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Context for Maritime Situation Awareness

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Chapter 3

Context for Maritime Situation Awareness

Anne-Laure Joussetme and Karna Bryan

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Introduction

Military shortfalls in information processing, exploitation, and dissemination will be partially addressed by current industrial and academic research in areas like Artificial Intelligence and Big Data. The Big Data challenge is often recognized in terms of Volume, Velocity, Variety, and Veracity. This highlights the need to process an always increasing amount of data (challenges with volume) within strong time constraints (challenges with velocity) originating from diverse sources with different formats, requiring some alignment in time, space, or semantics (challenges with

variety) and with many imperfections such as uncertainty, imprecision, errors, and conflict (challenges with veracity). In addition to these challenges in data processing, there is also an underlying semantic challenge of providing valid interpretations and meanings of the information to the decision-maker.

Moving toward improved synergy between humans and machines, research on the automation of data processing should be accompanied with research on the automation of reasoning. The Artificial Intelligence (AI) community, and more recently that of Information Fusion, address challenges in automation and information processing. While “[d]ata fusion refers to the combination of data from multiple sensors (either of the same or different types), [...] information fusion refers to the combination of data and information from sensors, human reports, databases, as well as a broad range of contextual data.¹ Contextual information is a fundamental aspect of the reasoning process, and the notion of context has become a key component in many studies of these fields. In Snidaro et al. (2015), the authors survey the recent works on context-based information-fusion systems, mapping them to the Joint Directors of Laboratories (JDL) levels (Llinas et al., 2004). They discuss the use of context in the classical lower-level tasks of sensor characterization, signal fusion, data association, filtering, tracking, and classification, and consider as well the higher-level tasks of knowledge representation, situation assessment, decision-making, intent assessment, and process refinement. In relation to natural language processing, context is also used in hard and soft fusion (Jenkins et al., 2005) to incorporate soft information (i.e. from human sources) with hard information (i.e. from sensors) using fuzzy membership functions to define the semantics of vague concepts. Indeed, with the growth of social media data processing, the notion of context is instrumental to natural language processing techniques, where words and sentences often need some contextual setting to be properly understood.

Effective Maritime Situation Awareness (MSA) relies on high-level information fusion tasks that benefit from a formal approach to context-based reasoning. Indeed, MSA requires not only detecting, tracking, and classifying vessels but also detecting, classifying, and predicting any abnormal behavior, which includes detecting relationships between vessels and vessels’ behaviors. MSA operations occur in both peacetime and times of conflict, and involve the understanding of the patterns of life of all entities operating in and influencing the maritime domain. Situational awareness includes the development of context by military operators. This context applies to various aspects of a processing chain with the layers of the chain building on each other. At the core of this task is the compilation of a maritime picture (Lane et al., 2010; Laxhammar, 2008), which involves extracting relevant contextual information (for instance, maritime routes or loitering areas [Pallotta et al., 2013]) but also monitoring the real-time maritime traffic. The use of a set of sensors mixing cooperative self-identification systems, such as the Automatic Identification

¹ www.buffalo.edu/cmif/center/what-is-MIF.html.

System (AIS), and noncooperative systems, such as coastal radars or satellite imagery, provides the necessary complementarity and redundancy of information to overcome the possible (and quite common) spoofing of AIS signals while increasing the clarity and accuracy of the maritime picture. In many cases, intelligence information is also of great help to refine and guide the search in the huge amount of data to be processed, filtered, and analyzed, and can be contextual information for some MSA problems.

In this chapter, we discuss the relative notion of context through the problem of Maritime Situation Awareness. In the section “Maritime Situation Awareness,” we introduce the MSA problem, exemplifying the three embedded problem-solving and associated contexts of route extraction, maritime anomaly detection, and threat assessment. In the section “Context-Based Maritime Situation Awareness,” we introduce some definitions of context and discuss the impact and use of context from an information fusion perspective on the MSA problem. We revisit the MSA problems and present a scheme with embedded problems constrained by different contexts. We conclude in the section “Conclusions and Future Work” and discuss future works.

Maritime Situation Awareness

In order to present an overall and structured vision of the different contextual dimensions within a MSA perspective, this section presents three subproblems of MSA that are: route extraction (Section “Route Extraction”), maritime anomaly detection (Section “Maritime Anomaly Detection”), and threat assessment (Section “Threat Assessment [Identification]”). We highlight that context is a relative notion on these three embedded subproblems.

