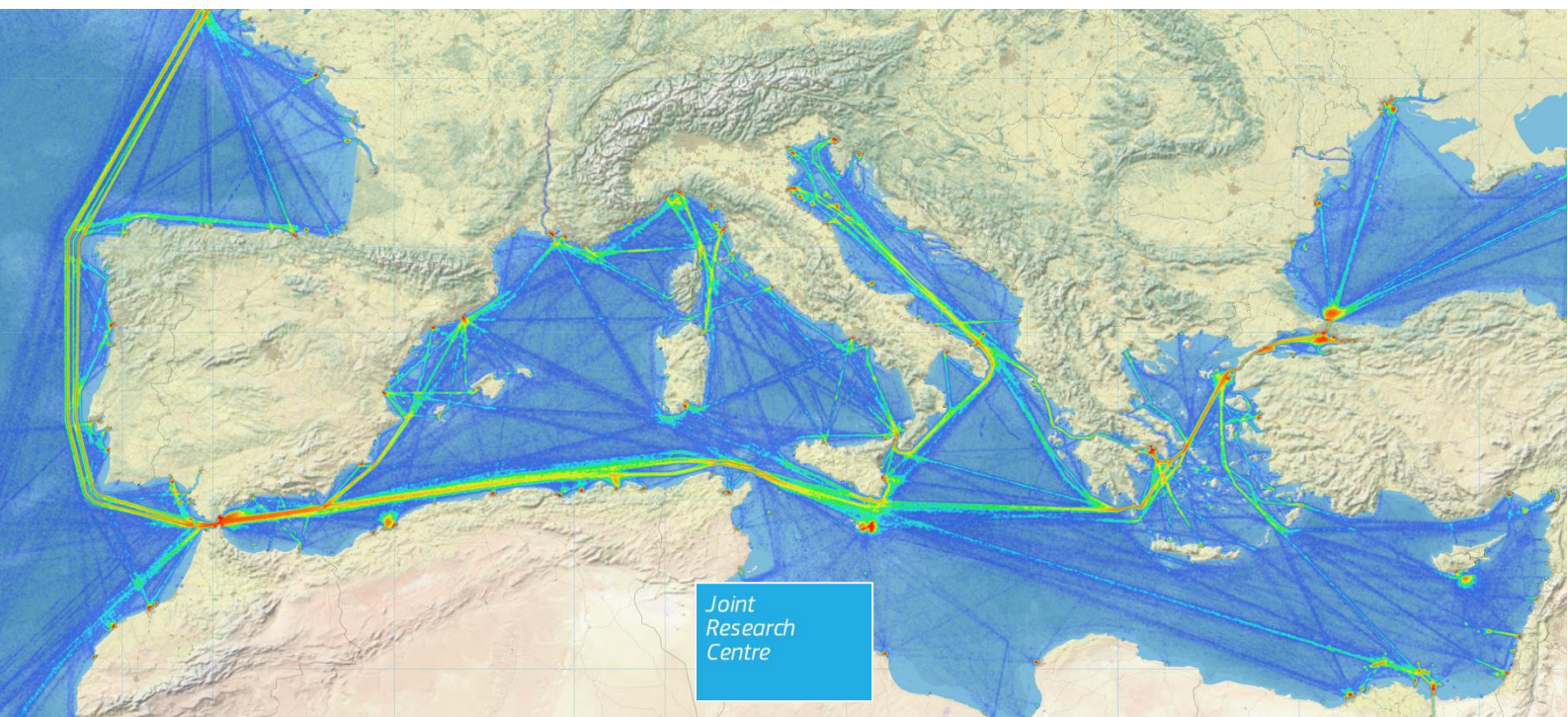# JRC CONFERENCE AND WORKSHOP REPORTS

Maritime Knowledge Discovery and Anomaly Detection Workshop Proceedings

Ispra, 5-6 July 2016

Edited by Michele Vespe and Fabio Mazzarella

2016

Contact information
Name: Michele Vespe, Fabio Mazzarella
Address: European Commission – Joint Research Centre, Via Enrico Fermi 2749, 21021 Ispra (VA)
E-mail: michele.vespe@jrc.ec.europa.eu, fabio.mazzarella@jrc.ec.europa.eu
Tel.: +39 0332 785024 ; +39 0332 789154

