AGENT APPROACH TO SITUATION ASSESSMENT

Giuseppe Paolo Settembre, Daniele Nardi
Department of Computer and System Science, Sapienza University, Rome, Italy
lastname@dis.uniroma1.it

Roberta Pigliacampo
SESM s.c.a.r.l. - a Finmeccanica company, Via Tiburtina km 12.4, Rome, Italy
rpigliacampo@sesm.it

www.icaart.org

Keywords: Knowledge Representation and Reasoning, Industrial Application of AI

Abstract: The Situation Assessment process is evolving from signal-analysis based centralized models to high-level reasoning based net-centric models, according to new paradigms of information fusion proposed by recent research.
In this paper we propose a knowledge-based approach to Situation Assessment, and we apply it to maritime surveillance. A symbolic model of the world is given to an agent based framework, that use Description Logics based automatic reasoning to devise on estimate of the situation. The described approach potentially allows distributed Situation Assessment through agent collaboration. The goal is to support the understanding of the situation by relying on automatic interpretation processes, in order to provide the human operators with a synthetic vision, pointing out which are the elements on the scenario that require human intervention.
The success of high level reasoning techniques is shown through experiments in a real maritime scenario, in which our approach is compared to the performances of human operators which monitor the situation without any support of an automatic reasoning system.

1 INTRODUCTION

Data Fusion is the basis for a huge industrial research field (e.g. signal processing and sensor fusion) whose aim is to develop techniques for security related systems.
According to 1999 revision of JDL Data Fusion Model and its recent reformulations (Llinas et al., 2004), the purpose of the third level of information fusion (Situation Assessment) is “estimation and prediction of relations among entities, to include force structure and cross force relations, communications and perceptual influences, physical context, etc.”; it is also pointed out that understanding and predicting relations among entities within a scenario have become critical issues in surveillance activities. In fact, the quality of information provided by low level analysis (level 1 and 2) does not suffice anymore the applications’ requirements, due to the increasing complexity of the scenarios and the high operators’ workload.

The success of new technologies and standards for formal knowledge representation offers the motivation to explore new approaches in order to provide effective solutions to Situation Assessment. In our approach, we consider Situation Assessment as the problem of extracting the best explanations of the extensional knowledge of each agent, through situation classification, providing meaningful aggregated information, to improve situation comprehension and support decision making activities.

The approach described by this paper includes the following innovative aspects. (1) It partially fills the lacking of a formal definition of the Situation Assessment process. In our formalization, the new standards of reasoning techniques (e.g. OWL, http://www.w3.org/TR/owl-guide/), and the evolution to distributed paradigms are taken into account. (2) It provides an algorithm to perform Situation Assessment with a single agent, with a solution which is suitable for an evolution to multi-agent contexts.

The proposed approach allows a synergy between autonomous and standard human analysis, since the extraction of a high level description of the evolving situation helps operators to focus only on few potentially relevant elements of the global scenario. This is coherent with the situation awareness theory (Endsley and Garland, 2000), and with cognitive experiments (Giompapa et al., 2006).

In order to show the advantages of our approach to perform Situation Assessment, we made experiments in a real world seacoast scenario. We modeled some complex relationships which are monitored in a protected area, comparing the agent-based system's performances to the human operators' ones, in collaboration with a company working on radar surveillance.

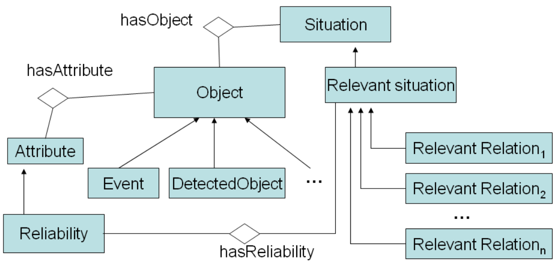

Figure 1: Organization of components of Situation Assessment (UML inspired by (Matheus et al., 2003))

2 PROBLEM FORMALIZATION

We considered a certain number of objects $V = \{v_1, ..., v_n\}$ moving in the scenario each with a private goal, and a set of agents $A_1, ..., A_m$. Each agent has a world model, has perceptions, communicates with the others, and takes part pro-actively in the classification process. The intensional knowledge is shared among all the agents, and constitutes a common language for communication.

We define an event (perception) e_i as a logical condition, which is the output of a feature extraction process, based on the observations of the environment. A *situation* at a certain time t_i is commonly defined as the state of all the observed variables in the world at time t_i and in the past (at time $t_j, j \in \{0, ..., i-1\}$). However, this definition doesn't suit in the scope of Situation Assessment, because such a process does not aims at considering all the variables in the scenario, but instead at estimating the state of subsets of these variables, in order to extract a few number of relevant elements.Hence we consider the set of the relevant situation classes $\Sigma = \{S_1, \ldots, S_n\}$, in which S_i is a class of situations, significant with respect to the context. Basically, each relevant situation class represents a group of semantically equivalent circumstances of the world.

