This document is published in:

2012 *15th International Conference on Information Fusion* (FUSION 2012), Singapure, 9-12 July 2012, pp. 1546-1553.

Applying the Dynamic Region Connection Calculus to Exploit Geographic Knowledge in Maritime Surveillance

M.A. Serrano, J. Gómez-Romero, M.A. Patricio, J. García, J.M. Molina
GIAA Research Group
Universidad Carlos III de Madrid (UC3M)
Colmenarejo, Spain
miguel.serrano@uc3m.es, jgromero@inf.uc3m.es, mpatrici@inf.uc3m.es, jgherrer@inf.uc3m, molina@ia.uc3m.es

***Abstract*— Concerns about the protection of the global transport network have risen the need of new security and surveillance systems. Ontology-based and fusion systems represent an attractive alternative for practical applications focused on fast and accurate responses. This paper presents an architecture based on a geometric model to efficiently predict and calculate the topological relationships between spatial objects. This model aims to reduce the number of calculations by relying on a spatial data structure. The goal is the detection of threatening behaviors next to points of interest without a noticeable loss of efficiency. The architecture has been embedded in an ontology-based prototype compliant with the Joint Directors of Laboratories (JDL) model for Information Fusion. The prototype capabilities are illustrated by applying international protection rules in maritime scenarios.**

High-Level Fusion; Region Connection Calculus; Ontology-based Application; Spatial Data Structure

I. INTRODUCTION

Along the last decade the world has been beaten by terrorist actions, many of them perpetrated against public transport services. As a result of these incidents, global organizations have taken measures to regulate the security in public spaces. According to this, the International Maritime Organization adopted the International Ship and Port Facility Security (ISPS) code [1] for the protection of vessels and harbor facilities. The ISPS code applies to ships on international voyages (passenger, vessels, cargo vessels of 500 gross tonnage and upwards and mobile offshore drilling units) and port facilities serving these ships.

The need of management of the information sources available in these environments has become critical. Knowledge-based approaches for Information Fusion systems provide desirable characteristics for fast processing and a readable response of preconceived data from different sources, such as the Automatic Identification System (AIS) which provide reliable data –unique ship identification, position, kinematic states, and so on– from vessels larger than 65 feet and merchant ships over 300 GRT.

The maritime environments face with two levels of threats: (i) threats which affect facilities, traffic of land vehicles and people, (ii) threats which are related with maritime traffic, only applicable to ships. The ISPS code specifies rules for both levels, for instance, for protecting a vessel there should be monitored the “deck areas and areas surrounding the ship” while for safeguarding a port there might be control the “restricted areas to ensure that only authorized people have access”. These rules can be easily modeled through ontology approaches able to represent and reason with qualitative spatial relationships.

Despite of the fact that the spatial reasoning has been defined as a basic process for the interpretation system [2], ontology-based spatial representations are not expressive enough to directly support widely-use spatial or topological theories [3]. This paper presents an architecture for on-the-fly updates of qualitative spatial relationships in ontology-based approaches. The architecture, named Dynamic RCC, deals with the efficient calculation of Region Connection Calculus (RCC) relations by relying on a spatial data structure. RCC is a fully axiomatized first-order theory [4] which allows inferring implicit knowledge from explicit knowledge representing topological relationships between spatial entities.

Calculations are made using a Euclidean planar linear geometric model which discovers, maintains and provides qualitative spatial relationships. To keep the spatial relationships updated, it is necessary to perform a pairwise comparison of all the geometries updated at a given instant. This calculations has a quadratic complexity which may act as a bottleneck of the system performance. Dynamic RCC uses an auxiliary data structure that reduces the number of checks and improves the scalability by comparing only close objects.

This architecture has been designed to be embedded in an ontology-based prototype [5, 6] inspired on the Joint Directors of Laboratories (JDL) [7] fusion model. This model is able to manage both context data coming from users and dynamic spatial data coming from sensors. The prototype is being currently tested against security examples in harbor scenarios respecting and making use of the international standards related with the maritime environment. In this paper, we present the organization of the architecture, the methods used to calculate and represent spatial relations, and some interesting implementation details. We illustrate the advantages of this approach by depicting a simple example in the domain of harbor surveillance.

The paper is organized as follows. Section 2 discusses several current practical approaches for qualitative spatial representation. Section 3 describes the ontology-based prototype as the framework to embed the Dynamic RCC architecture, which is defined in Section 4. Some application examples to detect maritime threatening situations applying the prototype are illustrated in Section 5. Finally, Section 6 explains the conclusions obtained and the future work.