TABLE OF CONTENTS

FOREWORD

Thousands of vessels cross EU waters and hundreds enter into EU ports every day, generating an overwhelming amount of tracking data and reports that make it possible to disguise illegal operations. Detecting steadily changing deceptive behaviours at sea is becoming like trying to find a needle in a haystack and calls for advanced automatic and adaptive tools to discover useful information from the data.

Data mining, information fusion and visual analytics are becoming central to the discovery of knowledge from the increasingly available information on vessels and their movements (e.g. Automatic Identification System - AIS, Long Range Identification and Tracking - LRIT, radar tracks, Earth Observation) at global scale. This enables the automatic detection of structured anomalies, the prediction of vessel routes up to a few days in advance, the behavioural characterisation of vessels, the understanding and mapping of activities at sea and the analysis of their trends over time. Such knowledge provides a new set of possibilities for improving Maritime Situational Awareness and safety of navigation, understanding what is happening and might be happening at sea.

This event brought together technology and research providers (academia, industry) and users (operational authorities) in the field of Maritime Knowledge Discovery to identify current capability gaps and highlight the most promising research strands.

Authorities set the scene either through presentations (Section I), speeches and live demos introducing the current operational capabilities. This was followed up by industry (Section II), showing the latest state-of-the-art on big data services in the maritime domain. Finally, academia and research centres introduced the latest research efforts and methods to improve knowledge discovery in the maritime domain (Section III).

A final round-table discussion helped collecting suggestions from authorities and industry to highlight the most promising and relevant areas of research and identified, together with research providers, possible solutions. This is summarized in the Conclusions and Remarks Section.

SECTION I: OPERATIONAL AUTHORITIES

STATISTICAL ANOMALY DETECTION FOR MARITIME SURVEILLANCE AND MONITORING

Anders Holst[1], Peter Ryman[2], Anders Linse[3]

[1]SICS Swedish ICT
[2]Swedish Coast Guard
[3]HiQ

ABSTRACT

In a six year research collaboration between authorities, academy and industry, a module for anomaly detection has been developed, the SADV module, which is since 2016 in operation in the maritime surveillance system SjöBASIS used by Swedish authorities. The SADV module detects anomalies in the maritime situational awareness picture, which increases the maritime authorities capacity to discover, react and prevent risks at sea.

The module is generic, in the sense that it can be adapted for several maritime surveillance systems, and it can be extended with new statistical, rule based, or hybrid anomaly detection capabilities. Currently implemented anomaly detection functions include detection of unusual movement patterns, meetings at sea, and risk of grounding. The interface between the anomaly detection module and the surveillance system is thin to make adaptation easy.

Index Terms— Maritime surveillance, Anomaly detection, Movement pattern, Meetings at sea, Risk of grounding

1. BACKGROUND

Maritime traffic is constantly increasing, and is expected to continue to grow. Only around the coasts of Sweden there are around 8000 maritime vessels at any instant. It is a demanding task for the maritime surveillance operators to monitor all these vessels and find those that are involved in incidents, hazardous behaviour, or illegal activities. The purpose of the six year research collaboration SADV, "Statistical Anomaly Detection and Visualization for Maritime Domain Awareness", has been to develop a tool that can support the operators by finding and highlighting vessels with anomalous or suspicious behaviour. To solve this, a module for anomaly detection for use within maritime surveillance platforms was developed. The project was jointly lead by the Swedish Coast Guard responsible for development of SjöBASIS, HiQ that implements and maintains the SjöBASIS system, and the computer science research institute SICS with over 15 years experience of developing and applying methods for anomaly detection. Other participants were the Swedish Customs Service, the Swedish Armed Forces, Saab AB, the Swedish Space Company, and Blekinge University.

