assessment technique (SAGAT), in: Proceedings of the IEEE 1988 National Aerospace and Electronics Conference, NAECON., 789–795 vol.3, 1988.
17. M. R. Endsley, M. M. Robertson, Training for situation awareness in individuals and teams, Situation awareness analysis and measurement (2000) 349–366.