



**HAL**  
open science

# A Self-adaptive Multi-Agent System for Abnormal Behavior Detection in Maritime Surveillance

Nicolas Brax, Éric Andonoff, Marie-Pierre Gleizes

► **To cite this version:**

Nicolas Brax, Éric Andonoff, Marie-Pierre Gleizes. A Self-adaptive Multi-Agent System for Abnormal Behavior Detection in Maritime Surveillance. 6th KES International Conference on Agent and Multi-Agent Systems: Technologies and Applications (KES-AMSTA 2012), Jun 2012, Dubrovnick, Croatia. pp.174-185, 10.1007/978-3-642-30947-2\_21 . hal-03792685

**HAL Id: hal-03792685**

**<https://hal.science/hal-03792685>**

Submitted on 30 Sep 2022

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# A Self-adaptive Multi-Agent System for Abnormal Behavior Detection in Maritime Surveillance

Nicolas Brax, Eric Andonoff, and Marie-Pierre Gleizes

IRIT, 118 Rte de Narbonne, 31062 Toulouse Cedex, France  
{nicolas.brax,eric.andonoff,marie-pierre.gleizes}@irit.fr

**Abstract.** This paper presents a Multi-Agent System (MAS) dedicated to abnormal behaviors detection and alerts triggering in the maritime surveillance area. This MAS uses anomalies issued from an experienced Rule Engine implementing maritime regulation. It evaluates ships behavior cumulating the importance of related anomalies and triggers relevant alerts towards human operators involved in maritime surveillance. These human operators evaluate triggered alerts and confirm or invalidate them. Invalidated alerts are sent back to the MAS for a learning step since it self-adapts anomalies values to be consistent with human operators feedbacks. This MAS is implemented in the context of the project I2C, an EU funded project<sup>1</sup> dedicated to abnormal ships behavior detection and early identification of threats such as oil slick, illegal fishing, or lucrative criminal activities (e.g. goods, drugs, or weapons smuggling).

**Keywords:** Maritime Surveillance, Alert, Learning, Adaptive MAS.

## 1 Introduction

Nowadays, maritime activity, which has grown rapidly in recent years, provides support for numerous and various traffic (e.g. arms dealing, goods or drug smuggling) or illicit activities (e.g. illegal fishing). As a consequence, States having long coastlines or vulnerable trading lanes want to have efficient maritime surveillance systems helping them in identifying these criminal activities in order to deal with the threats they represent [1].

To be efficient, a maritime surveillance system must be able to permanently track and monitor all type of maritime activities in order to detect abnormal behaviors, to analyse them and to early identify threatening situations. However, currently there does not exist a system that can handle all the necessary information needed to detect all abnormal behaviours. More precisely such a system must provide [2]:

---

<sup>1</sup> Integrated system for interoperable sensors and Information sources for common abnormal vessel behavior detection and Collaborative identification of threat. See [www.i2c.eu](http://www.i2c.eu) for more information.

- a permanent and all weather coverage of border maritime areas,
- a continuous collection and fusion of heterogeneous data provided by various types of sensors deployed on coast and on mobile platforms and other information from external sources,
- an automatic detection of abnormal ship behaviors (in track and performed activity) and the triggering of alerts if these abnormal behaviors represent potential threats,
- the understanding of these threats in order to allow decisional authorities to deal with them,
- an adapted interface intended to human operators involved in maritime surveillance.

Significant technical progresses have been made in wide maritime area coverage by different sets of sensors [3], in heterogeneous data processing and fusion [4], and in detection of abnormal behaviors methodologies [5] that could be usefully integrated together to built up a new generation of maritime surveillance systems for efficient security applications in high density traffics area [6].

The aim of I2C is to provide maritime surveillance actors with such a system [7]. However, this paper does not report propositions to track ship behavior or to integrate collected information into I2C. It rather focuses on automatic detection of abnormal ship behavior and alert triggering, which is a challenging issue in surveillance systems. The system interacts with and helps human operators in identifying suspicious behaviors among the large amount of ships they observe (hundreds of ships) and for which it is necessary to trigger an alert.

