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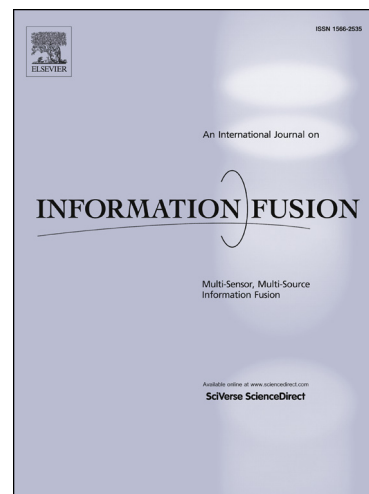
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Context-based multi-level information fusion for harbor surveillance

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Abstract

Harbor surveillance is a critical and challenging part of maritime security procedures. Building a surveillance picture to support decision makers in detection of potential threats requires the integration of data and information coming from heterogeneous sources. Context plays a key role in achieving this task by providing expectations, constraints and additional information for inference about the items of interest. This paper proposes a fusion system for context-based situation and threat assessment with application to harbor surveillance. The architecture of the system is organized in two levels. The lowest level uses an ontological model to formally represent input data and to classify harbor objects and basic situations by deductive reasoning according to the harbor regulations. The higher level applies Belief-based Argumentation to evaluate the threat posed by suspicious vessels. The functioning of the system is illustrated with several examples that reproduce common harbor scenarios.

Keywords: context; higher-level fusion; ontologies; belief argumentation system; maritime surveillance.

1. Introduction

Maritime security is an area of strategic importance for the international community. As stated in [1], "a terrorist incident against a marine transportation system would have a disaster impact on global shipping, international trade, and the world economy in addition to the strategic military value of many ports and waterways." For that reason, one of the principal goals of strengthening maritime security is to "increase maritime domain awareness" by building a "surveillance picture as complete as possible to assess the threats and vulnerabilities in the maritime realm." In particular, harbor surveillance is a critical part of maritime security procedures because of its multiple objectives: recognition of terrorist threats, prevention of maritime and ecological accidents, detection of illegal

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immigration, fishing and drug trafficking, and so forth. However, it is nowadays mostly developed by human operators [2], who have to evaluate an overwhelming amount of information. This makes it very difficult to keep track of the event stream with the required level of attention due to distraction, fatigue and oversight. In addition, their decisions may be strongly affected by sensor data imprecision and subjective judgment.

Next-generation harbor surveillance systems are envisioned to automatically identify potential threats with a high degree of confidence [3]. Their objective is obtaining not only tracking information about vessels, but also an abstract picture of the situation to make informed decisions. According to the JDL data fusion model, the latter task belongs to the domain of Situation Assessment, defined as the estimation of "sets of relationships among entities and their implications for the states of the related entities." [4] In this domain, it requires understanding the intrinsic information provided by coastal sensors in the context determined by extrinsic factors, like harbor environment, operational regulations, traffic data and intelligence reports.

Recently, the increasing interest in higher-level information fusion has led to several proposals for context management –see for example the special sessions on context-based information fusion celebrated in the International Conferences on Information Fusion since 2007. Detection and characterization of activities and threats require assessing the states of situational items and their relationships within a specific context. From the perspective of the fusion process, context can be informally defined as the set of background circumstances that are not of prime interest to the system, but have potential relevance towards optimal estimation [5]. When a context is activated (i.e., some circumstances hold), more information is available to obtain and improve estimations on problem entities. This contextual information, expressed in the form of complementary knowledge or constraints, encompasses information about objects, processes, events, and relationships between them, as well as particular goals, plans, capabilities, and policies of the decision makers. Such diversity makes formal context representation a significant challenge.

Ontologies are an appropriate formalism to represent contextual and factual knowledge in higher-level fusion [6, 7, 8]. However, ontology languages based on Description Logics, and in particular the standard ontology web language (OWL 2) [9], present several unsolved challenges when applied to Situation Assessment because: (i) they do not allow for reasoning with uncertain knowledge; (ii) they do not directly support abductive reasoning to create and validate situational hypotheses that change in time.

In this paper we describe an Information Fusion system that uses contextual knowledge represented with ontologies to detect and evaluate anomalous situations. By contextual knowledge we mean knowledge about external information that completes, influences or constrains the situations or events of interests; e.g. physical characteristics of the environment such as terrain or weather, or knowledge about the expected behavior of the objects. The architecture of the system is arranged in two processing levels. Firstly, the

system applies deductive and rule-based reasoning to extend tracking data and to classify objects according to their features. Secondly, the Belief-Argumentation System (BAS), a logic-based paradigm for abductive reasoning [10], is used in combination with the Transferable Belief Model (TBM) [11] to determine the threat level of situations involving objects that are not compliant to a normality model. A prototype implementation of this system adapted to the harbor surveillance problem is available for experimental evaluation at the authors' web page[2].

To the best of our knowledge, this is the first attempt to combine ontologies and TBM-based uncertain reasoning to implement multi-level information fusion. Similar approaches in the literature have focused on alternative probabilistic models; namely, Multi-Entity Bayesian Networks [12, 13] and Markov Logic Networks [14]. Ontologies facilitate the creation of a computable model representing complex situational context (problem entities, scenario geometry, spatial relationships, etc.), since they can be formally encoded in a logic-based expressive language. The examples show that this integrated approach reduces the number of false alarms with respect to purely ontological proposals through quantifying the threat level.

The remainder of the paper is structured as follows. In the next section, we discuss the definition and the role of context in Information Fusion. We also describe the advantages and drawbacks of common context representation formalisms, and compare our proposal with related works on ontology-based and probabilistic Situation Assessment. Section 3 studies the data sources that must be taken into account in the harbor surveillance domain, and presents the overall design of the system. Section 4 analyzes the procedures for vessel classification and abnormal situation detection. Section 5 presents a reasoning method based on the BAS for situation interpretation. Section 6 illustrates the functioning of the system in a threat detection scenario. The paper concludes with discussions on the contributions of the work and directions for future research.

2. Context and Ontologies in Information Fusion

2.1. Context Definition and Representation

The Webster dictionary defines context as *"the interrelated conditions in which something exists or occurs"* or "*the parts of a discourse that surround a word or passage and can throw light on its meaning"* [15]. The concept of context has been studied in many research fields (see for example [16]). One of the first approximations to the formalization of the notion of context in Artificial Intelligence is due to McCarthy [17], who proposed the use of the relation *ist(c, p)* to represent that a given proposition p is true in the context c. Sowa extended this theory with the *dscr(x, p)* relation [18], which states that p describes entity x. Since x can be a situation, *dscr* semantics subsume those of *ist*. Giunchiglia defines a similar epistemological framework in which a context is a subset of the complete state of an entity

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[2] http://www.giaa.inf.uc3m.es/miembros/jgomez/simulator/HarborSimulator.html

that is used in reasoning to solve a task [19]. It has been proved that these multi-context logics are more general than *ist*-based formalisms [20]. These approaches have been investigated to address context modeling with ontologies in the Semantic Web, which has led to proposals including new language constructors [21, 22, 23] or annotations with specific semantics [24]. Unfortunately, they are neither widespread nor supported by the current version of the standard language OWL and associated reasoning engines.

In the Information Fusion community, context has been considered from different points of view. One of them, which in our opinion is prevalent, is to refer to external knowledge that is useful or influences the fusion processes, including background knowledge (e.g. tactics, doctrine), situation-specific knowledge (e.g. terrain), existing reports and databases, and so forth [25, 26]. Sycara et al. state that part of the context are the significant features or the history of a situation that influence the features of other situation, as well as the expectations on what is to be observed and the interpretation of what has been observed [27]. They also propose the HiLIFE (High-Level Information Fusion Environment) fusion model for battlefield management. To these authors, situational context is a "*first class entity*", but not exactly in the sense of McCarthy. In their sense, it is rather a computable description of the terrain elements, the external resources and the possible inferences that is essential to support the fusion process. Our work follows the same principle. We create a model of the scenario and use background, situational and expert knowledge to drive the high-level fusion process. The specific contents of the context model for the harbor surveillance problem are described in section 3. Context can thus be used to explain observations, to define hypotheses, to identify areas of interest to focus new data collection, to refine ambiguous estimations, and to provide for interrelationship between different fusion levels [27, 28].

In [29, 30], several major types of context models were considered, of which the three ones most applicable to data fusion can be characterized as key-value models, ontology-based models and logic-based models. Key-value models are the simplest way of representing context. They provide values of context attributes as environmental information and utilize exact matching algorithms on these attributes. These models may suffice for use in Level 1 fusion to work with data constraints [31], but they lack capabilities for complex context representation required by higher-level fusion. Ontology-based models provide a formal way for specifying core concepts, sub-concepts, facts and their inter-relationships to enable realistic representation of contextual knowledge [6, 7, 8]. Current approaches to ontology-based context modeling can be classified into three main areas: contextualization of ontologies, ontology design patterns, and context-aware systems [32]. Ad hoc logic-based models can be applied to extend or replace ontologies in knowledge-intensive applications. They represent context as facts and information inferred from rules. These models are generally more expressive, and allow for the development of more sophisticated representations and reasoning procedures.