II. QUALITATIVE SPATIAL APPROACHES

The Open Geospatial Consortium [8] is one of the most important organizations that is currently proposing standards to represent and manage topological information. OpenGIS Simple Features standard [9] is a specification for digital storage of geographical data with spatial and non spatial attributes. It defines a set of methods to evaluate the spatial relationships, like overlaps and contains; a set of methods to support spatial analysis, like distance, union and difference; relational operators between entities; and several kinds of representation point, like multipoint, curve and surface.

RCC is a logic theory for qualitative spatial representation and reasoning. The RCC is an axiomatization of certain spatial concepts and relations in first order logic. The basic theory assumes just one primitive dyadic relation: C(x, y) read as "x connects with y". Individuals (x, y) can be interpreted as denoting spatial regions. The relation C(x, y) is reflexive and symmetric. Of the defined relations, Disconnected (DC), Externally Connected (EC), Partially Overlaps (PO), Equal (EQ), Tangential Proper Part (TPP), Non Tangential Proper Part (NTPP), Tangential Proper Part Inverse (TPPi) and Non Tangential Proper Part Inverse (NTPPi) have been proven to form a jointly exhaustive and pairwise disjoint set, which is known as RCC-8. Similar sets of one, two, three and five relations are known as RCC-1, RCC-2, RCC-3 and RCC-5.

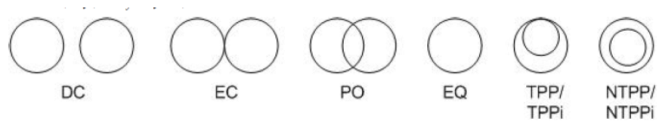

Figure 1. RCC-8 relations.

Currently there are implementations of this theory for two of the most powerful reasoning systems based on ontologies, Pellet [10] and RACER [11].

The 9-intersection model [12] is an alternative representation to RCC which associates three sets of points with every region –interior, boundary and complement. Every entry in a 3x3 matrix denotes if the intersection of the point sets is empty or not. The 9-intersection set of relations seems similar to RCC-8 however RCC allows much more general domains and its computational properties makes reasoning an easier task.

Orientation of spatial entities is usually shown as a very suitable approach for qualitative classification. Unlike topology, orientation is a ternary relationship depending on a located object, a reference object and a frame of reference [13]. The most widely used orientation-based approaches are the cone-based method and the projection-based method [14, 15]. These methods are based on cardinal points to determine different sectors corresponding to single directions.

Distance estimation is a cognitive capability usually manifested in qualitative approaches as imprecise numerical values (A is about a meter from B), qualitative categories (A is next to B) or qualitative compared categories (A is closer to B than C). These approaches can also distinguish between absolute and relative distances.

It is advisable to combine several qualitative methods [16] in the same system since descriptions provided are complementary and hardly redundant.

A fundamental assumption about the qualitative relationships is the change along the time. Therefore a complete description of the scene must include knowledge about the time instants and a relative representation of the temporal knowledge using temporal intervals as primitive. Even though RCC representation is also possible for time intervals, the most influential approach is the jointly exhaustive and pairwise disjoint set of 13 relations proposed by Allen [17].

III. OVERALL ARCHITECTURE

The Dynamic RCC is an essential part of the knowledge-based prototype for Information Fusion proposed in previous works [5, 6]. The aim of Dynamic RCC is to solve efficiently the calculations of the relationships between objects in a maritime scenario. Fig. 2 shows a simplified representation of the overall framework including the Dynamic RCC component.

A. A Knowledbe-based Framework for Information Fusion

The architecture's basic inputs are three: a variable amount of a priori knowledge, sensor data coming from different information sources and data formalisms. The data formalisms include a set of terminological boxes (TBoxes) each of which contains sentences describing concept hierarchies. In turn, an assertional box (ABox) contains facts about individuals of the domain of discourse. These TBoxes make up the structure of the Information Fusion Symbolic Representation (IFSR).

The IFSR [5, 6] is based on the JDL data processing model for Information Fusion systems. It is stepped in several levels ranging from low-level track data to high-level scene situations. Each ontology level provides a skeleton that includes general concepts and properties to describe entities and relations. These levels are:

- Tracking Entities (TREN) level, to model input data coming from sensors.
- Scene Objects (SCOB) level, to model real-world entities, properties, and relations.
- Activities (ACTV) level, to model event and behavior descriptions.
- Impact (IMPC) level, to model the association between a cost value and an activity description.