2. SADV MODULE ARCHITECTURE

The SADV module is designed to be highly generic, in the sense that it can be adapted for several maritime surveillance systems, and it can be extended with several different anomaly detection capabilities. To make it easy to adapt to different surveillance systems, the module communicates via a restful web interface, which is kept minimal for simplicity: In essence, maritime situational data is fed from the surveillance system to the module, which analyses it and sends back generated alarms for presentation in the surveillance system. It is also possible to configure the module via the interface, to control which kind of detection is activated and with what parameters.

There are different approaches for anomaly detection. They can essentially be divided in three classes: Statistical methods, in which a statistical or data driven model is build up of the ``normal'' behaviour, and a new situation is compared to this model; Rule based methods, where conditions are formulated that describes the
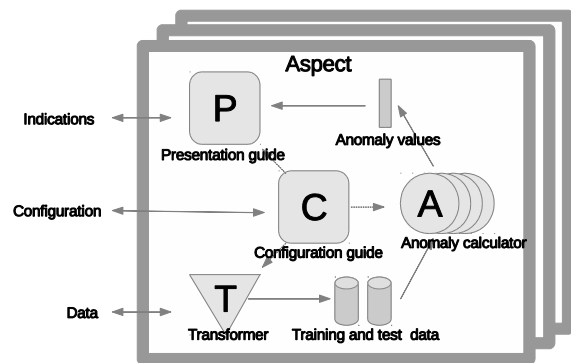
Figure 1 Internal Architecture of the Anomaly aspects in the SADV module.

anomalous situations of interest; and Model based methods, in which a physical model or simulator is created to mimic the real system, and when the real system diverges from the simulation there is an anomaly. The most common approach in maritime surveillance has been rule based, i.e conditions can be formulated for ships to detect. When statistical methods are used they are often quite simple, such as focusing on momentary speed and direction. The goal in the SADV project has been to create a framework that can handle all the approaches [1] and to significantly advance the use of statistical anomaly detection.

There are different ways for a vessel to be anomalous. Which anomalies that are found by a specific detector depend on which features in the data that are considered. The SADV module uses the concept of *Anomaly Aspects*, each of which focuses on a specific type of anomaly, i.e. checks for anomalies with respect to a certain set of features, using one or a combination of the anomaly detection approaches. Figure 1 shows the internal structure of an Aspect. The most critical part of an Aspect for what anomalies are found is the *Transformer*, which converts the stream of raw situational data into the relevant high level features. The *Anomaly calculator* assesses the anomaly score based on those features, and the *Presentation guide* maintains a set of anomaly indications based on those scores.

3. IMPLEMENTED ANOMALY DETECTORS

Currently there are three Anomaly Aspects implemented and used in operation today. They are described here. The SADV module is designed to make it easy to add new aspects in the future.

3.1 Movement pattern

The *Movement pattern aspect* is a statistical anomaly detector. Rather than focusing on momentary speed and course, it characterises a vessel in terms of how many stops and turns it performs during a journey. The idea is that each vessel type has a certain probability of performing different movements at any instant, and the movements will give some indication of the activities of the vessel. Based on previously reported data there is an estimation of an expected number of movements, during a certain period of time, connected to a certain type of vessel. If the number of movements exceeds the accepted statistical variation, this is considered an anomaly that could be worth checking manually. The aspect takes into consideration various movements typical of standard vessels, such as speed changes, stopping, waiting still, turnings and rotation, and also whether the movement was performed close to the shore or in open sea. The aspect uses the ISC framework for

statistical anomaly detection [2], based on parametric models and Bayesian statistics.

When a ship starts to move in an uncharacteristic way, e.g. turns unexpectedly or stops too many times, the alarm will go off. One example is a container ship which in October 2015 was en route from Poland to Ystad in the south of Sweden in rough weather. The system detected that the ship had lost the ability to steer and started to drift, due to its irregular movements.

Patterns of movement that does not match the boat type can also reveal that the ship is doing something illegal, such as a recreational boat who behaves like a fishing boat can try to escape the fishing quotas.