Route Extraction

The analysis of historical, spatiotemporal traffic data streams provides baseline information on Patterns-of-Life (PoL). The AIS (Automated Identification System) cooperative self-reporting system provides a rich data stream that can be used to extract PoL for maritime vessel traffic. Machine-learning algorithms are one way to derive PoL, as they provide a suitable degree of automation and efficiency in detecting and characterizing inconsistencies, anomalies, and ambiguities, and ultimately transform this information into usable and actionable knowledge (Pallotta and Joussetme, 2015). The Traffic Extraction and Anomaly Detection (TREAD) tool (Pallotta et al., 2013) developed at the Centre for Maritime Research and Experimentation (CMRE) implements an unsupervised classification approach, deriving a dictionary of the maritime traffic routes using spatiotemporal data streams from terrestrial and/or satellite AIS receivers. Figure 3.1 displays the overview of the TREAD process, from raw AIS data trajectories to route definitions.

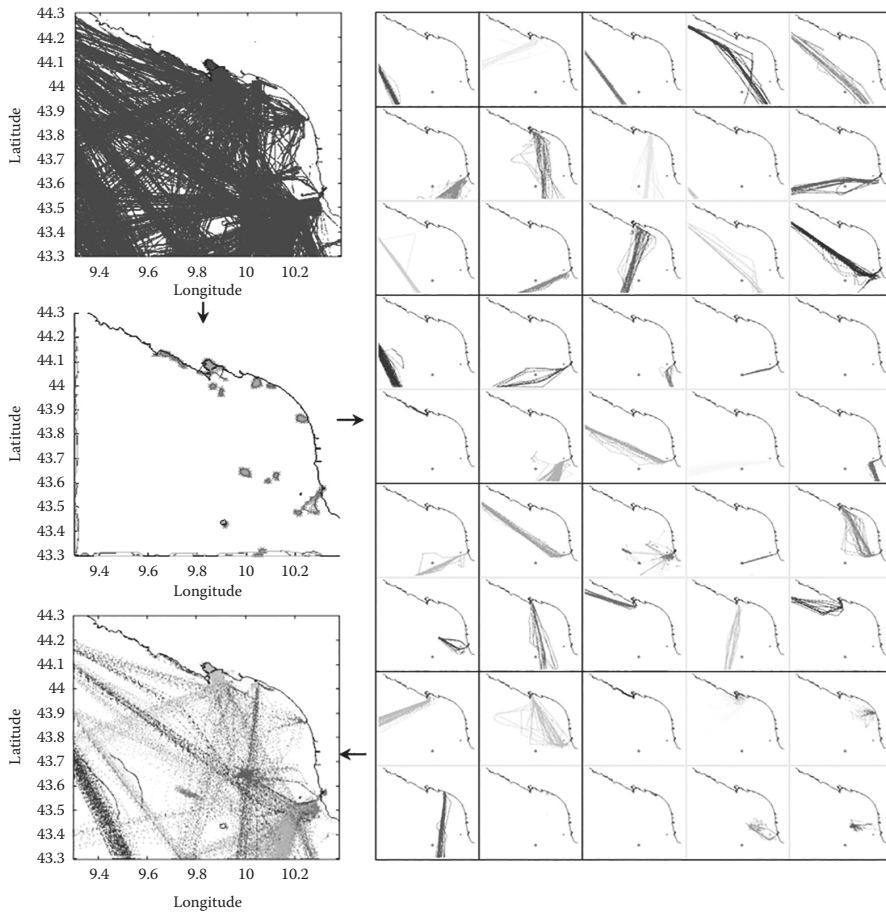


Figure 3.1 The general overview of the TREAD Knowledge Discovery Process: The raw AIS data stream is processed, vessel movements are clustered, and as a result, the discovered traffic route system is organized as a dictionary of motion models. (From Pallotta, G. et al., *Entropy*, 5, 2218–2245, 2013.)