The complex uncertain harbor surveillance scenario calls for a hybrid context representation combining ontology and logic-based models enriched by uncertainty

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consideration. We propose a fusion system in which the description of the domain entities, such as vessel types and harbor areas, the relations between them, and applicable regulations are modeled as a certain set of ontological concepts, relations, instances, axioms and rules. Deductive reasoning is applied to detect inconsistencies between the situations obtained as a dynamic instantiation of the scene model and the situational patterns defined in the normalcy model. Normalcy rules are local to a navigational context, which depends in most cases on the geographical situation of the vessel (as in [14]). Inconsistencies denote abnormal situations that may indicate a potential threat. A probabilistic reasoning process is then triggered to investigate whether these inconsistencies are the result of insufficient quality of observations, contextual knowledge, and fusion processes, or the result of the change of context; e.g. discovered potential or imminent threat.

2.2. Ontologies, Logic and Uncertainty in Higher-Level Fusion

During the last decade, several approaches using ontologies have emerged in the higher-level Information Fusion research area. The SAW Core ontology represents general concepts used in situational awareness [33]. It was used as a meta-model in [34], which applied deductive reasoning for Situation Assessment in a traffic-management scenario. The Situation Theory Ontology (STO) has been recently proposed as a formal upper model to represent the abstract concepts involved in Situation Awareness under the semantics of Barwise and Perry's situation theory [8]. In the harbor domain, ontologies have been also used to represent *a priori* and contextual information. In [35], a MDO (Maritime Domain Ontology) was created to automatically classify vessels and situations from perceived situations by applying deductive reasoning. Similarly, in [36] the authors showed that ontologies are useful to capture ancillary knowledge on the elements of the application domain and behavioral patterns.

In these works, situation recognition is mostly achieved by instance classification as follows. Context models include ontological descriptions of categories of entities and situations. When a new object is created or its property values are modified, a deductive reasoning process finds matches to these descriptions and determines the class or classes to which the new instance belongs. However, this procedure is insufficient in complex Situation Assessment problems, because there is an inherent uncertainty in this process that is not considered, and more than one hypothesis may explain the current situation, but only one is generated. In general, ontologies are not suited for abductive inference and reasoning under uncertainty [37]. In addition, they are not particularly effective to represent *perdurants*; i.e., entities that change in time. This requires the creation of artificial representational patterns [38] or the use of non-standard extensions to the standard languages [39]. As introduced in the previous section, we propose a combined architecture that extends the typical deductive reasoning with probabilistic abductive reasoning.

The final report of the Uncertainty Reasoning for the World Wide Web Incubator Group distinguishes the three most common approaches to incorporate uncertain, unreliable and

imprecise knowledge to Web ontologies: Fuzzy Logic, probability theory and belief functions [40]. Among them, the former two have been considered in Information Fusion. One of the most notable proposals is PR-OWL 2, an extension of the OWL language with Bayesian probability theory [12], that has been illustrated with examples on higher-level fusion in the maritime domain [13, 41]. PR-OWL 2 represents factual and contextual knowledge in terms of instances and properties with associated uncertainty. Currently, there are no reasoners available that entirely supports this language. However, the resulting ontologies can be transformed into a probabilistic network and processed with the UnBBayes[3] tool. The main difference regarding our work is that we do not embed the probabilistic formalism into the ontology. Instead, we use ontologies as a unified representation in a deductive layer to extend data with available knowledge, and delegate threat assessment tasks to the upper layer implementing the BAS-based reasoning process. This adds more flexibility to the system and reduces the computational cost that is usually associated to ontology-based reasoning, which may make the application unusable under real-time restrictions.

A related proposal is presented in [14]. The authors use Markov Logic Networks (MLNs) to represent uncertain context knowledge and automatically detect anomalies in the maritime domain. MLNs combine the expressiveness of first order logic and the uncertainty management of Markov Networks, thus providing a very intuitive and powerful knowledge framework. The treatment of context information is very similar as in our approach, since it is conveniently integrated into the representation and exploited to properly interpret the available data. The paper does not study in detail the possible effects of the semi-decidability of first order logic, which may be a drawback compared to decidable Description Logics ontologies. Besides, they assume that information is already available and expressed in a symbolic form, as in [13, 41]. It is not clear how the raw sensor data is incorporated into the logic model, a problem that is explicitly tackled in our architecture.

Building a common framework for the evaluation of probabilistic higher-level Information Fusion systems is a research topic that has received considerable attention recently. The Evaluation of Techniques for Uncertainty Representation Working Group[4] (ETURWG), hosted by the International Society of Information Fusion (ISIF), is an ongoing initiative purposely formed in 2011 to address this problem. The URREF (Uncertainty Representation and Reasoning Evaluation Framework) ontology is an initial proposal towards the formal description of the concepts involved in a probabilistic fusion system and the applicable comparison criteria [42]. Nevertheless, the state of this proposal at the time of this writing makes it still unfeasible to carry out a detailed comparison among different systems.

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[3] http://unbbayes.sourceforge.net/
[4] http://eturwg.c4i.gmu.edu/

3. Sensorial and Contextual Information in the Harbor Surveillance Scenario

Surveillance picture formation in the harbor scenario is the result of a multi-level fusion process, which includes:

- Data acquisition from heterogeneous sources about single objects.

- Object tracking to integrate sensor data and obtain the tracks (location, kinematics, identification) representing all objects present in the scene.

- Object property estimation for object categorization.

- Utilization of context knowledge about expected object properties, identification, and behavior to classify objects and to infer basic relationships and situations.

- Matching expected behavior provided by the context of entities to the observed situation in order to detect a possible anomaly as an initial step towards scene recognition.

- Abductive reasoning to explain inconsistency, to detect possibly threat to alert an operator, and to improve the overall functioning of the system and the knowledge base.

Input data encompasses hard and soft sources, ranging from sensor measurements to intelligence reports. Sensor data is automatically acquired by primary coastal sensors or cooperatively emitted by ships. The main primary-sensor technology for object detection and location in the harbor is the coastal radar, which does not require cooperative equipment installed onboard of ships. Therefore, the low level input of the system is either raw position measurements (in a centralized architecture) or fused estimates obtained by a processing node (in a decentralized architecture). In both cases, the fusion node involves three basic functions: (i) data alignment or common referencing involving coordinate or units transformations, uncertainty normalization, and inter-sensor alignment; (ii) data association to determine to which entity measurements are associated to; (iii) state estimation involving the computation of entity attributes at Level 1 –e.g., location, velocity, and other classification attributes such as size or category. Ships also emit identification data according to IMO (International Maritime Organization) security protocols, mainly Automatic Identification System (AIS) data. The AIS system broadcasts basic data obtained by the available navigation equipment (identification, position, course, and speed) together with extended data (intended route, cargo description, etc.) Other relevant data sources are Vessel Traffic Systems (VTS), which usually collect all available inputs in an integrated tracking image [43], and Port Traffic Management Systems (PTMS) [44].

We will assume a preexisting decentralized tracking schema with a working fusion node located after a set of single-source target tracking systems. This schema provides vessel tracks with reasonable accuracy already available to be processed. The decentralized solution is more realistic in the maritime surveillance scenario, since it allows using available legacy tracking systems and taking into account the very different data types and update rates of AIS and VTS. The tracking sub-system could also benefit from the available context information. For instance, ships trajectories might be constrained to follow the

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assigned channels according to deep draught category and water depth. A dynamic model for vessel track prediction can be used to incorporate this knowledge into the tracker. The tracker includes a filter for each type of target, while the selection of the appropriate model for each target according to its context is managed by a context-sensitive interacting multiple model (IMM) filter [45]. A detailed study of the use of IMMs is out of the scope of this paper.

In previous works, authors have considered two complementary dimensions of context knowledge that are relevant to characterize an entity *X* [29, 46]: *in the Context of X* (CO) and *Context for X* (CF). *CO* encompasses the sets of situations or events that form the environment itself; e.g., the context of normal operations in the harbor (all the rules defined by port authorities are obeyed). It defines expectations about the entities, and may be used to predict observations or to trigger abductive reasoning in case of deviations. On the other hand, *CF* defines the items externally related to and referenced by X. In the harbor surveillance domain, it includes extraneous characteristics such as the weather, time of day, harbor geometry, buildings, etc. Table 1 describes some elements of static –*a priori,* or configuration data– and dynamic –*a posteriori,* or information inferred at the same time as sensor data is obtained– contextual information of interest.