3.2 Meetings at sea

When two boats meet at sea, it may be indicative of fraudulent activity. It may be smuggling, attempted piracy, or unloading the catches to avoid fishing quotas. Another kind of meeting is two boats running in parallel, which may indicate trawling, which is not permitted everywhere.

Most surveillance systems offer the opportunity to check for meetings with an in advance specified vessel. However, the *Meeting aspect* is a rule based detector which employs an indexing scheme to be able to quickly detect meetings between *any* two vessels not of a type that are expected to meet. Especially interesting are meetings when one of the vessels is lacking any transponder signal such as AIS.

3.2 Risk of grounding

The *Grounding aspects* is a combination between a rule based and statistical detector which tries to predict if there is a risk of running aground. A vessel that moves off the fairway and approaches waters shallower than the draught of the vessel will generate an alarm. The rule based part compares the draught with the depth ahead of the vessel according the sea chart. The statistical part compares the vessels position and course with how other vessels have moved to see if it is significantly different.

A grounding alarm is generated about 3 minutes before the grounding will happen, which will give the vessel time to react and steer away. Since the grounding of tankers is one of the most serious threats to our oceans, the possibility of real-time monitoring of grounding risk is an important functionality.

4. DISCUSSION

The SADV module is used in operation since January 2016 at the Swedish Coast Guard. The basic principles are based in more than 15 years research. Yet it is a major endeavour to actually make these methods work in practice.

First, of course, real world data is never clean. There are missing data, noisy data, and even deliberate misinformation in the data, all of which must be handled. This requires robust methods that do not rely on perfect data. Unrealistic or improbable sensor readings, such as rapidly fluctuating speeds or positions, should be filtered out. It is otherwise a common phenomenon that issues with the data quality will give rise to false alarms, i.e. the vessel is quite normal but noise in the data make it appear strange (like rapidly jumping between two distant locations).

Much work has been done to minimise the number of false alarms. A system that gives too many false alarms is not trusted by the operators and will soon be ignored. Therefore, the goal has been that the number of false alarms must be in the same order as the number of real interesting events. This is a very high ambition in fact, as the number of interesting events is so much smaller than the number of evaluated events, and there are so many artifacts in the data that may give rise to false alarms.

The sampling frequency differs much between different sources. Some sources are sampled in the order of once every ten seconds, whereas others are only sampled once every six minutes. To be able to detect the risk of grounding with three minutes margin, or detect vessels that are drifting by noting their irregular movements, six minutes is clearly too long. Furthermore, data from some sources are delayed, sometimes up to 20 minutes, before they reach the surveillance system, which poses a similar problem. When designing future surveillance systems this should be kept in mind.

Many surveillance systems offer the possibility for the operators to design rules for what to detect. One experience from this project is that designing a useful detection rule takes considerable effort, and knowledge both of the maritime surveillance domain and of anomaly detection methodology. Fine tuning the rule to avoid false alarms take even longer. It is not feasible to assume that the operators can spend their time to design such rules. Useful rules need to be provided for the operators by the system.

There is currently a strong demand for tools and decision support in surveillance and monitoring, and development within statistical machine learning and anomaly detection is very rapid. There will be many more systems appearing for maritime anomaly detection in the near future. No doubt there is much more to do, but the SADV project has given many valuable insights and experiences in this process.

5. REFERENCES

[1] A. Holst, B. Bjurling, J. Ekman, Å Rudström, K. Wallenius, M. Björkman, F. Fooladvandi, R. Laxhammar, and J. Trönninger, "A Joint Statistical and Symbolic Anomaly Detection System: Increasing performance in maritime surveillance," in *15 th International Conference on Information Fusion (FUSION)*, 2012 pp.1919-1926.

[2] A. Holst, J. Ekman, "Incremental stream clustering for anomaly detection and classification," in *11th Scandinavian Conference on Artificial Intelligence*, 2011 pp.100-107.