The synthesis of the activity at sea summarizes the maritime traffic over a given period of time and a given area and is referred to as the maritime routes. A TREAD route is then defined by a starting point and an ending point, together with a subset of waypoints, describing a path on a portion of the sea. Starting and ending points for the routes are stationary areas. Stationary areas can either be coastal areas such as ports, including island or offshore ports, or open-sea areas, such as fishing areas. They can also be entry or exit areas within the area of interest. The TREAD algorithm clusters individual vessel contacts, each cluster then corresponding to a route.

The problem of Route Extraction (RE) can be formalized as:

$$\Psi_{RE} : \mathcal{X}_{P,\Delta t} \rightarrow \mathcal{R} \tag{3.1}$$

$$\mathbf{x} \mapsto R \tag{3.2}$$

where $\mathcal{X}_{P,\Delta t}$ is the measurement of space and by extension, the dataset of positional data streams for a set of vessels over a given period of time Δt ; \mathbf{x} is a trajectory; R is the label assigned to \mathbf{x} belonging the \mathcal{R} , the finite set of routes. The route extraction problem aims at assigning each contact \mathbf{x} to a class R such that $\Psi_{RE}(\mathbf{x}) = R$ is the route label associated with \mathbf{x} , and R is the corresponding route. Within an unsupervised classification method (clustering), such as the one used by TREAD, the decision space is not known in advance and the set of labels emerges from the data, thus building the decision space. While only temporal streams of positional information are processed to extract the set of maritime routes, the routes are further characterized by additional attributes representing the traffic of the vessels composing it, such as the speed, the type, and the heading. The associated uncertainty characterization of the route along these attributes can be more or less complex, ranging from average values only, added variance parameters, complete probability distributions, or sets of distributions. Table 3.1 lists an excerpt of the dictionary of routes together with some possible uncertainty representations (Jousselman and Pallotta, 2015).

Table 3.1 Dictionary of Routes and Associated Uncertainty Representation

Route	Synthetic Route	Traffic Information			
	Position	Course	Speed	Length	Type
	$\{(p_i^{(k)}, \theta_i^{(k)})\}_{i=1}^N$ $\pm w^{(k)}$	$\bar{\theta} \pm 2\sigma_\theta$	$\bar{s} \pm 2\sigma_s$	$[l_{\min}; l_{\max}]$	P over \mathcal{X}_T
R_1	$\{WP\}^{(1)} \pm 5 \text{ km}$	$210 \pm 25^\circ$	$\mathcal{N}(11, 2)$	$[80; 200]$	$[1 \ 0 \ 0 \ 0 \ 0]$
R_2	$\{WP\}^{(2)} \pm 2 \text{ km}$	$245 \pm 30^\circ$	$\mathcal{N}(12, 3)$	$[20; 170]$	$[0.43 \ 0.43 \ 0.05$ $0.05 \ 0.04]$
R_3	$\{WP\}^{(3)} \pm 1 \text{ km}$	$280 \pm 30^\circ$	$[2; 16]$	$[20; 290]$	$[0.5 \ 0.5 \ 0 \ 0 \ 0]$
R_4	$\{WP\}^{(4)} \pm 4 \text{ km}$	$185 \pm 10^\circ$	$[10; 16]$	$[20; 230]$	$[0.75 \ 0 \ 0 \ 0 \ 0.25]$
R_5	$\{WP\}^{(5)} \pm 1.5 \text{ km}$	$325 \pm 20^\circ$	$(\mathcal{N}(12, 2);$ $\mathcal{N}(19, 2))$	$[110; 200]$	$[0.67 \ 0.11 \ 0 \ 0.11$ $0.11]$

For instance, the speed attribute for Route R_i is defined by the tuple $(\bar{v}_i; \sigma_i^1)$ representing the mean and variance of speed values estimated on the training data set of trajectories used to build R_i of a possible normal distribution law. Another representation could be $(\bar{v}_i; \pm\sigma_i^1)$ defining an interval of speed values for R_i .

The maritime traffic (and thus the set of routes extracted) may be influenced by the meteorological conditions (i.e. some areas may be avoided due to specific bad weather), seasonality, economical conditions (i.e. ships may decide or change their destination based on the current stock market linked to their cargo), or even areas of conflict that they would like to avoid. Consequently, the route extraction process would benefit from considering contextual information. For instance:

- The location of specific geographically defined areas such as channels, restricted areas, fishing areas, borders, harbors (fishing, recreational, etc.), shipping lanes, ferry lanes, military, or Liquefied Natural Gas (LNG) anchorage areas can assist by excluding some zones from the route trajectory.
- A port index with geolocalization would help to refine the starting and ending points of the routes.
- The economical situation relative to the objective or vessel of interest for the period when the data were collected would favor some trajectories.
- The period of the year, such as the season, or real-time meteorological conditions could eliminate some outliers in the route construction.
- The user's goals when extracting the routes could define a finer or coarser granularity of the clusters to be built.