Static context knowledge
Ships characteristics and behavior restrictions, such as speed, functions, etc.
Geographic knowledge with environmental maps: harbor configuration, coastline, currents, channel navigability, restrictions, etc.
Navigation knowledge describing how vessels maneuver as they progress along shipping channels, meet other vessels, and encounter different weather.
Sensor characteristics: areas of poor radar coverage, presence of clutter regions.
Operational rules about coordinated motion of several vessels; e.g., mandatory use of tug boats to escort the cargo ships from the inner port entrance until the final mooring position.
Allowed proximity to other vessels, protocols for collision avoidance, and rules of precedence.
Information on intended vessel trajectory: sailing plan or pre-established route, estimated times of arrival, etc.
Dynamic context knowledge
Environmental parameters: modifications of channel navigation restrictions, allowed areas depending on time of day, etc.
Sea conditions, ice.

Table 1. Contextual information sources in the harbor surveillance scenario
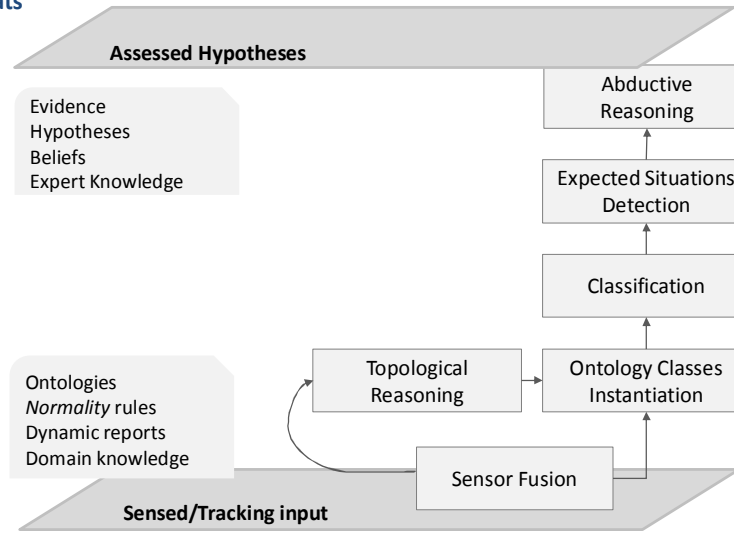
Figure 1. Workflow of the multi-level fusion system in the harbor domain

Figure 1 depicts the processing layers for dynamic surveillance picture formation. Firstly, tracking and object identification data is fused to obtain track features and used to update the scene model. In this layer, the scene ontology defines the concepts and relations of the surveillance problem. Concepts are represented by ontology classes, whereas relations are represented by ontology properties. Accordingly, tracked entities are asserted into the model as class instances. Spatial relations among vessels and other elements in the scene (harbor channels, mooring positions, constrained areas, etc.) are also calculated at this point. Purposely, topological reasoning is performed to detect and update qualitative topological relations. This procedure is explained in Section 4.1.

Once sensor information is symbolically represented in the scene ontology, a classification procedure is performed to determine the type of the vessels according to their features and their topological properties. Here we use 'type' in a wide sense, since the output of this process are statements describing vessels by their features (size, flag, function, etc.) and behaviors (stopped, exceeding channel speed, too close to other object, etc.) Next, contextual information together with all available transient information is used to classify the situations as expected or not for each object or group of objects. That is, the behavior of estimated situational items is compared with the corresponding expected behavior in the context under consideration. This procedure is explained in Section 4.2.

When the estimated situational items are different from expected, it is necessary to understand the source of this discrepancy. The difference can be attributed to the poor quality of the observations and the limitations of the tracking process (e.g., sensor noise, bad resolution, continuity problems, and association errors), the use of imperfect or

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erroneous knowledge, or the existence of a real threat. To make a distinction, the system triggers the abductive reasoning process aimed at explaining the source of inconsistency and assessing the possible threats (Section 5).

4. Detection of Normal Situations

The procedure of deviation detection from the normalcy model is performed in several steps, as explained before. In this section, we present a context model for vessel objects based on an ontology encoded in the Ontology Web Language 2 (OWL 2) [9]. We also describe the reasoning procedures that are applied for vessel classification and expected situation detection based on rules expressed in the Semantic Web Rule Language (SWRL) rules –the *de facto* standard for rule-based reasoning with OWL ontologies [47]. In addition, we detail the procedure to encode and instantiate the topological predicates.

4.1. Representation of Vessel Characteristics and Harbor Areas

Vessels are represented as instances of the ontological model. Most vessel properties, such as speed and position are transient; i.e., they change during the existence of the vessel object. To represent these changes in the ontology, we need to associate vessel snapshots to vessel instances. A snapshot groups a set of property values that are valid in a limited time period. More details of the ontological representation of these entities can be found in [48]. For the sake of simplicity, in the remaining sections we will assume that transient properties are directly assigned to vessel instances without using snapshots.

Geographic knowledge of the harbor can be represented at different levels of granularity. Typically, there are two different areas in a harbor: the land area including inner water, which is the *port*, and the outer water area, which is called the *road*. No ship can enter in the port without the permission of Harbor Master's Office after reporting requested details such as identification code, nationality, length, draught, cargo, and so forth. The *anchorage* is the designated area on water where ships wait for the entrance to the port. Inside the port, we can identify different facilities used for ship mooring and berthing. Harbor authorities define navigation areas for different categories of vessels, e.g. separated channels for small power-driven vessels, big power-driven vessels and non-power vessels. In addition, navigation near to certain facilities may be restricted or even forbidden.

Figure 2 shows an excerpt of the ontology representing a scenario with a vessel, two navigation channels and a restricted facility. At a basic level, zones are manually described by means of the global coordinates of their delimiting polygon. Vessel location, in turn, is represented with a punctual position estimation resulting from fusing radar and AIS information. At a higher level of abstraction, vessel relative positions with respect to zones, as well as zone relative positions with respect to other zones, are represented through qualitative properties that relate different entities, rather than entities and data values.

The Region Connection Calculus (RCC) is a logic theory for qualitative spatial knowledge representation and reasoning [49]. RCC is an axiomatization in first order logic of certain spatial concepts and relations: partially overlaps (PO), proper part (PP), inverse of proper part (PPI), and so forth. RCC semantics cannot be fully represented with ontologies [50], but typical reasoning engines provide support for them through an extended processing layer. Additional abstract spatial relations are defined inside the scene model; e.g., *close to* (between vessels or vessels and facilities) and *aligned to* (between vessels and channel navigation direction).
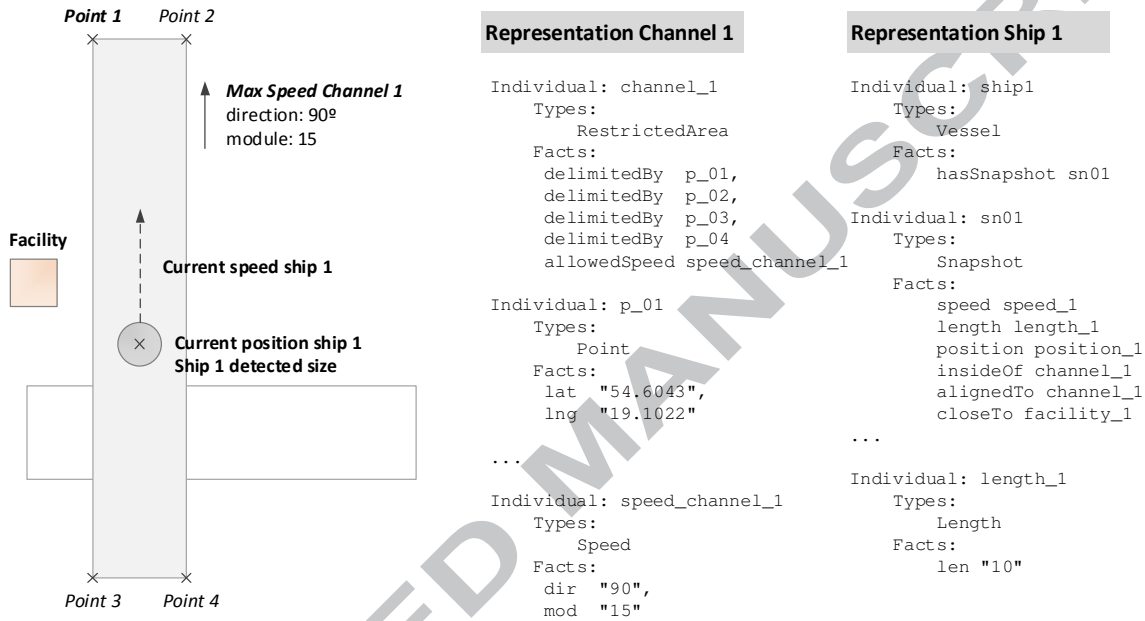

Figure 2. Representation of harbor zones, facilities and vessels

These relations require some geometrical calculations to be instantiated. For example, it is necessary to determine if the distance between two entities is less than a threshold in order to instantiate the property *close to*. This process is performed by the topological reasoning module. For the implementation of this module, we have used the OpenGIS standard and the Java Topology Suite[5], a programming library to calculate geometrical relations between positioned entities. It is important to notice that in a first 'brute force' approach, topological relations are calculated between each pair of entities when one of them is updated. This requires a considerable amount of computations, and necessarily calls for the implementation of optimized geometric models able to segment the space in influence zones, in such a way that the number of property calculations would be dramatically reduced [51].