PORTUGUESE NAVY PERSPECTIVE IN MARITIME SITUATIONAL AWARENESS – THE ANOMALY DETECTION

LCDR Pedro Serafim
Portuguese Navy

1. INTRODUCTION

In the last few years, a significant increase in marine traffic has been registered in the Portuguese Sea Lines of Communication. A 65%-fold increase[1] in Automatic Identification System (AIS) contacts alone has been reported. This kind of heavy traffic brings a whole new challenge in the management and tracking of the full spectrum of marine activity. An increased flow in activity brings an increased number of subsequent illegal activities. To face this situation, the Portuguese Navy is committed in the development of its maritime systems, preparing itself to face new challenges in the maritime security domain, in order to control, protect and act in its areas of interest. Portugal has a large maritime area of responsibility and therefore a high effectiveness is required to the Portuguese Navy, in terms of surveillance. The Portuguese Navy Maritime Operations Centre (COMAR) performs an important role in this regard, in order to develop a full Maritime Situational Awareness.

In terms of law enforcement, the Portuguese Navy major tasks range from patrol and surveillance of maritime activities, to direct combat of illicit activities (such as illegal fishing, drug trafficking, illegal immigration or piracy) never forgetting the sustainability of the ocean and its resources.

2. COMAR AND THE MARITIME SITUATIONAL AWARENESS

COMAR was created in June of 2008, under the Portuguese Navy's Command Fleet structure. The Centre is co-located with the Maritime Rescue Coordination Centre Lisboa. The mission of COMAR is to support the operations of the Portuguese Navy, the Maritime Authority activities and the Hydrographic Institute in conducting operations, exercises and other activities at sea, in order to ensure the freedom of navigation and protection of the sea lines of communication as well as a more effective and efficient

---

[1]2014 – 198 028 AIS Contacts
  2015 – 305 690 AIS Contacts

State Authority in the areas under national sovereignty and jurisdiction.

On the other hand, COMAR is also responsible for collecting, processing and sharing the information required for the acquisition and maintenance of a maritime situational awareness in the Portuguese State area of interest, in coordination with the Joint HQ (EMGFA) and other national and international operational centers.

To accomplish its mission, COMAR has a diverse array of technological systems (military and civilian) and the necessary human resources and organization. The centre is equipped with many information systems that can be divided in two broad categories:

<u>Coastal Systems:</u> A network of Automatic Identification System (AIS) Support Structures, Vessel Monitoring System (VMS), Vessel Traffic Services (with Coastal Radars), Integrated Maritime Data Environment (IMDatE) from EMSA;

<u>Offshore Systems:</u> Which include Satellite AIS (SAT AIS), the Long Range Identification and Tracking (LRIT) the VRMTC coordinated by Italian Navy, and NATO Military Systems (MCCIS, C2PC, and MMHS).Both of those systems rely heavily on the information and validation gathered by the Navy and Air Force assets. The management of all the information in a coherent decision making support structure is crucial. Therefore, all the processes ranging from analysis to validation, contribute cumulatively to the overall superiority of information for decision making, in all three levels of operational activity (tactical, operational and strategic). This constitutes the main mission and purpose of COMAR: to provide a coherent and integrated support for decision making.

In terms of human resources, the complement of the Centre is comprised of teams of 7 people in 12-hour shifts, on a 24/7 basis. The modular arrangement of the centre allows the installment of several extra workstations, which upgrade the planning and execution capacity for a large spectrum of operations and other actions at sea.

2.1. The anomaly detection

Since 2012, COMAR use a system developed by Portuguese Navy and the National Company Critical Software, OVERSEE.

OVERSEE is a system of systems that provides a geo-referenced display of traffic information (AIS, SAT AIS and VMS), Global Maritime Distress System (GMDSS) distress alerts (COSPAS - SARSAT) and Meteorological information, all spread out in cartographic and hydrographic layers, available in a single screen. This system is based on three pillars: Law Enforcement, Search and Rescue and Environmental Protection.