No matter of the application area (maritime surveillance or medical [8], sociological [9], network security areas [10]), we distinguish between two kinds of systems. First, those that model authorised behaviors, using neural networks for instance, and indicate that the observed behavior is abnormal if not described in the model [11, 12]. However, in such systems, unknown behavior is considered as abnormal, which is not necessarily true in our context. Secondly, there are systems modelling domain regulations (*e.g.* maritime regulations) using rules and rule engines to identify abnormal behaviors according to observed events in the supervised areas [13–16]. This solution detects anomalies corresponding to unexpected ship behaviors. But it is inadequate and has to be improved in the maritime surveillance context for three main reasons. First, most of the time, abnormal ship behavior is the result of the violation of several rules simultaneously, and each violation considered independently of one another is not an anomaly and does not require alert triggering. Unfortunately, provided rule engines do not deal with that. Second, maritime regulation is very complex and moreover, alerts are sometimes ship-dependant. Therefore, it is difficult to model this dependence using rules. Third, by using a fully rule-based approach it is impossible to discover new behavior of law offenders who are creative, financially and politically motivated. The system has to be able to identify new abnormal behaviors, and ideally it also has to be able to learn the new strategies by the law offenders [17].

In the project I2C, we advocate to combine a Rule Engine (RE) implementing maritime regulations and an adaptive Multi-Agent System (MAS) [18–20] responsible for ship behavior evaluation and alert triggering. The MAS evaluates the ships behaviours according to the anomalies identified by the RE and triggers alerts. In order to be able to compute this evaluation, the MAS models anomalies and their values as agents and features learning capacity in order to self-adapt anomaly values according to feedbacks of human operators involved in maritime surveillance. This MAS is an important added-value in I2C since maritime surveillance systems have to face evolving situations and law offender behaviors are often unpredictable and have to be discovered [21]. The learning capacity of this MAS is an important skill of I2C [22], and the major contribution of the paper is the proposed self-adaptive MAS for abnormal behavior detection.

The outline of the paper is as follows. Section 2 introduces the architecture of the I2C system and focuses on the role of the MAS. Section 3 describes the Operative Multi-Agent System (OpMAS), the first MAS component dedicated to the evaluation of ships behavior and alert triggering. Section 4 presents the Parameter Adjustment Multi-Agent System (PAMAS), the second MAS component introduced for anomalies values modelling and learning. Section 5 illustrates alerts triggering through an example. Finally, section 6 concludes the paper.

## 2 Architecture of I2C Maritime Surveillance System

This section first introduces the general architecture of I2C and then focuses on the role of the MAS it integrates.

### 2.1 General Architecture of I2C

The architecture of I2C is presented in Figure 1. It integrates several components which are sensors and databases, an intelligent traffic picture called SITU, a RE

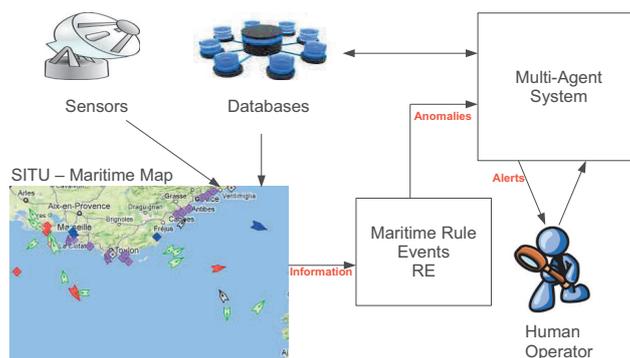


Fig. 1. I2C architecture

dedicated to anomalies detection from maritime regulations and observed events in the supervised area (e.g. ship stopped in international waters), and a MAS responsible for alert triggering if the suspicion level of the cumulated anomalies is too high (e.g. illegal fishing, smuggling of drugs). These alerts are then evaluated by human operators involved in maritime surveillance. If they correspond to threatening situations, authorities perform actions in order to deal with them (e.g. boarding a ship after triggering a drug smuggling alert).