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[5] http://www.vividsolutions.com/jts/

4.2. Reasoning for Vessel Classification and Expected Situation Detection

Ontologies provide strong support for deductive reasoning, defined as an automatic procedure aimed at inferring new implicit axioms that have not been represented but are entailed by the explicit axioms. Basic ontological reasoning is concerned with the inference of subsumption axioms (i.e., determining the implicit taxonomy according to asserted classes features) and instance membership axioms (i.e., determining the type of an instance according to asserted classes and individual features). Reasoning algorithms are implemented by inference engines like Pellet [52], the one used in our prototype.

Instance membership inference is used to classify vessel instances. For example, we can define a class for small boats to include all ships that have a length less than or equal to 15 meters. To do so, an equivalence axiom is used. If a new vessel instance is asserted into the ontology with length 10 meters, or the length property value of an existing vessel instance changes to a compliant value, the vessel is automatically inferred as a member of the small boat class. Accordingly, the boat detected in Figure 2 would be classified as a small boat. We show a few example class definitions to classify vessels in Section 6.2.

Context knowledge is included not only to classify vessel types, but also to represent and reason with the harbor regulations that determine whether a vessel is exhibiting a normal behavior. This is the normalcy model of the harbor: a collection of rules that are used to classify vessel behavior as compliant to the navigation rules or not. The model characterizes predictable behaviors according to harbor rules, rather than describing the features of an attack, since the complete enumeration of such unexpected events is, by definition, incomplete. The open world assumption, which stands when reasoning with ontologies, favors this kind of representation. This assumption states that, by principle, the set of axioms in the knowledge base is not complete, and therefore, new knowledge cannot be inferred inductively. In practice, that means that an axiom that is not entailed by the model is not inferred as false, but as unknown. For instance, according to the previous example, if a vessel instance has a length larger than 15 meters, trivially the reasoner would not conclude that it is a small vessel. Nevertheless, it would not conclude that the small vessel assertion is false, because there is not enough knowledge to confirm the latter inference. But notice that, if other assertions lead to classify this instance as a small vessel, then the ontology would be inconsistent.

The normalcy model includes not only the description of "good", expected, behaviors (positive information/vessels *musts*) but also the description of situations that obviously break the harbor rules (negative information/vessel *prohibitions*). The former are useful to directly include harbor rules into the model (compliance conditions), whereas the latter allows the inference system to check the existence of predefined suspicious or threatening behaviors (violation conditions). This is made to improve system performance, because selected situations are directly classified as abnormal, and to facilitate modeling, because in some cases it is easier to express a harbor navigation rule by presenting the cases that

are not compliant to it. In any case, as mentioned, vessel behavior can be classified only if there is enough evidence according to its properties. Among classified behaviors, we have vessels that are: (i) compliant to harbor rules, (ii) not compliant to harbor rules, or (iii) compliant to some harbor rules and not compliant to some harbor rules. In Section 6.2 we show an excerpt of the hierarchy of expected situations of the example.

Harbor rules are expressed in the normalcy model with class inclusion axioms and rules. Class inclusion axioms can be used to describe under which circumstances a vessel is included in the compliant/not compliant behavior classes, in a similar way as it is done for vessel classification from properties. More interestingly, SWRL rules generalize class inclusion axioms by allowing the use of bounded variables in the antecedent and the consequent of the rule. SWRL supports deductive inference with OWL ontologies under certain safety restrictions to guarantee decidability of the representation [53]. Essentially, the safety restrictions limit the use of variables in rules to pre-existing named entities. This forbids adding new factual knowledge (i.e., creating new instances) during reasoning, which also implies that scene interpretation through abductive reasoning is not directly supported. We use SWRL rules to classify vessels behavior according to the harbor navigation rules. This gives an initial description of the scene in terms of the expected situations detected. For example, we can define a rule to state that a vessel aligned to its enclosing navigation area is satisfying the navigation direction requirements of the harbor. Note that harbor restrictions can be easily modeled by using the concepts defined in the ontology as an abstract vocabulary.

If we consider the processing architecture shown in Figure 1 and the ship depicted in Figure 2, the workflow for object classification and situation deduction is as follows. First, the topological reasoning module detects that the ship is inside a navigation channel, and consequently instantiates the property *inside of*. The topological module also detects that the ship is aligned to the enclosing zone(s) and instantiates the relation *aligned to*. Next, the corresponding rule is fired and the behavior of the ship is automatically classified as compliant to the harbor rules. If it were non-compliant, this information would be provided to the uncertainty module for the construction of threat beliefs.

5. Hypothesis Evaluation for Situation and Threat Assessment

As it was described in the previous section, knowledge of the harbor describing objects, their properties, and behavior is used to define the expected surveillance picture. Detected deviation from the normal surveillance picture may have several possible explanations, or underlying causes. It can be the result of insufficient quality of Level 1 estimations; e.g. inaccurate and unreliable tracking. It can be also caused by utilization of the wrong environmental conditions –wrong CF– in processing sensor information (e.g. failure to correctly take into account fog in computing sensor reliability), or by employment of a certain type of sensors (e.g. a night vision sensor during day time) leading to incorrect classification of the objects and their behavior (such as noisy estimation of heading, wrong vessel category, etc.) The deviation may be as well a consequence of poorly estimated or

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described characteristics of the current situation, or underlying change in the current situation –change in CF. These cases can happen as a result of possible terrorist or pirate threat leading to the change of the global harbor procedures and constraints. Therefore, it is important to detect and understand the cause of anomaly to alert the operator and trigger an appropriate response. This abductive process of inferring the cause as an explanation of the effect encompasses the creation of hypotheses to explain the state of the world, the computation of the credibility of these hypotheses, and the selection of the most credible hypotheses [54, 55]. The hypothesis evaluation process needs to consider: (1) to what extent the selected hypothesis is better than the alternatives; (2) how credible the hypothesis is, without regarding the alternatives; (3) the quality of incoming data and information on objects and their behavior, which requires explanations.

Let $\Theta^t = \{\theta^t_1,...,\theta^t_K\}$ be the set of hypotheses that are considered at the time instant t. Since we assume that anomaly can be the result of the insufficient quality (reliability, uncertainty) of the information on vessels and their behavior, this set of hypotheses includes a hypothesis representing "normal operations". The set of hypotheses $\Theta^t = \{\theta^t_1,...,\theta^t_K\}$ may not be exhaustive, since not all the causes of anomaly may be included in the frame of discernment and some of them can be unknown or even unimaginable (open world assumption). This means that plausibility of an unknown hypothesis can be different to zero.

There are two major types of models of reasoning under uncertainty: graphical models, such as Bayesian and causal networks (see, e.g. [56, 57]), and logic-based models. Since normal situation is based on context of normal operations expressed in rules, we select here a logic-based model. One of the logic-based paradigms that can be considered for abductive reasoning under uncertainty is the Belief-based Argumentation System (BAS)[6], a generalization of the Probabilistic Argumentation System (PAS). Following [58], we describe PAS as a hybrid approach that combines logic and probability theory. It aims at assessing hypothesis about present or future worlds by relying on available uncertain, unreliable, incomplete and contradictory knowledge. Logic represents the qualitative part of PAS. It is applied to determine arguments that support (i.e., *in favor*) and refute (i.e., *against*) each hypothesis. An argument is a conjunction of propositions and uncertain assumptions coupled with *a priori* probabilities of their trueness that make a hypothesis true or false. The probabilities that the arguments are valid are combined to obtain the quantitative judgment on the validity of the hypothesis, which is then used to decide whether it can be accepted, rejected, or knowledge is not available to make an appropriate judgment at this time.

Precise knowledge of *a priori* probabilities for assumptions is hardly available in the uncertain dynamic maritime environment, in which different and even unimaginable

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[6] The formal description of the Belief-based Argumentation System below follows the explanation introduced in [10].

behaviors (types of threat) can occur. Therefore, they have to be replaced by dynamic subjective beliefs. Moreover, $P(A)$ –additive subjective belief that assumption A is true based on expert subjective opinion– is not generally $1-P(\neg A)$, because of this high uncertainty. Consequently, PAS needs to employ sub-additive subjective belief measures of the form $Bel(A)+Bel(\neg A)\leq 1$. This sub-additive property makes it possible to explicitly express ignorance, and does not force one to reduce total uncertainty to the assumption that all the hypotheses under consideration are equally probable. Thus the belief theories allow for representing only our actual knowledge "without being forced to overcommit when we are ignorant" [59].