In addition to showing how the route extraction process could be improved and refined by contextual information, a further observation can be made about context: This synthetic information, provided as the set of routes together with its associated uncertainty, characterizes part of the context for another problem-solving situation, the detection of anomalies at sea. Thus, the decision variable X_R becomes a context variable for another problem.

Maritime Anomaly Detection

While the extraction of PoL mainly relies on the statistical processing of large amount of data, generally using a single source of information, namely the AIS receiver, the use of several complementary sources of information is crucial for the anomaly detection task. Indeed, although the deviation from normalcy (i.e. pre-extracted PoL) can rely on a single source of information, it appears that other situational indicators may be revealed only by correlating the output of several sources, including cooperative and noncooperative ones. For instance, fusing the Synthetic Aperture Radar (SAR) imagery with the AIS may help in detecting purposefully incorrect self-reported AIS information about the type of the vessel.

Let us thus consider a vessel of interest v among a set \mathcal{O} of objects of interest ($v \in \mathcal{O}$) observed by a series of sources $\mathcal{S} = \{s_1, \dots, s_n\}$ possibly being of different natures, such as a coastal radar and its associated tracker (s_1), a SAR (Synthetic Aperture Radar) image with associated Automatic Target Recognition (ATR) algorithm (s_2), a human analyst (s_3), a visible camera operated by a human analyst (s_4), Automated Information System (AIS) information sent by the vessel itself (s_5), or other intelligence sources. The association problem (i.e. the task of associating a piece of information to an object v), although critical, is not considered here, and it is assumed that all the pieces of information are already associated to v .

Let $\mathcal{A} = \{\text{Position, Heading, Speed, Length, Type}\}$ be the set of attributes of interest to be observed by the set of sources, and let \mathcal{X} be the corresponding observation space:

$$\mathcal{X} = \mathcal{X}_P \times \mathcal{X}_H \times \mathcal{X}_S \times \mathcal{X}_L \times \mathcal{X}_T$$

Estimations of each attribute value a are possibly provided by more than one source, providing redundant information, while the same source may also provide information about different attributes, that is, complementary information. Let us denote $\mathbf{x}_t = \{\phi_{p,t}^{(s_1)}, \phi_{\theta,t}^{(s_2)}, \phi_{s,t}^{(s_3)}, \phi_{l,t}^{(s_4)}, \phi_{T,t}^{(s_5)}\}$, a set of heterogeneous observations jointly provided by the set of sources about the attributes in \mathcal{A} . This notation covers the general case where sources are able to provide some uncertainty about their statement and thus ϕ denotes each source's statement either as a single measurement, a probability vector, a natural language declaration, or another quantity. In the specific case of precise and certain measurements from the sources, \mathbf{x}_t is a vector of \mathcal{X} . The Maritime Anomaly Detection (MAD) problem aims at establishing a mapping:

$$\Psi_{AD} : \mathcal{X} \rightarrow \Omega_{AD} \tag{3.3}$$

$$\mathbf{x} \mapsto \omega \tag{3.4}$$

from the observation space \mathcal{X} to the decision space Ω such that $\omega = \Psi_{AD}(\mathbf{x})$ is the anomaly label assigned to a vessel v under observation, itself represented by the observation vector \mathbf{x} (at time t). The decision space Ω_{AD} could be built, for instance, from a series of anomalies of interest such as:

- ω_0 : "The vessel is physically off-route."
- ω_1 : "The vessel is physically on-route with too high of speed."
- ω_2 : "The vessel is physically on-route travelling in the reverse direction."
- ω_3 : "The vessel is physically on-route with incompatible vessel type."

In this case, we note that Ω is neither exhaustive (v can follow other abnormal behaviors) nor exclusive (v can follow more than a single abnormal behavior above).

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The consideration of these two hypotheses in the problem model is crucial as, for instance, probability theory requires that the universe of discourse is a both exhaustive and exclusive set of hypotheses.