More precisely, SITU integrates and merges information issued from different sources which are both sensors and databases [23] in order to provide a maritime map representing positions of ships in real time. Information from SITU (e.g. position of a ship, speed of a ship, black-listed ship) are then sent to the RE whose aim is to detect anomalies which correspond to suspicious events. The RE integrates maritime regulations described as atomic rules whose conditions refer to information issued from SITU. For instance the following rule expresses that a speed anomaly is detected during an excessive speed of a ship in an harbour: *IF speed > 15 AND area = "Harbour" THEN Detect(Speed\_anomaly)*.

These anomalies are then sent to the MAS whose aim is to trigger relevant alerts towards human operators involved in maritime surveillance. The human operators validate or invalidate these triggered alerts. Validated alerts are transferred to a group of experts for identification of threats and eventual actions (e.g. boarding of a suspicious ship). Invalidated alerts are sent back to the MAS for learning.

## 2.2 Role of the Multi-Agent System

As described in the introduction, the RE that handles maritime regulations is combined with our adaptive MAS for abnormal behavior detection and alert triggering. The role of the MAS is threefold. First, the MAS evaluates ship behavior as a numeric value, called *SBv*, measuring the importance of anomalies identified by the RE. Second, it triggers alerts towards human operators if this numeric value is greater than a threshold given by the human operators. Third, it learns by self-adaptation the importance of anomalies when the human operators invalidate triggered alerts.

## 3 Operative MAS to Compute Ship Behaviour

This section presents our MAS architecture and then focuses on the MAS component dedicated to ship behavior evaluation and alert triggering.

### 3.1 MAS Architecture

As illustrated in Figure 2, our MAS integrates two main components: OpMAS and PAMAS. In OpMAS, a ship-agent is created for each ship monitored by I2C in the real world. OpMAS evaluates ships behaviors considering issued anomalies from the RE. It computes for each ship-agent its corresponding *SBv*, i.e. a

numeric value representing the ship behavior cumulating the importance of its anomalies. It triggers an alert if this value is greater than a threshold defined by a human operator. On the other side, PAMAS models the importance (value) of anomalies through anomaly-agents and parameters-agents. PAMAS distinguishes three values for each anomaly, called parameters, which correspond to the value the anomaly has when it appears (*Init*), the increasing value it has while it lasts (*Incr*) and the decreasing value it has after its disappearance (*Decr*).

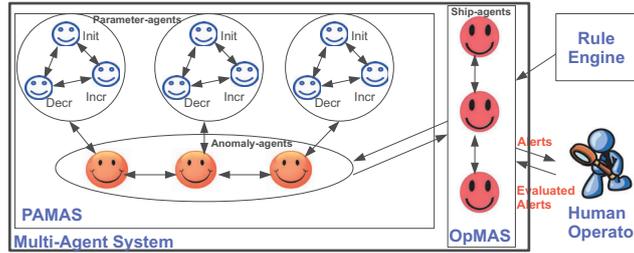


Fig. 2. OpMAS and PAMAS Components

### 3.2 Ship-Agents in OpMAS

Basically, each ship-agent represents a ship and it is filled with skills and abilities in order to reach its goals. First, it integrates abilities to interact with three other components of I2C:

- the RE in order to receive detected anomalies which will be used to evaluate ships behavior according to their corresponding values described in PAMAS,
- PAMAS in order to ask for values of anomalies or for a learning step by self-adaptation of anomalies values,
- human operators who receive triggered alerts from OpMAS, which after evaluation and if invalidated are sent back to OpMAS for a learning step.