Concepts that belong to a less abstract ontology are the building blocks of a more abstract ontology. The complete knowledge model has been designed to promote extensibility and modularity. This means that the general structure can be refined to apply this model to a specific domain. Local adaptations should not cause cascade changes in the rest of the structure.

Ontologies may contain both perceptual and context data. Perceptual data is automatically asserted from different information sources, while the context data is external knowledge used to complete the comprehension of the scene. Context data includes information about scene environment, information previously computed, user-requested information and so forth. For example, the description of a static object (size, position, kind of object and so on) is regarded as context data.

The output of the knowledge-based architecture is a coherent and readable interpretation of the scene logically justified from the low-level data to the high-level interpretation.

B. *Implementation*

The implementation of the architecture above is based on the RACER reasoner. RACER has been chosen because it includes support for different kind of inference rules through the new Racer Query Language (nRQL), such as deductive, abductive, spatial and temporal [26].

As we discussed previously, ontological reasoning with spatial objects is very expensive, RACER is the first inference engine able to manage the spatial knowledge through an implementation of the Region Connection Calculus (RCC) as an additional substrate layer. A substrate is a complementary representation layer associated to an ABox. The RCC substrate offers querying facilities, such as, spatial queries and combined spatial and non-spatial queries. Although spatial instances from the ABox are not automatically connected with the RCC substrate, there is an identifying correspondence between them and the objects stored in the substrate.

A temporal dimension can be represented as temporal intervals or timestamps. Temporal intervals may be represented in the RCC substrate thanks to their proper relationships [27]. Timestamps are represented using snapshots of capturing data. This implies that a temporal dimension can be applied in both ways into the antecedent of rules, for example, “if the time interval permitted for a vessel docking exceed a recommended time interval...” or “if a vessel is stopped in a restricted area in a specific timestamp…”.

The reasoner hosts the IFSR, which includes the three lowest levels of the JDL-based model; namely, TREN, SCOB and ACTV. The ABoxes of these levels are filled with assertions from predefined context knowledge, previous inferences and sensor data (AIS, radar, on board and harbor video cameras, etc.).

Beyond the standard ontology reasoning mechanism based on subsumption, RACER also support abductive and deductive rule-based inference. During the execution, abductive nRQL rules defined in a sub-ontology create new instances that are asserted into the same level or into an upper level. Eventually, the creation of new instances as defined in the consequents of the rules draws instances corresponding to an interpretation of the scene in terms of the ACTV ontology. Deductive rules, in turn, are used to maintain the logical consistency of the scene. The consistency verifies whether all concepts in the TBox admit at least one individual in the corresponding ABox.

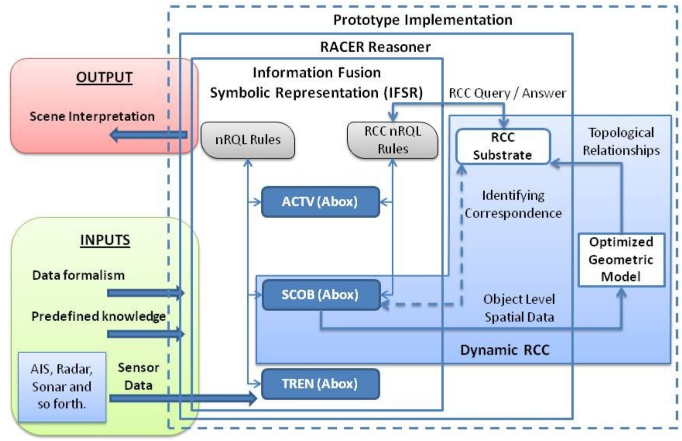

Figure 2. A simplified view of the knowledge system with the prototype integrated.

A significant amount of knowledge of SCOB and ACTV is obtained by abductive rules that include spatial properties in their antecedent. As previously mentioned, reasoning with spatial entities is very expensive in terms of computation time, since it grows with the number of entities and the complexity of the scene increases. The Dynamic RCC module, integrated into the system prototype, solves this problem.

The area shaded in blue in Fig. 2 indicates the integration of the Dynamic RCC architecture into the overall system. The optimized geometric model receives spatial data from the SCOB level. These data is instantiated into the Java Topology Suite (JTS). The JTS is an open source Java software library of two-dimensional spatial predicates and functions compliant to the Simple Features Specification SQL published by the Open GIS Consortium. JTS provides a complete, fast, consistent and robust implementation of basic two-dimensional spatial algorithms.