For this problem of anomaly detection, the context provides not only the normalcy conditions (or what is expected) based on historical PoL, but also current information about anything that may impact (and thus explain) the actual behavior of the vessel. The contextual elements of interest for anomaly detection include:

- The set of extracted routes (see Section “Route Extraction”), $\mathcal{R} = \{R_1, \dots, R_K\}$ for the given area over the period of time corresponding to the actual period, therefore providing the set of routes the vessels are expected to follow.
- The site, including harbor zone characteristics such as water depths, channels, restricted areas, fishing areas, borders, harbors (fishing, recreational, etc.), shipping lanes, ferry lanes, military, or Liquefied Natural Gas (LNG) anchorage areas that would explain any deviation from a normal path (expected trajectory).
- The geopolitical situation or the global security alert state, which directly impacts the rules and decisions.
- The meteorological conditions (sea state, weather, etc.).
- The traffic density, which would give expected speed values for the vessel.
- Prior information about the situation, for instance, just before the triggering event.
- Sources and devices providing the information, including their quality.
- The user’s goals in detecting anomalies.

We note that the notion of “anomaly” is itself contextual, as it depends on the user’s information needs as well as on the particular circumstances of the situation. What is abnormal to a given user is what does not match his/her expectations at a specific time. The expectations could be defined by some normalcy, dependent itself on a specific context.

Threat Assessment (Identification)

Detecting anomalies of interest is typically not an end in itself, as anomaly detection is often driven by the higher-level task of threat assessment. In threat assessment, the focus is the vessel’s intent together with the possible consequences of an undesired event. The threat could come from any suspect activity, for example, a terrorist attack, illegal fishing, smuggling, or illegal immigration, which would require an intervention based on an informed decision following a judicious risk assessment.

Target Identification (TI) is presented in Bryant (2009) (citing other authors) as an element of Combat Identification (CID) together with Situation Awareness (SA) and Tactics, Techniques, and Procedures (TTPs). CID is itself defined by Department of Defense (2000) as “[...] the process of attaining an accurate

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characterisation of entities in a combatant's area of responsibility to the extent that high-confidence, real-time application of tactical options and weapon resources can occur." While the recognition task mainly assigns a category (or class) to the vessel under observation, the threat assessment task aims at determining if the target is hostile or friendly. Although we easily understand how these two tasks are linked, especially in an asymmetrical threat context, any object may happen to be hostile, not only those in a particular category. Threat assessment thus relies as well on some behavior and intent assessment, some elements being provided by the anomaly detection task.

The measurement space for the threat assessment problem is built from variables corresponding to different attributes including some anomaly detection outputs, but also other classification information such as kinematic behavior, electromagnetic emission, IFF (Identify Friend of Foe) answers, origin, or nationality. The third edition of NATO STANAG 4162 "Identification Data Combination Process" (STANAG 4162, 2001) provides an exhaustive list of sources of information leading to the "identification" of an object.²

The identification task aims to build a mapping from the observation (or measurement) space to the decision space, for instance:

$$\Psi_{ID} : \mathcal{X} \rightarrow \Theta_{1241} \quad (3.5)$$

$$\mathbf{x} \mapsto \theta \quad (3.6)$$

where STANAG 1241 defines the list of standard identities (STANAG 1241, 2005):

$$\Theta_{1241} = \{ \text{Unknown(U), Assumed Friend (AF), Friend (F)} \\ \text{Neutral (N), Suspect (S), Hostile (H)} \} \quad (3.7)$$

so that $\theta = \Psi_{ID}(\mathbf{x})$ is the NATO standard identity label assigned to the vessel v under observation, itself represented by the observation vector \mathbf{x} (at time t).

While the level of automation for the recognition task can be higher, the identification task itself requires a closer interaction with the human: An information support system would at most suggest labels to the Identification Authority (STANAG 4162, 2001). The identification task does not only rely on sensors' measurements but also on contextual information and risk assessment. For instance, the same object may be assigned a Suspect ID label under a Harbor Protection Level (HPL) of 2, while the exact same vessel with the exact same behavior would be assigned a label Assumed Friend under an HPL of 1.