Second, a ship-agent associates to the ship it represents a behavior (suspicion) value, called *SBv*. The higher the value, the more the ship behavior is suspicious. This value is computed taking into account anomalies sent by the RE and according to the values of corresponding parameters as estimated by PAMAS. The following function is used to compute this value:

$$SBv = \sum_{i=1}^n Init(a_i) * Nb('Init', a_i) + Incr(a_i) * Nb('Incr', a_i) - Decr(a_i) * Nb('Decr', a_i)$$

The idea is to cumulate the importance of the different anomalies of a ship according to the values of their parameters and taking into account how long these anomalies last. As illustrated in Figure 3, a ship-agent also gives a graphical representation of its behavior as a curve and it also gives the corresponding inequality considering the threshold fixed by human operators. For instance, Figure 3 illustrates a ship behavior involving anomaly  $a_1$  from step0 to step13, and anomalies  $a_1$  and  $a_2$  from step14 to step19. We have the following value for

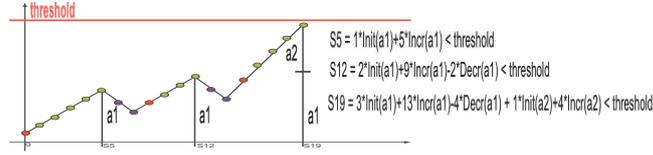


Fig. 3. Computing ship behavior

$SBv$  at step5:  $1 * Init(a_1) + 5 * Incr(a_1)$ . Indeed, at step5  $a_1$  appeared 1 time and lasted 5 times. At step 12,  $a_1$  appeared 2 times, lasted 9 times and decreased 2 times. At step19, both  $a_1$  and  $a_2$  are combined;  $a_1$  appeared 3 times, lasted 13 times, decreased 4 times while  $a_2$  appeared 1 time and lasted 4 times. For each of these values, the ship-agent can deduce the corresponding inequality expressing that the value is lower than the threshold.

Third, a ship-agent interacts with other ship-agents individually using direct messages or collectively using indirect messages. Regarding collective behavior, some illicit ship behaviors cases are difficult to identify as they result from a collective actions from supervised ships, each of them acting normally. Indeed, as they act as normal, the RE does not identify any anomaly since they do not individually contravene maritime regulations. To deal with these particular cases, OpMAS introduces stigmergy based detection mechanisms. As a consequence, a ship-agent can mark its location in the environment in order to inform the other ship-agents of an event that can be relevant to them. Just as pheromone tracks of ants, these marks are cheap in resources and can be a useful source of information [24]. A mark is deposited by a ship-agent with a critical value and a diffusion value giving the lifetime of the mark. When another ship-agent perceives a mark in its environment, it can in turn consider it as a relevant anomaly and then uses it to update its behavior suspicion value.

Finally, regarding individual interactions, a ship-agent can ask for information or data about another ship-agent, for example its suspicious level. A ship-agent can also send an alert to another ship-agent in order to possibly propagate it. Besides, it can send direct messages to another known ship-agent, either because it is in its direct neighbourhood or because of a mark left by the agent. This cooperation is used by the agents to determine the ones that are involved in a given anomaly and, accordingly, the ones that have to be marked as an alert.

#### 4 Parameter MAS to Self-adjust Parameters

This section presents PAMAS that tunes values of anomalies involved in alerts according to human operator feedbacks. It first introduces PAMAS agents, then explains how this tuning is performed, using a self-adjusting approach, and finally how situation historic can be taken into account to improve the tuning.

#### 4.1 PAMAS Agents

To each type of anomaly sent to OpMAS by the RE, there is a corresponding agent in PAMAS, called anomaly-agent. This anomaly-agent manages the value of the anomaly as a function of three parameters, each represented as a parameter-agent:

- the *initial value*, *Init*, of the anomaly which can be seen as the prime importance of the anomaly,
- the *increment value*, *Incr*, which is the increasing importance of the anomaly while it lasts and,
- the *decrement value*, *Decr*, which represents the time the anomaly is kept in memory once it has disappeared.

As these parameters are a representation of the human operators knowledge, it is difficult to give them a value. Therefore, PAMAS provides initial values to these parameters and then tunes them according to the human operator feedbacks in order to reach acceptable values which correspond to a stable state of the MAS, and consequently to trigger relevant alerts. This self-tuning is possible due to the cooperation between anomaly-agents and parameter-agents.