We say that $s_i \in S_j$ (s_i is *an instance of* S_j, where $S_j \equiv f(e_1, \ldots, e_n)$), if $\exists e_1, \ldots, e_n$ *s.t.* $f(e_1, \ldots, e_n) = true$, where $f(e_1, \ldots, e_n)$ is a logical definition in a given formalism. From the point of view of the agent's knowledge, with $K_p(s_i \in S_j)$ we indicate that an agent A_p *knows that* $s_i \in S_j$, where $S_j \equiv f(e_1, \ldots, e_n)$. This happens iff $\exists e_1, \ldots, e_n \in KB_p$ *s.t.* $f(e_1, \ldots, e_n) = true$, where KB_p is the knowledge base of that agent. A situation class $S_i \equiv f(e_{p_1}, ..., e_{p_n})$ is *more specific* than $S_j \equiv g(e_{q_1}, ..., e_{q_m})$, indicated with $S_i \subseteq S_j$, iff every instance of S_i is also an instance of S_j.

We can now proceed in providing a formal definition of the Situation Assessment process.

Definition 1 We say that s_i *is classified as* S_i by an agent A_p iff $K_p(s_i \in S_i)$ and $\nexists S_j$ *s.t.* $K_p(s_i \in S_j) \wedge S_j \subseteq S_i$. We indicate with $c_p(KB_p, s_i) = S_i$ that the agent A_p, given its knowledge base KB_p and a situation instance s_i, classifies s_i as S_i.

Definition 2 We say that a classification $c_p(KB, s_i) = S_i$ is *correct* if $s_i \in S_i$.

Definition 3 We define *Situation Assessment (SA)* the classification of all the instances s_i. SA is *correct* iff $\forall s_i$, $c_p(KB, s_i) = S_i$ is correct. SA is *complete* if $\forall s_i \in S_i$, $c_p(KB, s_i) = S_i$.

The relation occurring among the elements of the Situation Assessment process is illustrated in Fig.1. By classifying the significant situations as instances of the *Relevant Situation* concepts that are represented into a taxonomy of situations (see Sec.3), and thus using the Description Logics (DL) inference capabilities, we did not need to use any rule propagation engine (which would not be supported by reasoners).

3 SITUATION CLASSIFICATION

We modeled the agent's knowledge using ontologies formalized in OWL DL (http://www.w3.org/TR/owl-features), through the editor Protegé (http://protege.stanford.edu), while inference was performed through the RacerPro reasoner (http://www.racer-systems.com). In our approach, each agent is provided with two ontologies, the domain ontology and the situation ontology. The first is a *content* ontology (see (Llinas et al., 2004)), while the second is a *process* ontology.

The "domain" ontology. The domain ontology is the symbolic representation of the elements of the world, which have to be extracted from the scenario and organized in a taxonomic structure.

Once the intensional knowledge (concepts, relations) has been defined, the ontology is populated using data extracted from its own information sources, or provided by other agents. The main issues about the population of the ontology (building of the so-called ABOX) tipically concern the mapping from numeric data into their symbolic representation (e.g., map coordinates into regions). This is solved at sub-symbolic level, through specific procedures.

The "situation" ontology. Once the domain ontology has been populated, we can use our knowledge on the scenario to identify the set of *Relevant Situation* classes (see Sec.2), and organize them in a second taxonomy. Each relevant situation class is defined with constraints expressed in DL formalism, using the terms (concepts, relations) included into the domain ontology. Note that these definitions are not rules expressed in an external formalism, but DL defined concepts (rules are not included in the system).

At this point, we are able to use automatic reasoning and DL capabilities (Nardi and Brachman, 2003) on the available knowledge to classify the current situations instances. Now, the assessment of the situation is simply the most specific classification of each situation instance among the relevant situation classes.

From the point of view of the extensional knowledge, we must address carefully the creation of the correct number of situation instances. We decided to have as many situation instances as many independent circumstances are present in the world, and examine them separately. In this way, different aspects of the same global situation are perceived as different instances. Moreover, separating independent situation instances gives us a substantial advantage when we would start dialogues among different agents to compare their classifications.

Defining the right number of situation instances is not easy to solve. For example, if we would declare different situation instances for each location of the environment, then we would not be able catch those relationships (situation classes) which are aggregation of events in different locations. The solution we propose consists in identifying a subset E of event classes which trigger the generation of a new situation instance. When a new event $e_i \in E$ is detected, a new situation instance s_i is created, is declared as being a member of the generic *Situation* class, and it is connected through a relation (*hasObject* in Fig.1) with the event e_i. Whenever events are detected and for agent p verify the definition of a certain situation class S, s_i is classified as member of S, and $K_p(s_i \in S)$ holds.

4 VALIDATION IN A HARBOUR SURVEILLANCE SCENARIO

Experiments have been performed on a middle size italian harbour, in which an average of 80 vessels (military or civil) were moving at the same time with different goals. A radar was able to perceive on a 10km x 10km area.