To support the Law Enforcement, the system creates and manages different alarms, based on parameters such as vessel characteristics, position and status, cartographic elements such as Economic Exclusive Zone, Search and Rescue Area, Territorial Waters, or a specific area defined by the operator. This tool, allows operators to set up alarms to trigger when the system detects a vessel-related event based on a set of conditions:

Listed vessels enters area: will trigger an alarm whenever one of the vessels specified on a list enters one of the specified areas (e.g. whenever vessels X,W or Z enter the Portuguese EEZ).

Vessel with set of characteristics enters area: will trigger an alarm whenever a vessel with one of the specified set of characteristics (Type, Subtype, Flag, Length, Breadth, Deadweight, or Gross Tonnage) enters one of the specified areas (e.g. whenever a non-national fishing vessel enters the Portuguese EEZ).

To Analyse Track Records, it's possible to view the historical positions of a vessel, and navigational data, from the last 12 hours (past data ranging up until a 6 month period).The system also has a Time Machine Tool, that allows operators to navigate back and forth in time on the Maritime Picture, for instance to review the past position and movement of vessels and other objects on the map or to preview the weather conditions in the near future.

To support Search and Rescue Operations, the system, provides an estimate of the risk of the vessel being overdue, using an algorithm that assesses if the vessel is taking unusually long time to report its position, by taking into account the time of the last position report received, the distance to the coastline and other factors.

OVERSEE automatically creates an alert when a COSPAS- SARSAT distress alert is received in the Centre, showing the position, the details and the casualty of the distressed vessel.

The Time Machine Tool is also very valuable in Environmental Protection scenarios. In most cases, EMSA broadcasts a notification, regarding pollution spots (detected in CLEANSEANET). The Time Machine Tool is then used to investigate and correlate the spot with a specific contact.

2.2. Fusing and mining vessel traffic data

With so many Information Systems, the eyes of operators are no longer enough, and that is the reason why navies are actually developing systems capable to integrate multiple sources.

COMAR explores actually two systems with data fusion: VTS and OVERSEE.

The VTS, provided by the Directorate General for Natural Resources Safety and Maritime Services (DGRM) fuses the information of Coastal Radars and AIS, and offers an integrated Picture of all the Portuguese Coast.

The OVERSEE, fuses the information of Maritime Traffic Systems (AIS, AIS (S) and VMS) and integrates several sources of information into a aggregate product with cartography, emergency alerting system, weather and oceanographic data. In the near future this system will receive LRIT Data and Radar Information (currently being developed through a partnership between Navy and Maritime Authority).

3. CONCLUSION

The solution found by the Portuguese Navy, to fulfill its mission, and the national commitments assumed by Portugal under the framework of the International Maritime Organization results from a systemic approach, and can be translated in an effective gain of efficiency in the State action in the areas under the national sovereignty and jurisdiction.

Conceptually, COMAR is a Maritime Operations Centre which is also a Maritime Rescue Coordination Centre, that produces Maritime Situational Awareness and is able to command and control Naval Operations and to plan and coordinate Maritime Security Operations, in close support to external Agencies, if required.

Since 2013, COMAR has been using successfully the OVERSEE system to promote anomaly detection in support of military and non-military operations (operations planning, abnormal behaviour detection and operations conduction).

AUTOMATED BEHAVIOUR MONITORING (ABM) ALGORITHMS – OPERATIONAL USE AT EMSA

European Maritime Safety Agency (EMSA)

ABSTRACT

The European Maritime Safety Agency's (EMSA) Automated Behaviour Monitoring (ABM) tool is a computer rule-based system analysing vessel positions (approximately 18 million daily) for the detection and alerting of abnormal and/or user specific vessel behaviours. The aim of the ABMs is to support Integrated Maritime Service users in their maritime surveillance functions, by providing an enhanced situational awareness picture in real-time. Currently the set of abnormal and/or user specific behaviours includes: entering an area, encounters at sea, close approach to shore or an area, sudden changes in heading, speed or reporting frequency; are operationally used. When specific, user-defined criteria are met, operators can be automatically alerted via warnings in the graphical interface, e-mails or S2S connections. With the growing number of ABM users and the operational experience gathered within the context of EMSA's Integrated Maritime Services (IMS), a number of challenges and requirements for new user defined abnormal/specific vessel behaviours have been identified. These include: detection of transponders switched-off or vessels deviating from the usual routes, especially in the remote areas. Fake position or fake identity reports are also difficult to discover. Use of the Earth Observation (EO) based (Vessel Detection System - VDS) technologies as well as the operational use of the statistically aggregated position reports may be worth exploring for further enhancements of the ABM services.