² "[T]he term identification encompasses all the Military Operational Requirements related to identification: Allegiance, Civil/Military distinction, Platform, Platform Activity (or intent), Specific Type and Nationality" (STANAG 4162, 2001).

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Context-Based Maritime Situation Awareness

In the following, we discuss why the notion of context should be considered in the design of future information fusion systems for supporting Maritime Situation Awareness. We discuss some categorization of context in relation to the famous JDL model of fusion, and provide a general scheme of context-based reasoning in fusion applications.

Why Use Context?

While a unique reference for a definition of context probably does not exist, the ideas conveyed by the different definitions converge. For Dey (2001), “Context is any information that can be used to characterise the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves.” Brezillon (2003), Winograd (2001), and Bouramoul et al. (2001), from a rather philosophical perspective, state that “There is no context without context.” For Brezillon (1999), “Context is what constrains a problem solving without intervening in it explicitly,” and, “context is inseparable from its use.” For Winograd (2001), “The context is a set of information. This set is structured, it is shared, it evolves and serves the interpretation.”

We follow the conceptualization of context in AI, meaning that: [(1)]

1. Context exists only if it is useful, thus its strong relationship with the notion of relevance.
2. The use of context depends on the purpose (Bouramoul et al., 2011; Brezillon, 1999).
3. Context acts as a filter to focus on and better scope problem-solving.

Facing the huge volume of various information, which often lacks veracity, the operator does not only need the appropriate information with sufficient quality to make his/her decision, but also needs to understand its underlying meaning (its origin, how it has been obtained, processed, what was the context of its creation, etc.). For instance, it is of interest for the Vessel Traffic System (VTS) operator to understand how an “anomaly detector” came up with an alert: Which were the reference data? Which sources were processed? Was the information and associated uncertainty obtained in an objective or subjective manner? Did the process consider the sources’ quality, and if so, how? Was the contextual information considered? What is the meaning of the numerical value of the uncertainty output? What was the underlying logical reasoning providing the answer?

It is therefore expected that an adequate problem model explicitly including context specification and characterization will provide: [(1)]

1. The necessary simplicity to understanding the processes by a judicious filtering of information corresponding to the users' needs.
2. The suitable flexibility for the algorithm's implementation by separating the events of interest from their surrounding context.
3. The adequate uncertainty representation and processing considering the sources' quality and uncertainty's origin.
4. The expected human-system synergy for a better understanding of the system's outputs with associated explanations and simpler queries tuned to specific needs.

Categorization of Context and Fusion

Additionally, to the expected benefit of considering context to improve MSA, it is also acknowledged that the processing of a wide diversity of sources would improve the situation awareness of the user. On the one hand, the complexity of the process requires a categorization of the tasks to be performed, which leads in particular to the Joint Directors of Laboratories (JDL) functional model of information fusion (Llinas et al., 2004). On the other hand, the diversity of contexts and context-uses motivates the categorization of context, such as the work of Razzaque et al. (2006) who identified some conceptual contextual parameters for context categorization.

Table 3.2 lists the six categories of context—*user*, *physical context*, *network context*, *activity context*, *device context*, and *service context*—exemplified along three levels of the JDL model.

For instance, the user context of the VTS operator who needs to detect and filter out anomalies at sea (i.e. JDL level 2 task) would determine the level of granularity required for the anomalies, the set of anomalies to be detected, and so on. The physical context would be, in this case, the environmental conditions and the restricted areas, but also the critical infrastructure for the level 3 tasks where the impact needs to be assessed. The device context is the set of sensors available, their locations (which defines their coverage, i.e. the vessels about which they are able to provide information), their performance, and their lifetime.

Contextual Problem-Solving

Problem-solving involves the processing of information provided by hard sources (e.g. sensors, algorithms) and soft sources, provided by human-generated

Table 3.2 Examples of Contextual Information for the Six Categories of Razzaque et al. (2006) along Three JDL Levels