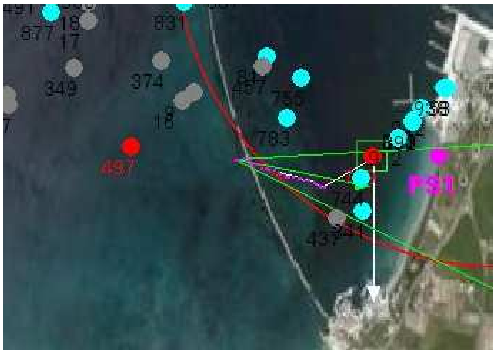

Figure 2: A splitting situation. Two boats (red circles) performed a splitting close to a surveilled area (red arc) and one of them is directed to the critical point (in purple).

We considered 2 suspect operations to be detected:

splitting: it is the manoeuver of remaining hidden staying close to another vessel, then suddenly move away directed to a critical area (see Fig.2).

suspect approach: it is verified if a suspect vessel is approached by other vessels. A suspect vessel is a vessel whose identification is not known, which stays near the border of a surveilled zone.

We compared the performances of human operators, provided with 5 different support systems. Every test session had a lenght of about 15 minutes.

In the first configuration, that we will call **Agent Support**, we provided the operator with the agent based system which performs autonomous Situation Assessment as described in this paper. The situation *Splitting* is defined by the constraint "classify as member, if and only if current situation contains a track, which was first detected close to a zone border and close to another vehicle, and either one or the other vehicle approaches a critical area", expressed with the DL formalism.

Whenever a vehicle v_1 is detected as appearing close to another vehicle v_2, a new situation instance s_{v_1} is created, and it is populated the relation $hasObject(s_{v_1}, v_1)$. When the other properties which are in the definition are verified, s_{v_1} will be classified as $splitting$. A similar constraint is used for the class $suspect\ approach$.

The 4 other configurations are:

No Support: the operator is provided with the output of a multi-tracking system, with no elaboration to support Situation Assessment.

Still Tracks Visualization: the system provides an additional information, visualizing the still vehicles with a different colour.

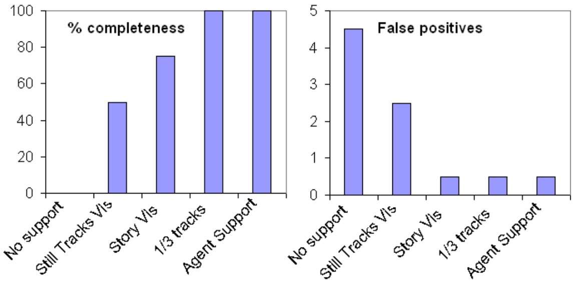

Figure 3: Comparison of completeness and correctness of Situation Assessment within 5 different configurations

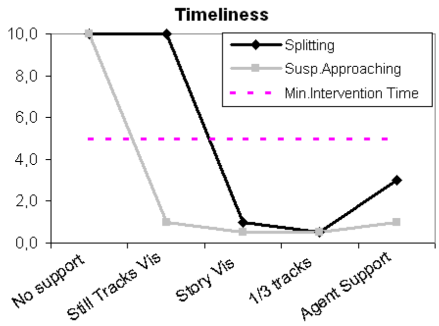

Figure 4: Comparison of timeliness of Situation Assessment within 5 different configurations

Story Vis: the system graphically shows also the trajectory, average and current speed.
1/3 tracks: the same as the previous policy, but the number of tracks in the scenario is reduced to 1/3.

First, we measured the completeness of the approach, in terms of how many correct (splitting or suspect approach) situations have been detected by operators (Fig.3a). In Fig.3b, the correctness of the approach is measured, in terms of the average number of incorrect detections of splitting and suspect approach situations (false positives). Both graphs show that the “Agent support” configuration performs similarly to the one in which operators are watching over only 1/3 of the real everyday amount of traffic. In the first 2 configurations, humans’ conclusions were completely unreliable.

Notice that the high absolute value of the shown results is biased by the unusually high (1) probability of the presence of anomalies during the test session, (2) attention level of the human operator.

Finally, we measured the timeliness with which the situations are revealed. In Fig.4, we show how long it took human operators to detect the presence of the malicious situations. The minimal intervention time threshold is the maximum available time to allow a prompt intervention. From the graph, it is shown that operators with few system support will not reveal the situations in time, even in our ideal setting. Notice also that the agent based reasoning can take more time to detect a situation: this happens because the agent will detect a certain situation only when all the events of a specific symbolic definition have been verified, while the operator conclusions are much more guided by an intelligent or skilled observation. A less strict definition would cause more prompt detections, but higher number of false positives.

5 DISCUSSION

In this paper we introduced a new model to approach Situation Assessment, based on agent knowledge reasoning. We validated our approach with experiments performed with real data in a maritime surveillance scenario.

With respect to state of art knowledge based approaches (Matheus et al., 2003), we succeed in avoiding the use of rules, which are not supported by current state-of-art reasoners. The main limit of our approach is that situations are defined using true-false membership of individuals to properties, therefore information uncertainty can be only partially included into the model.

Finally, it is valuable that the described approach potentially allows distributed Situation Assessment, which is a current study of different communities ((Llinas et al., 2004),(Mastrogiovanni et al., 2007)).

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