#### 4.2 Tuning Parameters

Whenever a ship-agent retrieves the values of some anomalies and combines them to compute *SBv*, PAMAS expects a feedback on these values. This feedback can be positive if OpMAS raises an alert and the operator confirms it or, if there is no confirmation, the MAS assumes the values are good enough. However, the feedback can also be negative if OpMAS raises an alert and the operator negates it, or when the system did not raise an alert and the operator spots one. In this case, PAMAS needs to tune the parameters values of the corresponding anomalies in order to correct the mistake it did. Basically, the anomalies-agents must lower or increase the values of anomalies according to the human operator feedbacks and the defined threshold.

In order to do this, anomaly-agents use two mechanisms to tune themselves. On one hand, a critical level is associated to each anomaly-agent. This critical level is calculated depending on the importance of the anomaly in the alert, and also on the use of this anomaly by other ship-agents. The suspicious value of a ship is directly influenced by the anomalies in proportion to their importance. And the constraints on an anomaly are dependent of its frequency in the behaviors of the other ships. Therefore, we can say that the critical level will weight the adjustment of the anomaly in a proportional way.

On the other hand, in most cases, an alert is the combination of several anomalies. Therefore, the different anomaly-agents involved have to cooperate in order to tune their values and adjust the global value of the ship behavior according to human operators feedbacks. This cooperation is based on the exchange of the critical level values of the anomalies. Knowing the critical level of the other involved anomalies, the agents can build a rank system and then update their critical level according to the other agents.

We can actually say that the basic adjustment of the anomaly-agents is based on the critical level of each one, which will weight the tuning of the parameters. Such a method, however, have a negative impact on the system. Indeed, when an anomaly-agent tunes itself, it can reach a state where its value goes against a past situation with no negative feedback. Then, if this situation happens again, PAMAS will have to tune the parameter values again. This can lead to a system that will never converge into a stable state and so will never be able to raise relevant alerts towards human operators. As a consequence, we have improved the learning of the MAS as explained in the next section.

### 4.3 Collective Learning from Past Situations

We propose to take into account past situations while PAMAS tunes itself. These situations can be of two kinds:

- situations where the system is in a highly constraint state, meaning that the value of at least one of the anomalies is estimated to be correct by the system because a change of this value would change the "alert state" of the corresponding ship,
- situations which are known to be a negative feedback in order to avoid the repetition of these negative feedbacks.

These situations are used to tune the values of anomaly-agents parameters. Each anomaly-agent tunes itself according to its own critical level and the critical levels of its neighbourhood, i.e. the other involved anomaly-agents. Basically, the agents learn from their history to avoid the repetition of past errors and this ensures the convergence of the system into a stable state.

In order to illustrate this idea, we take the example represented in Figure 3 and we suppose that a human operator sends a negative feedback at step19 indicating that  $SBv$  should be greater than the threshold. As explained before, this negative feedback induces a learning step from PAMAS and, more precisely, a self-adaptation of the parameters of the anomalies  $a_1$  and  $a_2$ , since these two anomalies are involved in the considered ship. In order to improve the tuning of these parameters, PAMAS considers the situation of step12 in addition to the situation of step19 and it self-adjusts the values of  $a_1$  and  $a_2$  considering the two following inequalities:

$$\begin{aligned}
 S12 : 2 * Init(a_1) + 9 * Incr(a_1) - 2 * Decr(a_1) &< threshold \\
 S19 : 3 * Init(a_1) + 13 * Incr(a_1) - 4 * Decr(a_1) + 1 * Init(a_2) + 4 * Incr(a_2) &< threshold
 \end{aligned}$$

Indeed, PAMAS considers the situation of step19 as it is a negative feedback from the human operator and the inequality used for self-adaptation of parameters values is  $3 * Init(a_1) + 13 * Incr(a_1) - 4 * Decr(a_1) + 1 * Init(a_2) + 4 * Incr(a_2) > threshold$  as the MAS did a mistake when calculating  $SBv$  which must be greater than the given threshold. It also considers step12 since the system is in a highly

constraint state. Thus, in order to deal with the situation of step19 (which is incorrect), PAMAS will increase the value of  $a_1$ , without contravening the situation of step12 (which is correct).