<i>Context Category from Razzaque et al. (2006)</i>	<i>Semantics</i>	<i>JDL Level 1 (Entity Assessment)</i>	<i>JDL Level 2 (Situation Assessment)</i>	<i>JDL Level 3 (Impact Assessment)</i>
User context	Who?	Tracking analyst with the goal of detecting and tracking all targets	VTS operator with the goal of detecting anomalies	Watch Officer with the goal of identifying relevant, suspicious, or hostile events
Physical context	Where?	Coast lines, sea state	Anchorage areas, channels	Critical infrastructures
Network context	Where?	Network of radars	AIS emission and communication network	Hierarchical chain of command, other command entities, intelligence analysts
Activity context	What occurs, when?	Usual tracks or routes	Season, routes, patterns of communication with port authorities	Social media activity, recent piracy/terrorist attacks
Device context	What can be used?	Radars, cameras, satellites	AIS coverage	Availability and accessibility of sources
Service context	What can be obtained?	Location (lat, long), heading (degrees)	Anomalies of interest	Standard identities (e.g. STANAG 1241)

Source: Razzaque, M. A. et al., *J. Auton. Trusted Comput.*, 2006.

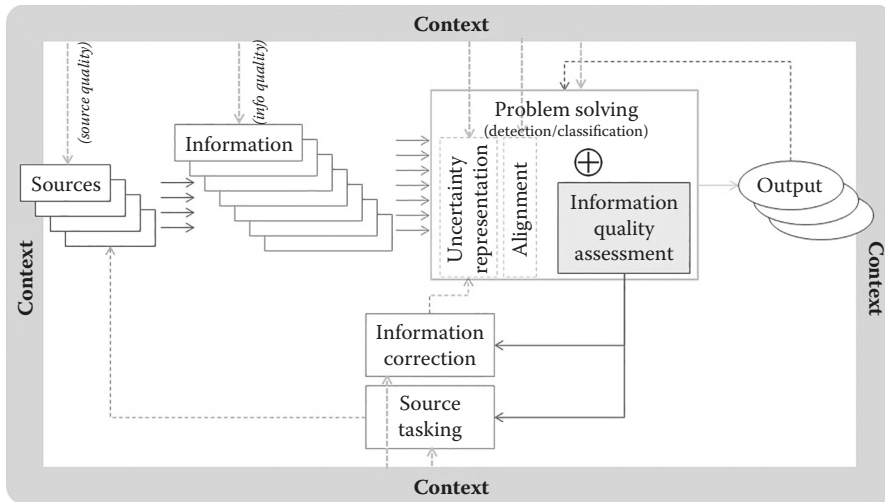


Figure 3.2 General overview of context-based information fusion.

information such as witnesses, social media, and intelligence reports. It outputs some inferred information with a possible feedback loop to either correct the information (e.g. based on conflict assessment and interpretation) or task the sources (e.g. modify or adapt the robot's pattern, reorient the radar). Figure 3.2 displays a general scheme of context-based reasoning with multiple sources of information, whose purpose is twofold: information correction and source-tasking for information gathering. These two corresponding tasks are two examples of the feedback (adaptive) loop recognized as the level 4 of the JDL model, where a system's performance is assessed and used to refine the process on the fly.

The information processing may be very complex but includes at least the following elements, which can possibly all be influenced by context (Llinas et al., 2015): [(1)]

1. Some aspects of uncertainty representation or processing.
2. Some alignment processes as required for combination or fusion functions.
3. A combination/fusion function, putting in relation the different pieces of information, inferring new information.
4. An information quality-assessment process to detect conflicts or characterize the output quality for further use by source-tasking.

One way of formally considering context in fusion processes is to partition the set of variables in context and problem variables, as suggested in Steinberg and Bowman (2013). The three examples of MSA discussed in the previous section highlight the relative notions of context and problem-solving situations.

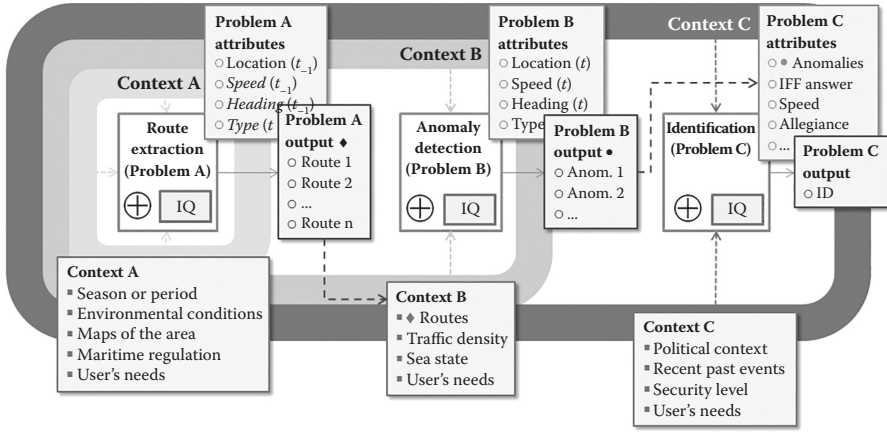


Figure 3.3 Embedded contextual problem-solving situations.