A spatial data structure indexes the geometries from the JTS. As it is shown in Section 4B there are not many alternatives on choosing a spatial data structure for moving objects. We have chosen TPR*-tree because it satisfies the conditions given in Section 4A. Furthermore TPR*-tree can handle predictive queries about the object’s future position. These kinds of queries are interesting on security environments where prediction of attacks and incidents in points of interest improves the managing of resources while minimizing costs and losses. In addition, the source code of the data structure developed by the author is available on the World Wide Web [28].

IV. DYNAMIC RCC ARCHITECTURE

Trying to find all the spatial relationships in a scene can become an expensive task. One of the aims in the Dynamic

RCC architecture is to reduce the number of checks between objects in the scene without taking into account any assumption about their features.

Dynamic RCC includes three main components: (i) a knowledge base with spatial features from individuals, (ii) an optimized geometric model, including a geometric model and an auxiliary data structure, and (iii) a Region Connection Calculus implementation where the resulting qualitative spatial relationships are stored. The overall architecture is illustrated in Fig. 3.

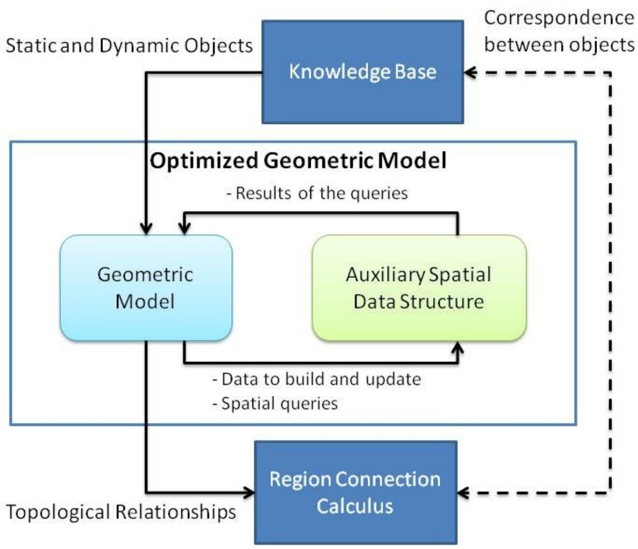

Figure 3. Dynamic RCC overall architecture.

The knowledge base of Dynamic RCC contains representations of both dynamic and static objects. These objects are instantiated into the geometric model in two cases: (i) if they do not exist previously in the model, (ii) if they were already instantiated but its position or size changed regarding the last update. To obtain the new topological relationships when the situation changes, it is necessary to perform a full topological analysis between the newly instantiated or updated geometries and the remaining the geometries. All the objects that change their position or size have to be checked against all the static (M) and dynamic objects (N). The total amount of checks (X) can be seen in (1).

$$X = N \,.\, (M + N - 1) \tag{1}$$

It must be taken into account that topological relationships are symmetric. In this case the total amount of checks is (2).

$$X = (N^2 + N \,.\, (2 \,.\, M - 1)) / 2 \tag{2}$$

According with (2), the analysis has a quadratic complexity. In scenarios where objects move in a consistent manner, topological relationships change between close objects in consecutive time instants. Therefore, for an efficient behaviour, topological analysis should be done only between close geometries. A disjoint status is assumed for non-calculated topological relationships. An auxiliary data structure can be used to determine the geometries that are candidates to modify the spatial relations of each geometry. These candidates usually form a clearly distinguished subgroup of the scene objects.

Once the candidates have been obtained by querying the auxiliary data structure, the topological relations of a geometry can be updated by analyzing only a few candidates. The topological relationships which change from the previous state are then updated in the RCC layer. There is an identifying correspondence between the individuals stored in the knowledge base and the topological relationships stored in the separated RCC layer.

A. Optimized Geometric Model

The optimized geometric model is composed of two sub-modules: (i) a geometric model, (ii) an auxiliary data structure.

The geometric model is a system that represents spatial objects in a Euclidean plane and obtains spatial relationships between two-dimensional objects quickly. It is implemented according to the OpenGIS Simple Features standard shown in Section 2. Although OpenGIS spatial predicates and RCC-8 are not directly compatible, the output from the geometric model can be easily mapped from the OpenGIS format –in some cases, it only involves translating the name of the relationships. A correlation table between OpenGIS spatial predicates and RCC-8 can be found in [25].

A spatial data structure maintains a hierarchical topological sort on the Euclidean space of the scene. It supports spatial queries to retrieve the candidate geometries involved into a topological analysis; e.g., 'which geometries share area 2 with geometry 2?'. These candidate geometries are the nearest geometries of the one in the query.