Index Terms— Maritime surveillance, Anomaly detection

1. EMSA

The idea of a European Maritime Safety Agency (EMSA) originated in the late 1990s along with a number of other important European maritime safety initiatives ('Erika' package). EMSA was set up as the regulatory agency that provides support to the European Commission (EC) and the EU Member States (MS) in the field of maritime safety and prevention of pollution from ships. EMSA was established by Regulation (EC) No 1406/2002 and subsequent amendments. Among other tasks, EMSA facilitates the technical cooperation between EU Member States and the EC for the exchange of EU vessel traffic information, the long-range identification and tracking of vessels and to support EU operational reporting services. Consequently, EMSA operates and manages a suite of maritime applications which receive, process, and distribute information on, inter-alia, vessel traffic reports (LRIT, SafeSeaNet), Earth Observation (EO) satellite monitoring (CleanSeaNet), and Port State Control (THETIS). The services provided by these maritime applications are shared with EU Member States the EC, and other EU Bodies.

EMSA has also developed a platform to guarantee the performance, availability and reliability of all the maritime information systems it hosts. This platform integrates and correlates different types of data, including data provided by the end-users, to produce customised services tailored to specific requirements. These services are called Integrated Maritime Services (IMS), and are used by MS authorities to obtain the most complete maritime situational awareness, building a common picture across EU maritime interests. A high-level description of the IMS datasets is presented in the Figure 1 below.
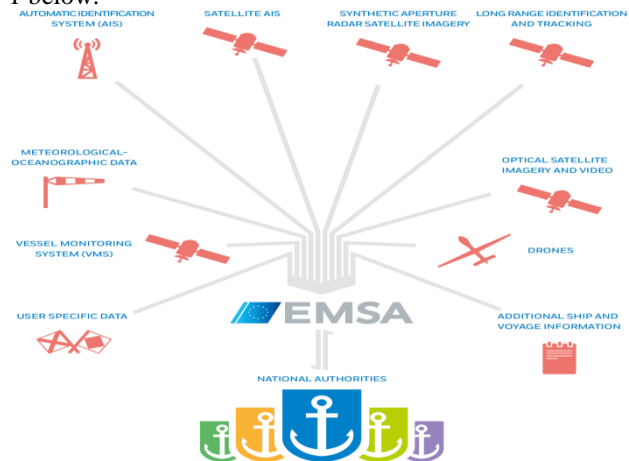
Figure 1 Integrated Maritime Services – capability to integrate data from different sources

In this paper we describe a tool available within the IMS - Automated Behaviour Monitoring (ABM) algorithms. The ABM is a computer, rule-based system analysing vessel positions for the detection of specific events. The objective of the ABMs is to support the maritime

surveillance operators, by automatically analysing position reports and alerting upon detection of abnormal events.

2. AUTOMATED BEHAVIOUR MONITORING (ABM) ALGORITHMS IN IMS

As previously stated, ABMs are a functionality of IMS which analyses real time vessel position reports provided for a specific time period and area of interest (AOI), as defined by the users. The system focuses on the detection of specific events, and therefore may be categorized as 'event' based. Table 1 summarizes the current technologies in terms of vessel position reports available in IMS and ABMs.

Position type	Description	Data volume
Terrestrial based Automatic Identification System (AIS)	T-AIS position reports, transmitted from ships to the shore-based stations of the EU member states (MS) and later relayed to EMSA for sharing with other MS. Position reports from the equipment of the class A and B are used. As far as the vessels tracking is concerned, this technology has all the limits of the VHF band, meaning that it depends on the availability of the shore-based component, height of the antennas of the transmitter and receiver and other factors.	Typical volume of this data reaches daily 10,000,000 positions and the frequency of these reports is, as agreed with the stakeholders, downsampled to 6 minutes in EMSA hosted systems.