Figure 3.3 displays the three embedded problem-solving situations and their associated context as tuples (Problem A; Context A), (Problem B; Context B), and (Problem C; Context C). For instance, the route extraction problem is seen as contextual information for the maritime anomaly detection problem, which itself provides both situational and contextual information to the threat assessment problem. Indeed, a high number of anomalies detected in a neighborhood area may provide enough justification to a more cautious threat assessment, possibly leading to an increased number of Suspect vessel labellings.

Problems may share some attributes and sources (e.g. both anomaly detection and route extraction use the location attribute) but are not necessarily gathered at the same instant in time: Route extraction uses historical data, while maritime anomaly detection uses current data.

The problem outputs can be either used as contextual information (e.g. the routes) or as a problem attribute for the next problem (e.g. anomalies). Also, the same contextual information can be used as an input to different problems, such as the meteorological conditions.

Just as context is defined relatively to the problem at hand, the measurement and decision spaces are also relatively defined. Indeed, the distinction between these two spaces defines the focus of interest (driven by the user's needs) as the decision space. However, a sequential problem would use this decision space as part of its measurement space. For instance, the different types of anomalies detected within Problem B are inputs (measurements) for the threat assessment problem, which aims at inferring some possible intent from these.

Each problem-solving contains at least an aggregation (or fusion) function, denoted \oplus that allows us to integrate and draw inferences from information provided by different sources, and an information quality assessment function, whose purpose is to detect conflict, assess, and characterize uncertainty about state estimation.

Conclusions and Future Work

The explicit consideration of context is part of the solution to the challenges of the formulation and implementation of naturally embedded problems. It provides greater flexibility and modularity to the design of information systems for more efficient computation. This idea is central to the development of most of the context-based approaches in information systems across different domains such as artificial intelligence, big data, information fusion, and natural language processing. It is expected that a formal consideration of context to the problem of Maritime Situation Awareness would improve the algorithmic solutions to its embedded and interrelated problems such as route extraction, maritime anomaly detection, and threat assessment.

In this chapter, we discussed the benefits of context-based reasoning for Maritime Situation Awareness in the design of information fusion systems. We presented three embedded problems of MSA (route extraction, maritime anomaly detection, and threat assessment) and described their own context. We discussed some benefit of formally introducing the notation of context in the design of MSA support systems within an information fusion perspective, when the variety of sources of information and the associated lack of information veracity is a key challenge. We discussed the system's dimensions influenced by context, and highlighted that context is a relatively defined notion compared to problem-solving situation. While this work is primarily focused on Maritime Situation Awareness where information processing is the core challenge, it can be extended to the information-gathering task, and therefore towards other application domains in which, for instance, the motion pattern of mobile vehicles is driven by an optimized performance of detection or classification (i.e. optimized-source quality).

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Author Query Sheet

Chapter No.: 3

Query No.	Queries	Response
AQ 1	Please provide closing quotation mark for “While “[d] ata fusion refers to the combination...”	
AQ 2	Please confirm the edit to the sentence “The analysis of historical, spatiotemporal...” provide the intended meaning.	
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<i>Abstract</i> <p>Effective maritime situation awareness (MSA) relies on high-level information fusion tasks that benefit from a formal approach to context-based reasoning. This chapter discusses the relative notion of context through the problem of Maritime Situation Awareness. It discusses the MSA problem, exemplifying the three embedded problem-solving and associated contexts of route extraction, maritime anomaly detection, and threat assessment. The chapter highlights the impact and use of context from an information fusion perspective on the MSA problem and argues that context is a relatively defined notion compared to problem-solving situation. Problem solving involves the processing of information provided by hard sources and soft sources, provided by human-generated information such as witnesses, social media, and intelligence reports. The chapter reviews the MSA problems and presents a scheme with embedded problems constrained by different contexts.</p>		
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