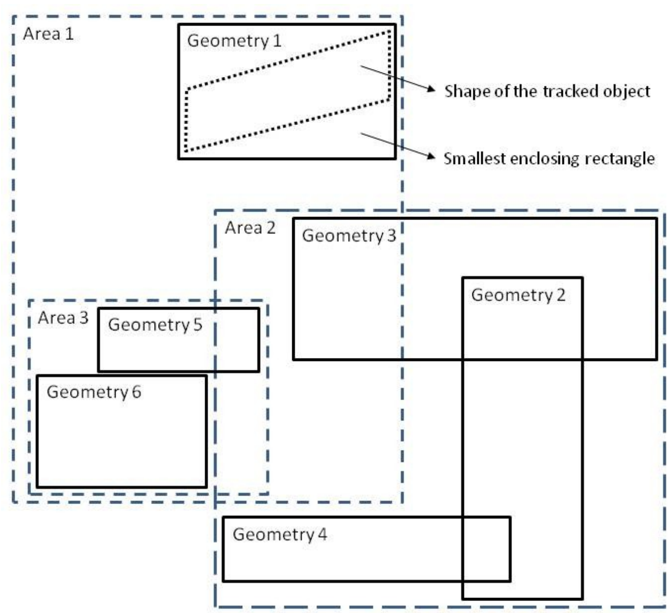

Figure 4. Example of structured spatial information.

The sorting of the auxiliary spatial data structure is not predefined by the architecture. It is required, however, to fulfill the following restrictions: (i) the spatial structure must be able to define a recursive spatial hierarchy throughout the time; (ii) it must handle the overlap between entities; (iii) query, deletion, insertion and update operations must not imply a high overhead.

Data structures assume that spatial objects are represented by axes-aligned bounding boxes, even though tracked objects do not satisfy this condition. Consequently, it is necessary to implement an algorithm to calculate the smallest rectangle that encloses the corresponding object. The geometry inserted into the data structure is not the track, but the smallest axis-aligned rectangle that includes it.

B. Spatial Data Structure Alternatives

The problem of the spatial storage and representation is very common in the spatial databases. Usually, spatial databases receive and store spatial data making use of an efficient indexing structure to optimize object searches. During the last two decades lots of approaches have been designed to obtain an efficient and reasonably simple spatial index. The R-Tree [18] has been one of the most efficient access structures for rectangles. An important number of variants for specific purposes have been developed during these years; for example, B+-tree, R+-tree and R*-tree. Despite the quality of these research works most of them are only applicable for static scenarios and do not take into account the past, present and future situation of the objects.

Accordingly, additional techniques have been developed trying to overcome these limitations. TPR-tree [19] was one of the first advances in the area of moving objects. This structure is capable of indexing moving objects up to three dimensions. In addition, it efficiently indexes the current and anticipated future positions of moving objects. This approach was significantly outperformed under all conditions by the TPR*-tree [20] and the Bx-tree [21]. In particular, the latter uses a new linearization technique that exploits the volatility of data values. Currently, Rdual-tree [22] is considered the state-of-art in this area. This dual space index is faster in query processing than TPR*-tree and improves the update times of the Bx-tree. BBx-tree [23] (a version of Bx-tree) and RPPF-tree can index historical, current and future positions of moving objects. Nevertheless almost all of this kind of approaches assumes a linear movement model.

Las but not least, it is important to notice that indoor and outdoor moving objects do not have similar behavior. Thus several techniques have been developed to address indoor objects from their trajectories, such as the RTR-tree [24] and the TP2R-tree.

V. Application Example: Perimeter Control

Maritime safety standards give to each ship a protection perimeter that must not be broken by other ships. In fact, perimeter protection of vessels and facilities in harbor scenarios is one of the concerns of the ISPS code. Perimeter can be inferred by knowing the type of ship thanks to the AIS sensor data. This section gives some examples of how our prototype deal with ship-ship interfaces –interaction between ships– and ship-port interfaces –the port services interaction to the ship or from the ship. The examples assume that the spatial entities are security perimeters of vessels.