In addition, the open world assumption, in which $Bel(\varnothing)$ may not be equal to zero, also requires an uncertainty representation allowing a non-exhaustive set of hypothesis, which calls for the Transferable Belief Theory [11] as an uncertainty framework in BAS. The dynamic beliefs assigned to the assumptions are based on current context and observations. The beliefs are approximated by a function of the estimated values of attributes and relationships characterizing the situation and related to the assumptions, or defined by linguistic labels (*low, medium, high*) with quantization of these values.

Formally, let $\Theta=\{\theta_1,...,\theta_K\}$ be a set of hypotheses under consideration. $Bel(\varnothing)\neq 0$ because, according to the open world assumption, this set of hypothesis is not exhaustive. BAS is a tuple (A,P,ξ,B), in which, as in PAS, $A=\{a_j\}$ is a set of uncertain assumptions, $P=\{p_i\}$ is the set of propositions, and $\xi\in L_{P\cup A}$ is a knowledge base representing a set of rules. At the same time, unlike to PAS, $B=\{bel_j\}$ are non-additive dynamic beliefs associated with $A=\{a_j\}$. Arguments Arg_{k_m} supporting (or refuting) each hypothesis θ_k are derived from the knowledge base, and are a conjunction of propositions and assumptions for which θ_k becomes true (or false): $Arg_n(\theta_k)=\underset{j}{\wedge}a_{n_j}\underset{k}{\wedge}p_{n_k}$. The support of each hypothesis θ_k is defined as the disjunction of all minimal arguments supporting θ_k: $Arg(\theta_k)=\underset{n}{\vee}ArgP_n\underset{m}{\vee}ArgC_m$, where $\underset{n}{\vee}ArgP_n$ is a disjunction of all arguments supporting hypothesis θ_k, and $\underset{m}{\vee}ArgC_m$ is a disjunction of all arguments refuting hypothesis θ_k.

Beliefs in support of each hypothesis θ_k can be computed by utilizing beliefs in arguments in the following way. Beliefs in support of and against of each assumption a_{n_j} invoke support functions on a frame of discernment $\Omega_{n_j}=\{T,F\}$, which have a single focal element (assumption *i* is true or false). Let us consider a mapping $M:\Omega_{n_1}\times...\times\Omega_{n_N}\to\Theta$. Then, a simple support function μ_k with focus θ_1 in support of argument $ArgP_n$ is:

$$\mu_{\mathrm{Arg}P_n}(\theta_k)=\prod_{\mathrm{Arg}P_n=\underset{j}{\wedge}a_{n_j}}bpa_{a_{n_j}}(T),\quad \mu_{\mathrm{Arg}P_n}(\Theta)=1-\mu_{\mathrm{Arg}P_n}(\theta_k). \qquad (Eq.\ 1)$$

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Analogously, the sum of the support functions over the set $\{\Omega_{m_j} \mid \underset{j}{\wedge} a_{m_j} = A \operatorname{rg} C_m, \forall m\}$ can be directly mapped into a support function ν_j:

$$\nu_{\operatorname{Arg}C_m}(\theta_k) = \prod_{\operatorname{Arg}C_m = \wedge_j a_{m_j}} bpa_{a_{m_j}}(F), \quad \nu_{\operatorname{Arg}C_m}(\Theta) = 1 - \nu_{\operatorname{Arg}C_m}(\theta_k). \qquad (Eq.\ 2)$$

Accordingly, arguments for and against each hypothesis are used to compute hypothesis belief as a combination of μ_k and ν_j for all k and j with the unnormalized Dempster rule. This result is used for decision state estimation.

As it was mentioned before, the process of hypothesis selection requires consideration of decision quality, which has to be evaluated against time required for additional observations/computations. In addition, decision process on any hypothesis under consideration has to take into account that something totally unexpected and not included in the possible causes of the observed situational elements can happen.

The decision rule considered is the following [10]:

- If $Bel^t(\varnothing) \geq \max(Bel^t(A)), \forall A \subseteq \Theta$ (i.e., the level of support for an unknown hypothesis exceeds the level of support for any hypothesis under consideration), then the expert operator is alerted to reassess the considered hypotheses set. Additionally, a sensor management process can be started to verify and improve the incoming information.

- Otherwise,
  - If $Bel^t(\Theta) \geq \max(Bel^t(A)), \forall A \subseteq \Theta$ (i.e., the level of ignorance exceeds beliefs in any hypothesis), then wait until additional information arrives at the next time step.
  - If $BetP^t(\theta_k) \geq th(t)BetP^t(\theta_n) \ \forall n \neq k$ then select θ_k, otherwise wait.

$BetP^t(\theta_k)$ is the pignistic probability[7] of hypothesis θ_k at time t [10]; $th(t)$ is a threshold varying in time that can be modeled by a context-specific decreasing convex function that is set to zero after a certain value.

In the harbor surveillance problem, the task of hypothesis evaluation is based on the analysis of:

- Vessel features (speed, direction, type, flag, etc.)
- Spatio-temporal relations between the vessels or relations between the boat and harbor zones.
- Beliefs assigned to assumptions based on the observed spatio-temporal relations and correspondence of the boat behavior to rules and regulations as well as quality of transient information.

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[7] The term *pignistic* was coined by C.A.B. Smith [60] from *pignus* –a bet in Latin– to define a probability function constructed from a belief function for decision-making.

For example, we can consider the following argument *pro* hypothesis "threat" from a boat: a boat is too close to a big vessel 'and' the big vessel is a tanker 'and' the boat is increasing its speed". Thus this argument is a conjunction of three assumptions:

(1) A boat is too close to a big vessel
(2) The boat is increasing its speed
(3) The big vessel is a tanker

In our use case, belief measures can be modeled as functions of boat dynamics (increased speed), type of the vessel (a tanker), and the relation "close" between the boat and a tanker. Thus, the belief in "too close" can be measured as a function of the difference between the observed and allowed distance between the tanker and the boat; and the accuracy and reliability of the distance observed. The next section illustrates this approach in detail.

6. Example: Traffic Surveillance in a Harbor Scenario

6.1. Description of the Scenario

The case study considers a frame of discernment with two hypotheses $\Theta = \{\theta_1, \theta_2\}$ corresponding to "threat" and "no threat", which are evaluated for each entity in the scenario. It has been built from available descriptions of regular operations in real harbors and the associated traffic regulations of daily activities[8]. This frame entails a simplification of the complete procedure explained in the previous section, because the number of hypothesis is reduced and we do not consider the hypothesis selection procedure. Hence, in the reminder of this section we will not refer to it as abduction, but just as threat detection.

Context information includes the geometry of the harbor navigation channels, the rules and restrictions related to the normal navigation patterns, and the special navigation procedures allowed in these channels. In particular, it includes special navigation procedures within inner harbor requiring the use of towing boats for certain size and cargo category of commercial vessels. The scenario considers four different kinds of channels (Figure 3): special container channels (SC) for ships with special cargos that must be towed; harbor ship channels (HS) for serving boats; general cargo ship channels (GC) used for transportation purposes; and small boats channels (SB), used by recreational boats and ferries. Each channel is denoted by two letters representing its type, and one or more letters to specify the allowed navigation directions (N, S, E, W). In addition, the harbor also includes a restricted navigation area next to the SCE1 channel in the surroundings of a liquid fuel terminal (LFT). The operation rules considered are described in Table 2.
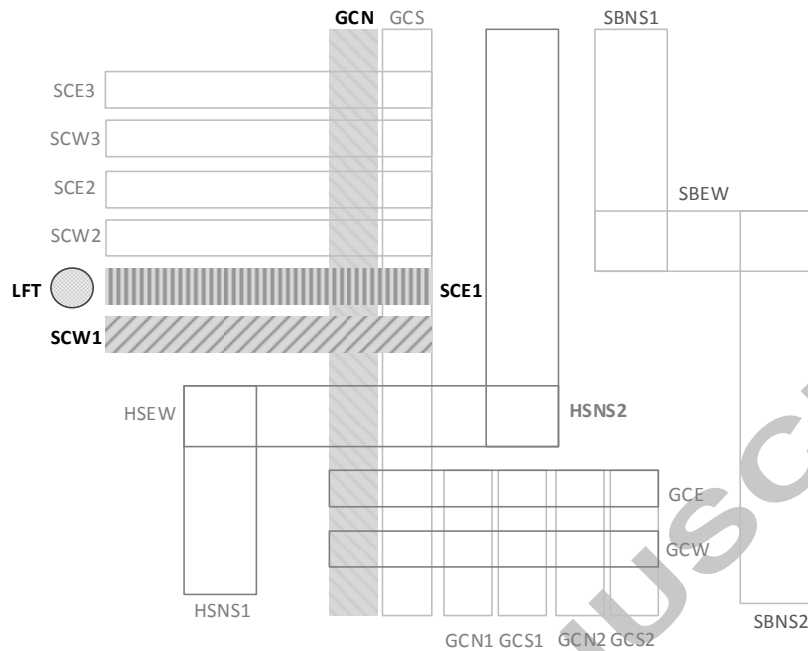
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[8] http://www.portgdansk.pl/events/vts-gulf-of-gdansk, http://www.victoriaharbor.org