### 5 Alert Triggering Example

This section illustrates the behaviors of the OpMAS and PAMAS agents through an example. This example considers three fishing ships A, B and C, and an unknown ship out of the surveillance coverage. This example also considers only the "stop in open sea" anomaly. This anomaly alone does not lead to an alert, but we will see how the collective behavior of the agents can trigger a relevant alert.

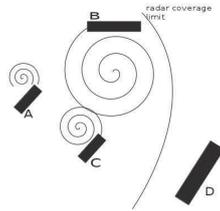


Fig. 4. Fishing ships A, B and C; unknown ship D

#### 5.1 Individual Behavior in PAMAS

According to Figure 5.a, at *step0*, the fishing ship A stops in open sea. This event is detected by the RE which sends an anomaly to OpMAS. The corresponding ship-agent retrieves the value of the anomaly in PAMAS and computes  $SB_v$ , the value of the behavior of the ship. The current anomaly is not enough to raise an alert, but the suspicious level of the ship is increased and the ship-agent leaves a mark in the environment, reporting the anomaly for others.

At *step10*, we can see on Figure 5.b that the fishing ship B also stops in open sea, near where the first mark was left by the ship A. The RE sends another anomaly to OpMAS in order to compute the value of the ship behavior. But this time, the ship-agent uses the mark in the environment in addition of the value

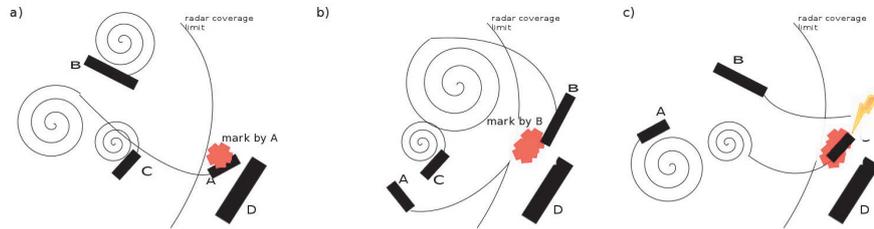


Fig. 5. a) *Step0*; b) *Step10*; c) *Step14*

sent by PAMAS to increase the suspicious level. Again, this is not enough to raise an alert but another mark is left, strengthening the first one.

At *step14*, the third fishing ship stops near the previous locations. This time, the value computed by OpMAS uses the value received from PAMAS as well as the two marks previously left by the other ship-agents. This computation leads to an increase of the suspicious level of the third ship, which is sufficient to raise an alert on this ship.

## 5.2 Collective Behavior in OpMAS

We have just seen that the ship-agents in OpMAS use the anomalies sent by the RE as well as the marks left in the environment in order to compute the suspicious level of the ships they represent. Furthermore, the ship-agent C which is detected as suspicious can use the information on the marks in the environment. Indeed, we can consider that if several ships have stopped at the same location in a limited amount of time, and one has a suspicious level high enough to raise an alert, the other ships are suspicious too. As shown in Figure 6, the ship-agent C will contact the two other fishing ship-agents and systematically inform them about the alert. Depending on the other available informations, the MAS can even detail the alert. In our example, the three involved ships are fishing ships. The MAS can consequently assume that the three detected stops are part of a transshipment operation and then spot the possible presence of a refrigerated ship, here our unknown ship D. Finally, the alert triggered by the MAS is *Illegal fishing*.