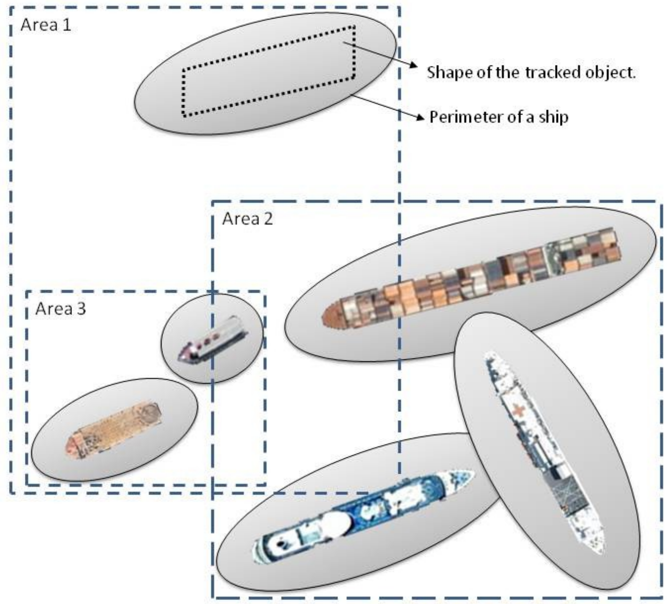

Figure 5. Using security perimeters as spatial entities.

We have used simulations of ships trajectories in the Canadian harbor of Victoria in the preliminary tests. This emplacement combines touristic services, air and sea traffic operations and international interchanges among other operations. The tests have validated the general functioning of the prototype without including the interaction with the spatial data structure, which remains as future work. Simulations show a simplified view of the harbor including navigation lanes (context data) and four trajectories of ships updated over the time (sensor data).

The event recognition has been addressed in terms of the topological configuration of the scene objects. Timestamps and temporal intervals are used to limit the search and to give a semantic approximation of temporal interactions. Time intervals representation is directly supported by the RCC substrate.

Sometimes the permanency of a ship or a group of them next to another in a given instant can be a hint of a threatening situation. Specific rules to detect these situations are easily developed with our prototype. The following abductive rule triggers perimeter violation between two ships.

Rule’s variables are denoted with a question mark at the beginning of their names (?), variables belonging to the RCC substrate are labeled adding a star (?*), concept types start with a hash (#) and RCC-8 relationships are labeled with a colon (:). For the sake of simplicity *?*ship1* and *?*ship2* variables represent ship security perimeters, rather than ships. Besides, the syntax of nRQL has been slightly simplified to make them more readable.

```
1  (firerule
2  (and //Antecedent
3     (?ship1 #!scob:Vessel)
4     (?ship2 #!scob:Vessel)
5     (or   (?*ship1 ?*ship2 :po)
6     (?*ship1 ?*ship2 :tpp)
7     (?*ship1 ?*ship2 :ntpp)))
8  ( //Consequent
9  (instance (new-ind ?perV) #!actv:PerimeterViolation)
10 (related (?perV ?ship1 #!actv:atRisk))
11 (related (?perV ?ship2 #!actv:atRisk))))
```

Figure 6. Rule to check perimeter violations.

RCC relationships partially overlap (po), tangential proper part (tpp) and non tangential proper part (ntpp) are used to detect the topological configuration of the vessels' perimeters (5-7). The consequent of the rule creates a new PerimeterViolation instance (9) and classifies the ships as vessels atRisk associated with the PerimeterViolation (10-11).

Figure 7. *Ship1* (green spot) and *Ship2* (pink spot) are *atRisk* involved in a *PerimeterViolation*.

In the rule above ships were directly considered scene object (SCOB) instances. However these assertions have to be founded on objective criteria supported by the low-level data from sensors. The rule below sets out several measures to discern the vessels from the rest of tracks. This classification exemplifies how abductive reasoning creates new refined knowledge towards the high-level.

The search is constrained to a specific Track (4-5) and current measures (6-7) using data capturing timestamps. Criteria that support the classification are the size of the vessel (8-11), in order to discard smaller ships, and its relationship with the environment. A second clause employs context data (3) and spatial relationships (12-13) to check if the Track is into a navigable area. In the consequent a new Vessel individual with an ID and associated to a Track is asserted (15-17) in the SCOB level.

```
1 (firerule
2 (and //Antecedent
3     (?area #!scob:NavigableArea)
4     (?t #!tren:Track)
5     (?t (equal #!tren:id  trackID ))
6     (?tsn #!tren:CurrentSnapshot)
7     (?t ?tsn #!tren:hasSnapshot)
8     (?dimension #!tren:2DDimension)
9     (?tsn ?dimension #!tren:sizeValue)
10    (?dimension (>= #!tren:width standardWidth))
11    (?dimension (>= #!tren:height standardHeight))
12    (or   (?*area ?*track :tpp)
13    (?*area ?*track :ntpp)))
14 ( //Consequent
15 (instance (new-ind ?ship) #!scob:Vessel)
16 (instance ?ship (equal #!scob:id trackID))
17 (related ?ship ?track #!scob:associatedTrack))
```

Figure 8. Vessels' classification rule.