Figure 3. Scenario harbor zones (zones used in the example are highlighted)

Speed Limits	
General Cargo Channel	15 knots for all ships
Special Containers Channel	10 knots for all ships
Small Boats channel	12 knots for all ships
Harbor Ships Channel	20 knots for surveillance ships 15 knots for other ships
Alignment	
North (N)	90º
South (S)	270º
East (E)	0º
West (W)	180º
Ships in crossing areas should be aligned at least with one of the directions	
Towage	
Ships of 70m and more in length, carrying dangerous cargo, shall be obliged to use tug service while entering the port (from the road to mooring position at the port), while leaving the port (from unmooring to the road), and at every change of berth within the port area. Specifically, 2 tugs are required for: • Ships of length over 170m • Ships and floating facilities without propulsion of length over 130m • Special ships of length over 150m	
Tug boats must be into the towing perimeter of the assisted ships and aligned while towing	

Table 2. Example harbor regulations

6.2. Context, Assumptions, Arguments and Beliefs

A simple OWL ontology has been developed with the Protégé 4[9] editor including the classes, properties, axioms and rules necessary for the example. It comprises 32 classes (16 of them for vessel classification purposes) and 30 properties (10 of them are topological predicates). Table 3 shows two class definitions used for classification of small boats and large power driven vessels. In addition, the ontology includes definitions for expected situations, corresponding to behaviors compliant and non-compliant to navigation rules. Figure 4 shows an excerpt of the taxonomy of consistent behaviors and safety violations.

	Properties	Vessel type
A	VESSEL *AND* (LENGTH *SOME* (LENGTH *AND* (LEN *SOME* DOUBLE[<= 15])))	SMALLBOAT
B	VESSEL *AND* (LENGTH *SOME* (LENGTH *AND* (LEN *SOME* DOUBLE[>=170])))	LARGEPOWERDRIVENVESSEL

Table 3. Definition of ontology classes to classify vessels according to detected properties
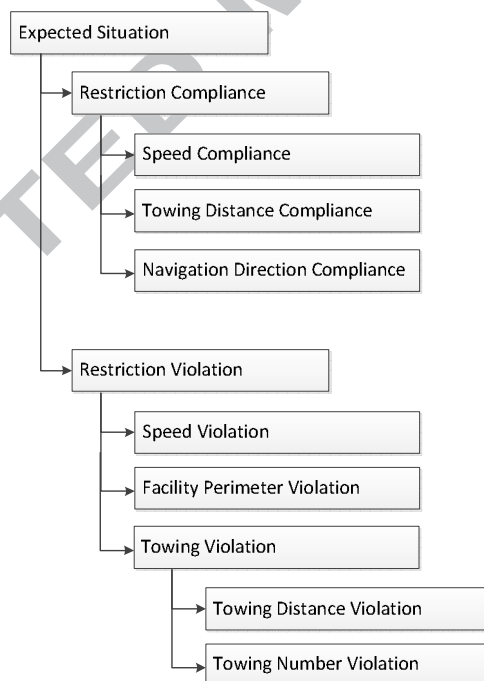

Figure 4. Excerpt of consistent behaviors and safety violations in the ontology

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[9] http://protege.stanford.edu

Table 4 describes the rules that define the assumptions and the arguments used to check the normalcy model of the scenario. Some of these rules are based on predicates that are instantiated by the topological reasoning module. For example, in rule 2 the normalcy model classifies a ship as a SPEEDVIOLATION instance since it is faster than the maximum speed allowed for the area in which it is currently moving. In our experiments, we have considered four types of arguments related to: violations of speed limit, violations of navigation direction, incorrect towing operations, and violation of protected facilities. For the sake of simplicity, all the arguments considered in the example are *pro* hypothesis "threat". The detected abnormal behavior at time t_i triggers reasoning aimed at explaining inconsistency and deciding whether this inconsistency points to a threatening behavior.

	Assumptions and arguments	
1	*Ship navigation angle is not compliant to the one of the including area or channel* VESSEL(?X), ALIGNEDTO(?X, ?A), INSIDEOF(?X, ?A)	NAVIGATIONDIRECTIONCOMPLIANCE(?X)
2	*Ship speed is faster than the maximum speed allowed for the including area* AREA(?A), VESSEL(?X), SPEED(?X, ?S), MOD(?S, ?VS), INSIDEOF(?X, ?A), MOD(?A, ?VA), GREATERTHAN(?VS, ?VA)	SPEEDVIOLATION(?X)
3	*Perimeter violation of a secured facility* DANGEROUSFACILITY(?F), VESSEL(?X), CLOSETOFACILITY(?X, ?F)	FACILITYPERIMETERVIOLATION(?X)
4	*Large power driven vessels must be towed by a predefined number of boats* LARGEPOWERDRIVENVESSEL(?X), CURRENTTOWINGBOATNUMBER(?X,?Z), RECOMMENDEDTOWBOATNUMBER(?X, ?Y), NUM(?Y, ?A), NUM(?Z, ?B), NOTEQUAL(?A, ?B)	TOWINGNUMBERVIOLATION(?X)
5	*A vessel is being towed by two boats, but they are not correctly aligned for this operation* VESSEL(?X), VESSEL(?Y), VESSEL(?Z), ISTOWEDBY(?Z, ?X), ISTOWEDBY(?Z, ?Y), NONALIGNEDTOTOW(?X, ?Y)	TOWINGALIGNMENTVIOLATION(?X), TOWINGALIGNMENTVIOLATION(?Y)

Table 4. Definition of ontology rules to classify vessels behavior according to expected situations

In the case of speed limit, the argument pro hypothesis "threat" (*Arg1*) is based on detected speed violation and represented by a conjunction of two uncertain assumptions (*A11* and *A12*) and a proposition (*P1*):

      Arg1 = A11 ^ A12 ^ P1

where:

      A11: The boat is inside area *X*
      A12: The speed of the vessel is greater than *Y*
      P1: The speed limit in *X* is *Y*

Beliefs in the arguments are calculated by combining beliefs that the assumptions are true. We consider hypotheses $\Omega = \{T^{Al}, F^{Al}\}$, where T^l is a hypothesis that assumption l is true and F^l is a hypothesis that assumption l is not true. The measures of belief for each assumption are modeled as follows.

bpa for assumptions *A11* and *A12* in *Arg1* are computed as follows:

- For *A11*:
  $$bpa(T^{A11}) = \exp(-\lambda_{A11} \cdot |DO - W|), \quad bpa(F^{A11}) = 0, \quad bpa(\Omega) = 1 - bpa(T^{A11}), \qquad (Eq.\ 3)$$
  where:
  - $DO = d_{left} + d_{right}$
  - d_{left}, d_{right} are observed distances to the left and right bound of the channel
  - W is the width of the channel

- For *A12*:
  $$bpa(T^{A12}) = 1 - \exp(-\lambda_{A12} \cdot |OV - MV|), \quad bpa(F^{A12}) = 0, \quad bpa(\Omega) = 1 - bpa(T^{A12}), \qquad (Eq.\ 4)$$
  where OV, MV are the observed and maximum boat speeds, respectively

($\lambda_l \in (0,1)$ are parameters, *l=11,12*)

Tug boats and vessels must be aligned to the channels in which they are into. An alignment violation may indicate threat. For instance, for a boat moving within SCW1, the argument in support of normal operations *Arg2* is based on correct alignment, and is represented by conjunction of two uncertain assumptions (*A21*, *A22*):

      Arg2= A21 ^ A22

where:

      A21: the boat is in SCW1
      A22: the boat is going in the right direction

The belief that these assumptions are true is computed based on features representing the position and direction of the movement, which are obtained from tracking and the allowed navigation directions. For example, *bpa* for *A22* can be computed as a function of the differences between observed and allowed angles:

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- *bpa* that the boat is going in the right direction is defined as follows:

$$bpa_1(T^{A22}) = \frac{1+\cos(\phi)}{2}\chi_{22}^1, \quad bpa_1(F^{A22}) = 0, \quad bpa_1(\Omega) = 1 - bpa_1(T^{A22}), \qquad \text{(Eq. 5)}$$

where ϕ is the angle between the observed and allowed directions

- *bpa* that the boat is moving in the opposite direction is defined as follows:

$$bpa_2(F^{A22}) = \frac{1-\cos(\varphi)}{2}\chi_{22}^2, \quad bpa_2(F^{A22}) = 0, \quad bpa_2(\Omega) = 1 - bpa_2(T^{A22}). \qquad \text{(Eq. 6)}$$

(χ_{22}^1, χ_{22}^2 are the scaling parameters for this *bpa*)

Another argument pro "threat" is based on the number of observed boats within a required towing distance from a vessel under consideration, and the type of the vessel defining the number of towing boats required. For a vessel type requiring two tug boats, the argument *Arg3* pro "threat" ("the number of towing boats is not the allowed one") is a conjunction of the following assumptions:

> *A31*: Tug boat 1 is within the prescribed distance for a tug boat
> *A32*: Tug boat 2 is within the prescribed distance for a tug boat
> *A33*: Tug boat 3 is within the prescribed distance for a tug boat
> *A34:* The vessel requires 2 tug boats

The belief in the argument is a combination of beliefs that there are 3 boats detected within the prescribed towing distance, and beliefs in the number of allowed boats, which comes from credibility of vessel ID recognition based on vessel characteristics. Beliefs that boats are within the towing distance is computed by an expression similar to Equation 4.