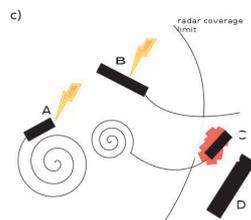


Fig. 6. The alert is spread to other ships

## 6 Conclusion

In this paper, we have presented a Multi-Agent System (MAS) dedicated to abnormal behavior detection and alert raising in the maritime surveillance domain. This work takes place in the European funded project I2C. Based on anomalies sent by an experienced Rule Engine (RE), the MAS evaluates ships behavior according to the importance (value) of the related anomalies and raises relevant alerts towards human operators involved in maritime surveillance. One of the main aspect of the MAS is its ability to learn from human operators feedbacks and it self-adapts the values of the anomalies to be consistent with these feedbacks. More precisely, the paper has presented the two main components of the MAS. First, the Operative Multi-Agent System (OpMAS) which represents the

real ships as agents, computes ship behavior values and sends alerts to human operators. Second, the Parameter Adjustment Multi-Agent System (PAMAS) is used to self-adapt the values of the anomalies according to the feedbacks from the human operators and takes into account an historic of events through past situations. This tuning allows the whole system to be consistent with the feedbacks and improves the relevance of the alerts raised by OpMAS.

This MAS is implemented in a simulation platform which integrates several other components in order to test and use our proposition. One component simulates the rule engine and sends anomalies to the OpMAS. Another simulates the human operators, receiving the alerts from the OpMAS and sending the needed feedbacks. Finally, there is also a component building random intelligent scenarios for each ship and managing the whole platform to maintain its relevance. Our current preoccupation is the implementation of the tuning of the PAMAS agents behaviour.

The next step will be the evaluation of the efficiency and the effectiveness of the MAS with respect to the real-world data provided by I2C, *i.e.* with a natural number of ships and a relevant number of anomalies.

**Acknowledgement.** The authors would like to thank DCNS who leads the European project I2C and who is involved with us and Clear Priority in the work packages dedicated to abnormal behavior detection. The authors would also like to thank Henric Johnson, from the Blekinge Tekniska Högskola in Karlskrona – Sweden, for the fruitful discussions we had together on this topic and for his comments on earlier versions of the paper.

## References

1. Henocque, Y., Lafon, X.: EUs Strategy on Maritime & Environmental Issues in the Four Seas: multilateral approaches in the Baltic, Black, Caspian & Mediterranean Seas. The EU and Europes Sea Basins, Tallinn (2011)
2. Ince, A., Topuz, E., Panayirci, E.: Principles of Integrated Maritime Surveillance System. Springer, Netherlands (1999)
3. Rasheed, Z., Shafique, K., Yu, L., Lee, M., Ramnath, K., Choe, T.E., Javed, O., Haering, N.: Distributed Sensor Networks for Visual Surveillance. In: Distributed Video Sensor Networks, pp. 439–449 (2011)
4. Battistello, G., Ulmke, M., Koch, W.: Knowledge-aided multisensor data fusion for maritime surveillance. In: Proceedings of SPIE, vol. 8047 (2011)
5. Wang, B., Ye, M., Li, X., Zhao, F., Ding, J.: Abnormal crowd behavior detection using high-frequency and spatio-temporal features. In: Machine Vision and Applications, pp. 1–11 (2011)
6. Aliakbarpour, H., Khoshhal, K., Quintas, J., Mekhnacha, K., Ros, J., Andersson, M., Dias, J.: HMM-Based Abnormal Behaviour Detection Using Heterogeneous Sensor Network. In: Camarinha-Matos, L.M. (ed.) Technological Innovation for Sustainability. IFIP AICT, vol. 349, pp. 277–285. Springer, Heidelberg (2011)
7. Morel, M., Claisse, S.: Integrated System for Interoperable sensors & Information sources for Common abnormal vessel behaviour detection & Collaborative identification of threat (I2C). In: Proc. of the Ocean and Coastal Observation: Sensors and Observing Systems, Numerical Models and Information Systems, Brest, France (2010)