Threatening situations are more recognizable if spatial and temporal knowledge is represented. Moreover, a better classification can be achieved if the duration of the events is represented by means of time intervals. Relationships between event' time intervals may transform a routine activity into a dangerous situation. The rule below illustrates how a transient situation becomes the violation of a restricted area if we take into account the time interval duration.

```
1 (firerule
2 (and //Antecedent
3       (?ship #!scob:NonIdentifiedShip)
4       (?area #!scob:RestrictedArea)
5       (?ts #!actv:TransientSituation)
6       (?ts ?area #!actv:hasGeographicArea)
7       (?ts ?permittedTime #!actv:hasPermittedInterval)
8       (?ts ?currentTime #!actv:hasCurrentInterval)
9       (or (?*ship ?*area :po)
10      (?*ship ?*area :tpp)
11      (?*ship ?*area :ntpp))
12      (or (?*permittedTime ?*currentTime :ntpp)
13      (?*permittedTime ?*currentTime :tpp)))
14 ( //Consequent
15 (instance (new-ind ?ts) #!actv:ThreateningSituation)
16 (related ?ts ?ship #!actv:isSuspicious)
17 (related ?ts ?area #!actv:isCompromised)))
```

Figure 9. Rule for threatening situation recognition.

As it is shown in Figure 7, a TransientSituation (5) comprises a geographic area, where it happens, a validity time interval, to set out an event's maximum duration and the current duration interval of the event (6-8). Similar to the rule in Figure 6, the spatial configuration between a non identified ship (3) and a restricted area (4) is checked (9-11). Eventually, the permitted time interval for the normal development of events is compared with the specific time interval of the event (12-13). Notice that RCC relations were used to compare time intervals.

Figure 10. The ship out of the navigational lanes (purple spot) eventually causes a *ThreateningSituation*.

In this case, the consequent does not generate new knowledge. Instead a TransientSituation is also classified as a ThreateningSituation (15). The ship is also classified as suspicious (16) and the restricted area is marked as compromised (17).

VI. Conclusion and Future Work

This paper presents an architecture named Dynamic RCC aimed to efficiently calculate and represent relationships between two-dimensional static and dynamic objects. The Dynamic RCC module is part of a framework for knowledge-based Information Fusion in the maritime domain. Some rules from the ISPS code related with topological issues in maritime scenarios illustrate the capabilities of the prototype. Some optimizations techniques have been applied to improve the performance of the calculations; namely, the use of specialized data structures to minimize update costs.

Future works will include a complete study about which spatial data structure may be more appropriate for each problem. Data structure integration, scalability analysis and performance results are also pending for future research.

Acknowledgment

This work was supported in part by Projects CICYT TIN2011-28620-C02-01, CICYT TEC2011-28626-C02-02, CAM CONTEXTS (S2009/TIC-1485) and DPS2008-07029-C02-02.

References

[1] International Ships and Port Facility Security (ISPS) code and SOLAS amendments 2002. International Maritime Organization (IMO).

[2] F. Bremond and M. Thonnat, "A context representation for surveillance system," European conference on computer vision (ECCV) workshop on conceptual descriptions from images, vol. 2, Cambridge April 1996.

[3] M. A. Serrano, J. Gómez-Romero, M. A. Patricio, J. Garcia and J. M. Molina, "Topological properties in ontology-based applications," 11th International Conference on Intelligent Systems Design and Applications (ISDA), pp. 1329–1334, Córdoba España 2011.

[4] D. A. Randell, Z. Cui and A. G. Cohn, "A spatial logic based on regions and connection," Proceedings of the 3rd International Conference on Knowledge Representation and Reasoning, vol. 92, pp. 165–176, 1992.

[5] J. Garcia, J. Gomez-Romero, M. A. Patricio, J. M. Molina and G. Rogova, " On the representation and exploitation of context knowledge in a harbor surveillance scenario," Proceedings of the 14th International Conference on Information Fusion (FUSION), pp. 1–8, 2011.

[6] J. Gómez-Romero, M. A. Patricio, J. García and J. M. Molina, "Ontology-based context representation and reasoning for object tracking and scene interpretation in video," Expert Systems with Applications, vol. 38, num. 6, pp. 7494-7510, 2011.