We also consider *Arg4* related to the rules of towing operations; specifically, "alignment of the towing boats is not correct." It is a conjunction of three assumptions based on the alignment of the boats. The beliefs on the assumptions are computed with expressions similar to Equations 5 and 6. *Arg5*, in turn, is a pro "threat" argument based on the fact that one of the boats is breaking a security perimeter. It is a conjunction of an assumption *A51* and a proposition *P5*:

> *A51*: Boat is close to restricted access facility
> *P5:* The facility perimeter must be protected

The *bpa* for *A51* is a function of the distance between the boat and the secured facility. We have used an equation similar to Equation 4.

6.3. Results

This subsection shows simulation results on the scenario depicted in Figure 3. In the simulation, three tug boats (*s1*, *s2* and *s3*) seem to be towing a power-driven vessel (*s4*) of length 180m. The operation is carried out from the south of the GCN channel to the dock at the end of the SCW1 channel. Harbor rules state that *s4* only requires 2 tug boats, but in the simulation we have three candidates. *s1* and *s3* are not compliant to the harbor

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requirements in several stages of the trajectory, which makes it difficult to determine which one is a real tug boat. The most noticeable misbehaviors happen at the middle of the operation, where *s3* increases its speed over the limits allowed for the navigation channel, and at the end, where *s1* heads to the secured facility. Simulation data includes position, size, angle and speed for each ship during 42 time instants (168 registers). Figure 5 shows in detail the ship trajectories and labels their behavior in order of appearance.

In Figure 6 we can see the tug boat *s3* increasing its speed at t=6 and exceeding the speed allowed for the channel. *s3* accelerates at t=[5, 9], and maintains a stable speed at t=[9, 13]. From t=14, the belief of the argument *Arg1* into hypothesis "threat" due to speed violation decreases, since the behavior is no longer incorrect. Similarly, *s1* accelerates at t=[36, 39] and then maintains a stable speed increasing the value of the belief. As expected, the actual belief values in these two cases are different, since the difference between the maximum allowed speed in the channel and the boat speed is larger in the latter.

1. The behaviors of the ships are compliant
2. s2 and *s3* exceed channel speed
3. Towing distance of s3 is not correct
4. All the ships change their alignment
5. s3 is at the wrong direction
6. s4 loses a towing boat (*s3*)
7. The behaviors of the ships are compliant
8. s1 is not aligned with the channel and the other tug boats
9. s1 is too close to other tug boats
10. s4 loses a towing boat (*s1*)
11. s1 is at the wrong direction and exceeds the channel speed
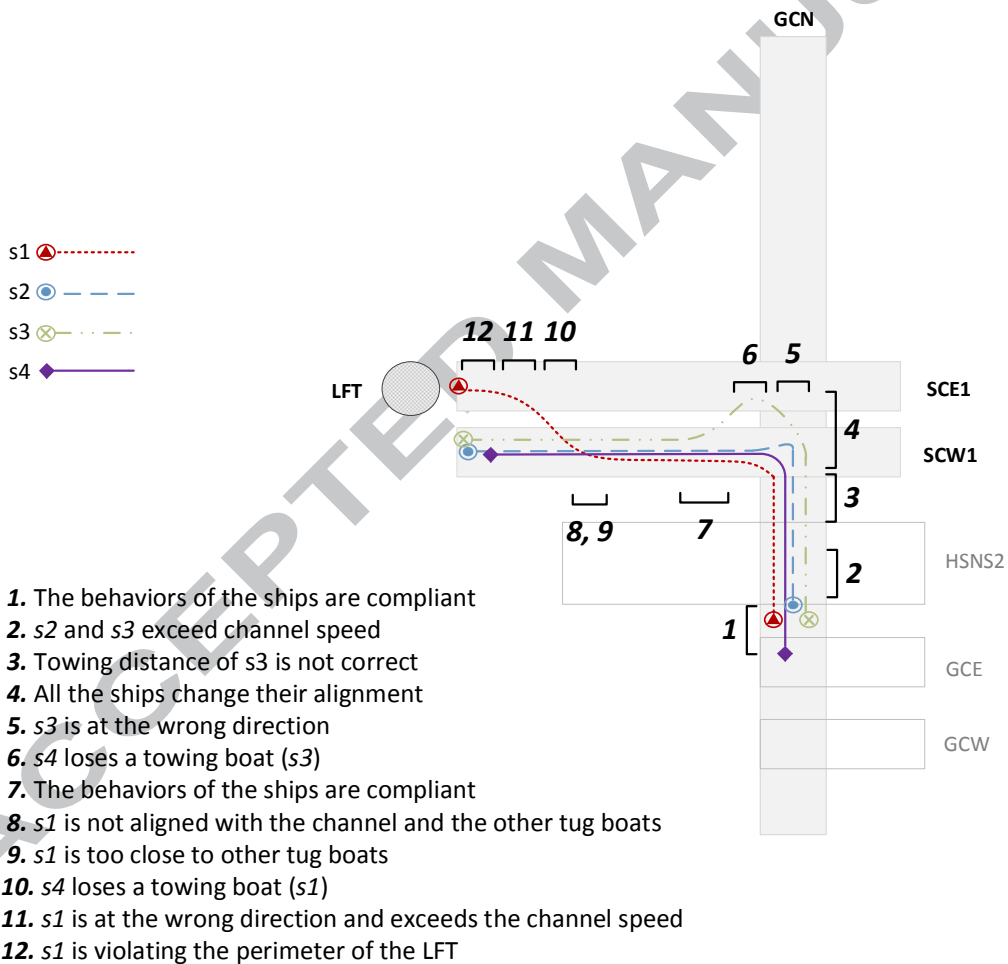*12. s1* is violating the perimeter of the LFT

Figure 5. Simulated trajectories and behaviors in the harbor scenario

To bring the vessel to the dock, all the ships must turn left into the overlapping area of the GCN and SCW1 channels. During this maneuver, the ships are not aligned to the channels in which they are into. This causes an increment in the value of the beliefs into the argument pro "threat" hypothesis *Arg2*, corresponding to the violation of the navigation channel direction, at t=[13, 18], as depicted in Figure 7. Later, *s3* navigates against the direction of the SCE1 channel, which increases the value of the belief. It is also interesting to highlight that at the beginning of the simulation, *s4* is simultaneously inside GCN and HSEW. For some time, *s4* infringes the alignment with the HSEW channel, but since it is aligned with the GCN channel, the value of the belief does not increase.
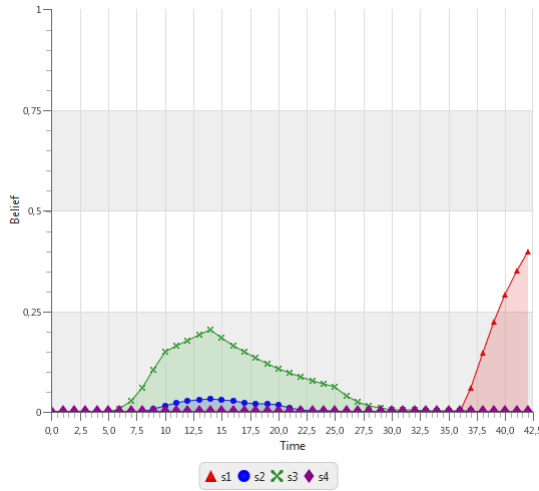

Figure 6. Dynamics of belief in *Arg1*
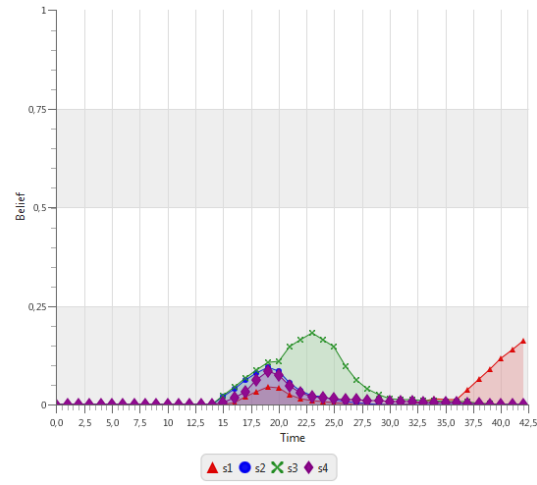(speed violations)