8. Li, X., Xue, Y., Chen, Y., Mali, B.: Context-aware anomaly detection for electronic medical record systems. In: Proceedings of the 2nd USENIX Conference on Health Security and Privacy, p. 8 (2011)
9. Gupta, S., Hossain, L.: Towards near-real-time detection of insider trading behaviour through social networks. *Computer Fraud & Security* 2011(1), 7–16 (2011)
10. Shi, Y., Tian, Y., Kou, G., Peng, Y., Li, J.: Network Intrusion Detection. In: Optimization Based Data Mining: Theory and Applications, pp. 237–241 (2001)
11. Fok, V., Lingard, D.M.: Using a Genetic Algorithm to Optimise Maritime Surveillance Performed by Space-based Sensors. National Committee for Space Science & National Space Society of Australia, Barry Drive, Australian National University, Canberra, ACT, Australia (2011)
12. Celik, M., Dadaser-Celik, F., Dokuz, A.S.: Anomaly detection in temperature data using DBSCAN algorithm. In: IEEE Innovations in Intelligent Systems and Applications (INISTA), pp. 91–95 (2011)
13. Tan, K.: A multi-agent system for tracking the intent of surface contacts in ports and waterways. Naval Postgraduate School Monterey CA (2005)
14. Jakob, M., Vaněk, O., Urban, Š., Benda, P., Pěchouček, M.: AgentC: agent-based testbed for adversarial modeling and reasoning in the maritime domain. In: Proceedings of the 9th International Conference on Autonomous Agents and Multiagent Systems, vol. 1, pp. 1641–1642 (2010)
15. Gupta, K.M., Aha, D.W., Moore, P.: Case-Based Collective Inference for Maritime Object Classification. In: McGinty, L., Wilson, D.C. (eds.) ICCBR 2009. LNCS, vol. 5650, pp. 434–449. Springer, Heidelberg (2009)
16. Nilsson, M., van Laere, J., Ziemke, T., Edlund, J.: Extracting rules from expert operators to support situation awareness in maritime surveillance. In: Proceedings of the Eleventh International Conference on Information Fusion. IEEE (2008)
17. Auslander, B., Gupta, K.M., Aha, D.W.: A comparative evaluation of anomaly detection algorithms for maritime video surveillance. In: Society of Photo-Optical Instrumentation Engineers (SPIE), vol. 8019, p. 3 (2011)
18. Bernon, C., Gleizes, M.-P., Peyruqueou, S., Picard, G.: ADELFE: A Methodology for Adaptive Multi-agent Systems Engineering. In: Petta, P., Tolksdorf, R., Zambonelli, F. (eds.) ESAW 2002. LNCS (LNAI), vol. 2577, pp. 156–169. Springer, Heidelberg (2003)
19. Gleizes, M.-P., Camps, V., Georgé, J.-P., Capera, D.: Engineering Systems Which Generate Emergent Functionalities. In: Weyns, D., Brueckner, S.A., Demazeau, Y. (eds.) EEMMAS 2007. LNCS (LNAI), vol. 5049, pp. 58–75. Springer, Heidelberg (2008)
20. Di Marzo Serugendo, G., Gleizes, M.-P., Karageorgos, A.: Self-organising Software - From Natural to Artificial Adaptation. Springer Natural Computing Series (2011)
21. Ristic, B., La Scala, B., Morelande, M., Gordon, N.: Statistical analysis of motion patterns in AIS data: Anomaly detection and motion prediction. In: 11th International Conference on Information Fusion, pp. 1–7 (2008)
22. Mano, J.-P., Georgé, J.-P., Gleizes, M.-P.: Adaptive Multi-agent System for Multi-sensor Maritime Surveillance. In: Demazeau, Y., Dignum, F., Corchado, J.M., Pérez, J.B. (eds.) Advances in PAAMS. AISC, vol. 70, pp. 285–290. Springer, Heidelberg (2010)
23. DCNS: Description of Work. Project I2C (2010)
24. Tsankova, D.D., Georgieva, V.S.: From local actions to global tasks: simulation of stigmergy based foraging behavior. *Intelligent Systems*, 353–358 (2004)