[7] J. Llinas, C. Bowman, G. Rogova, A. Steinberg, E. Waltz and F. White, " Revisiting the JDL data fusion model II," 7th International Conference on Information Fusion, pp. 1218-1230, Stockholm, Sweden, 2004.

[8] Open Geospatial Consortium http://www.opengeospatial.org/standards

[9] OpenGIS Simple Features Specification for SQL http://www.opengeospatial.org/standards/sfs

[10] M. Stocker and E. Sirin, "Pelletspatial: A hybrid RCC-8 and RDF/OWL reasoning and query engine," Proceedings of OWL: Experiences and Directions (OWLED 2009) vol. 529, 2009.

[11] Renamed ABox and Concept Expresion Reasoner. http://www.racer-system.com/

[12] M. Egenhofer and R. Franzosa, " Point-set topological spatial relations," International Journal of Geographical Information System, vol. 5, num. 2, pp. 161–174, 1991.

[13] J. Renz, Qualitative Spatial Reasoning with Topological Information, Berlin, 2002.

[14] A. U. Frank, "Qualitative spatial reasoning about distance and directions in geographic space," Journal of Visual Languages and Computing, vol. 3. pp. 343–373, 1991.

[15] D. Hernández, "Qualitative representation of spatial knowledge," vol. 804, Lecture Notes in Artificial Intelligence, 1994.

[16] E. Clementini, P. D. Felice, and D. Hernández, "Qualitative representation of positional information," Artificial Intelligence, vol. 95 num.2, pp. 317–356, 1997.

[17] J. F. Allen, "Mantaining knowledge about temporal intervals," Comunications of the ACM, vol. 26, num.11, pp. 832–843, 1983.

[18] A. Guttman, "R-trees: A dynamic structure for spatial searching," Proceedings of the International Conference on Management of Data, vol.14, num. 2, 1984.

[19] S. Šaltenis, C. S. Jensen, S. T. Leutenegger and M. A. Lopez, "Indexing the positions of continuously moving objects," Proceedings of the International Conference on Management of Data, vol. 29, num. 2, 2000.

[20] Y. Tao, D. Papadias and J. Sun, "The TPR*-tree: an optimized spatio-temporal access method for predictive queries," Proceedings of the 29th International Conference on Very Large Data Bases, vol. 29, pp. 790–801, 2003.

[21] C. S. Jensen, D. Lin and B. C. Ooi, "Query and update efficient B+-tree based indexing of moving objects," Proceedings of the 30th International Conference on Very Large Data Bases, vol. 30, pp. 768–779, 2004.

[22] M. L. Yiu, Y. Tao and N. Mamoulis, "The B dual-tree: indexing moving objects by space filling curves in the dual space," The VLDB Journal, vol. 17, num. 3, pp. 379–400, 2008.

[23] D. Lin, C. S. Jensen, B. C. Ooi, and S. Šaltenis, "Efficient indexing of the historical, present, and future positions of moving objects," Proceedings of the 6th International Conference on Mobile Data Management, pp. 59–66, 2005.

[24] C. Jensen, H. Lu and B. Yang, "Indexing the trajectories of moving objects in symbolic indoor space," Advances in Spatial and Temporal Databases, pp. 208–227, 2009.

[25] M. Schuele and P. Karaenke, "Qualitative spatial reasoning with topological information in BDI agents," ECAI Workshop on Artificial Intelligenceand Logistics (AILog), 2010.

[26] J. Gómez-Romero, M. A. Patricio, J. García and J. M. Molina, "Ontology-based context representation and reasoning for object

tracking and scene interpretation in video," Expert Systems with Applications, vol. 38, num. 6, pp. 7494–7510 2010.

[27] J. Gómez-Romero, J. García, M. A. Patricio and J. M. Molina, "Towards the implementation of an ontology-based reasoning system for visual information fusion," Evaluation, vol. 3, 2009.

[28] Source code of R-trees and variations. http://www.rtreeportal.org/code.html

[29] H. Samet, Foundations of Multidimensional and Metric Data Structures, Morgan Kauffman, St. Louis, USA, 2006.

[30] N. Jürg and W. Peter, "Spatial Data Structures: Concepts and design choices," Algorithmic Foundations of Geographic Information Systems, pp. 153–197, 1997.

A. M. Sánchez, M. A. Patricio, J. García and J. M. Molina, "A context model and reasoning system to improve object tracking in complex scenarios," Expert Systems with Applications, vol. 36, num. 8, pp. 10995–11005, 2009.