Figure 7. Dynamics of belief in *Arg2*
(alignment to channel navigation directions)

Figure 8 shows the effects of the detected high speed of *s3* to the values of the beliefs in the arguments related to towing operations. As a result of *s3* acceleration, the distance between *s3* and the towed vessel *s4* increases starting at t=20. After a while, *s3* is not considered to be towing *s4*, because the distance exceeds the maximum value to which a boat can be involved in a towing operation. Therefore, the belief on the argument pro "threat" *Arg3* decreases because the number of tug boats of *s4* is correct when *s3* is not considered a participant of the operation. A similar situation happens at the end of simulation, when *s1* moves towards the LFT.
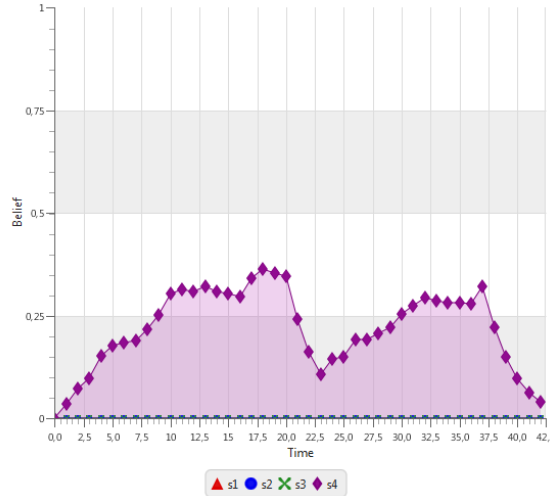
Figure 8. Dynamics of belief in *Arg3*
(number of towing boats)

Changes in the alignment of boats with respect to channels do not affect very much the belief in the argument *Arg4* related to alignment between towing boats, since boat trajectories in the simulation are consistent. As shown in Figure 9, the most noticeable situations are the trajectory deviation by *s3* at t=[17, 24] and *s1* at t=[31, 36]. Figure 10, in turn, depicts the dynamics of the belief in the argument pro "threat" hypothesis related to facility perimeter violations. As expected, *Arg5* quickly increases when *s1* approaches to the protected facility LFT.
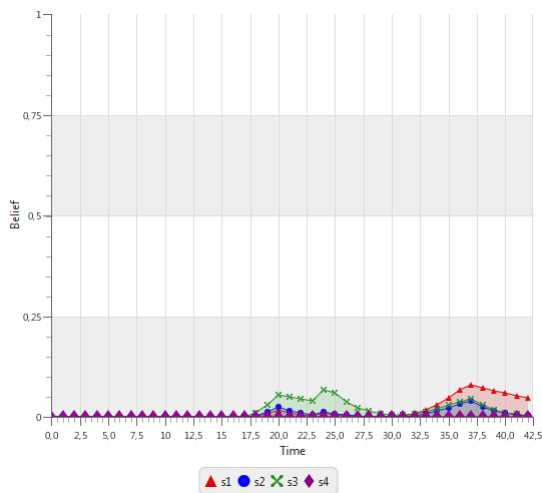

Figure 9. Dynamics of belief in *Arg4*
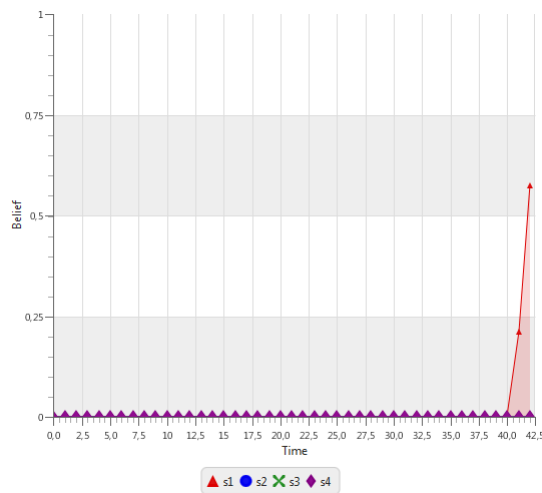(alignment between towing boats)

Figure 10. Dynamics of belief in *Arg5*
(close to facility)

Figure 11 shows the overall belief into the hypothesis "threat". It depicts several situations of interest through the simulation. At t=16, *s4* exhibits a combination of non-compliant behaviors; namely, number of tug boats and alignment to channel navigation direction. *s3*, in turn, has an erratic behavior in t=[5, 24], including violations of speed, direction alignment and tow alignment violations. Nevertheless, the evidence accumulated in favor of the "threat" hypothesis does not reach enough relevance to be considered. In contrast, the threatening behavior of *s1* at t=[30, 42] results in triggering an alarm when it approaches the LFT area.
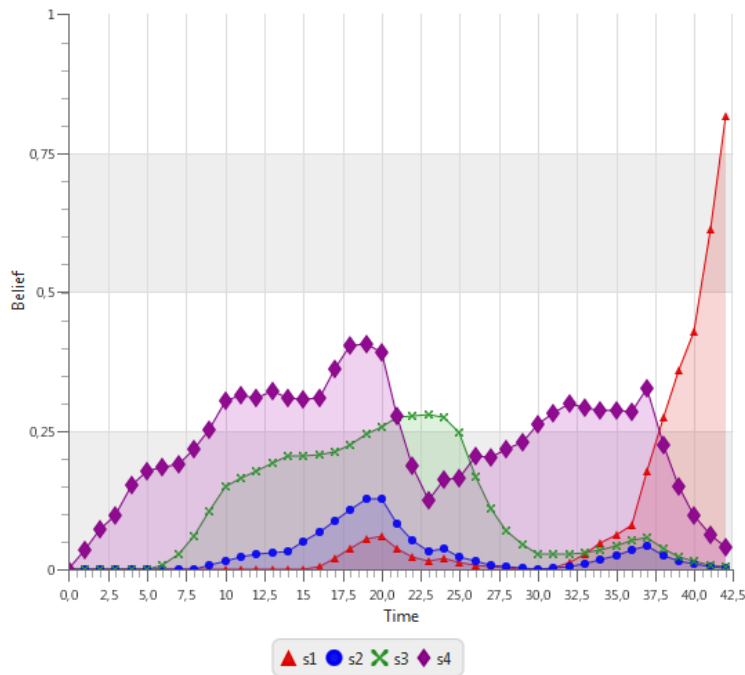

Figure 11. Dynamics of belief in "threat" hypothesis

7. Conclusions and Future Work

The paper has presented a system for context-based multi-level information fusion and its application to harbor surveillance. The system covers all processes from sensor data acquisition to threat assessment, which require integration of different fusion levels. This is achieved by using a common ontological model that symbolically represents the heterogeneous entities and relations of the domain. Contextual information is included into this model in the form of definitional classes, which are used to classify entities, and deductive rules, which are used to infer discrepancies with respect to the normal operations. In this problem, rules encode the restrictions defined by the port authorities based on the geometrical configuration of the harbor and navigational channels. To identify the deviations from the normalcy model that truly correspond to threatening situations and avoid false alarms due to spurious errors, the system utilizes an uncertainty reasoning method based on the Belief Argumentation System.

The example scenario and the simulation have shown the capacities of the approach. Our system can be easily adapted to different harbor configurations and, which is more important, to other application domains. It also considers the transformation from sensor data to abstract descriptions of entities and relations, which are dynamically integrated as part of the situational context, and decouples the ontology-based deductive and the abductive reasoning, which allows for a more flexible configuration of the fusion process. Compared to other works that do not manage uncertain knowledge, the number of alerts is notably reduced. The threshold on the belief of the "threat" hypothesis can be adjusted to customize the sensitivity of the system. Unfortunately, a detailed comparison is not possible at this moment, because public implementations, datasets, scenarios and criteria for the evaluation of higher-level fusion systems are scarce, if not inexistent. The creation of such evaluation framework, a task addressed by the ETURWG, is a prospective direction for future research.

Building a fully-deployable implementation of the system requires solving several additional problems that are outside the scope of this paper. It is necessary to develop a better integration of higher-level fusion processes (classification of abnormal situations, abductive reasoning) with lower level tasks (object detection, tracking and identification). This requires designing a detailed model of inter-level procedures, including processes for quality control and multiple feedbacks to improve the global performance of the system. Scalability issues of the topological reasoning module must be addressed as well. These problems can be exacerbated by the computational complexity of the Dempster rule, which may require the use of approximations. Applying a context selection technique, in turn, can optimize context exploitation by allowing the system to only search in the subset of the context model that is relevant to the current situation. It would be also convenient to incorporate vague knowledge into the normalcy model; e.g. imprecise definitions of objects and zones. Last but not least, the hypothesis generation problem has not been addressed. In that regard, it would be useful to increase the interaction of the system with human operators and decision makers in order to dynamically create and refine hypotheses.

Acknowledgements

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