Position type	Description	Data volume
Satellite-AIS	S-AIS are the same position reports transmitted by the ships, but they received by the satellites. In terms of limitations, the technology is linked to the availability of the satellite segment. Due to the applicable SOTDMA (Self-Organized Time Division Multiple Access) technology, which requires slot assignment and time synchronization, there are also issues related to the collisions of the position reports received by satellites. The Satellite AIS services are also described by the following elements: average target detection probability and the target timeliness (delivery of the latest positon report to the end user).	The daily average rate at EMSA is around 7,000,000 positions and the frequency depends on the service provider, but in average does not surpass 1 hour.
Long Range Identification and Tracking	LRIT is based on the satellite communication satellites (mainly Inmarsat C and Iridium). It has a global coverage and its basic frequency is 6 hours, but can be increased up to 15 minutes. The LRIT offers a global coverage and the position reports are not broadcasted to all ships but delivered to specific ground-based or shore-based nodes. LRIT covers only specific position reports without additional elements, like e.g. voyage data (destination, time of arrival). The LRIT position reports are owned by EU Member States and their distribution and access at EU level is managed via the EU LRIT Cooperative Data Centre (CDC). There are different access policies, set by the legal basis and their owners, and they vary from: national flags, coastal and port users to the unlimited access for SAR purposes.	Around 30,000 position messages are processed daily in the EU LRIT CDC.

Position type	Description	Data volume
Vessel Monitoring System	VMS uses similar satellite-based communication technology as LRIT, presenting similar limitations in terms of availability and frequency. Its basic frequency is 2 hours, but can be increased up to 15 minutes. VMS is limited to fishing vessels (or vessels involved in the fishing operations) only. In EU, these position reports are made available to the flag states and shared, as decided by each member state, based on the cooperation between European Fisheries Control Agency (EFCA) and EMSA. The information is usually made available only to the flag users.	EMSA processes around 5,000 VMS messages daily.

Table 1 - Position reports in the EMSA hosted systems

4. ABM TYPES

The 'event' based ABM technology currently used obliges the user to select the type of event to be detected, in addition to the AOI and time definition. Patterns, such as entering an area of interest, encounters at sea, approach to shore or ports, changes in the heading, speed and reporting frequency, and others, are analysed and detected. Table 2 illustrates the available ABMs and provides a concise description of the events detected.

ABM Type – description which events are automatically detected	ABM name
Entry of a particular vessel(s) to an area of interest	*InArea*
Passage of a vessel close to the shore	*DistanceToShore*
Vessels entering or leaving ports	*AtPortAtSea*
Anchored vessels	*Anchorage*
Frequency of vessels' position reports higher or lower than expected	*UnderOverReporting*
Vessels approaching one another closer than an indicated distance, with a speed below defined threshold	*AtSeaEncounter*
Change of heading higher than a threshold (e.g. more than 20 deg.)	*SuddenChangeOfHeading*
Sudden change of speed	*SuddenChangeOfSpeed*
Change of speed above or below a limit set	*SpeedAnomallyOverPeriod*
Passage of a vessel close to an area of interest	*DistancetoArea*
Vessels entering a closed area at a specific time	*TimeAndPeriodOfDay*

Table 2 - ABMs available to users via EMSA's interfaces, June 2016

5. ALERTING TECHNIQUES

Following the detection of particular events, end-users are automatically alerted. One of the advantages of the ABM related functionalities is that the system distributes the alerts in different forms:

- By email or via system-to-system (S2S) interface, to the off-line users;
- Via alerts (visual and audio) to online users of the IMS graphical interface (GI).

The operational experience proves that the alerts are produced and delivered to the users via the aforementioned interfaces rapidly – the minimum time for the delivery is ≤ 2 minutes in case of non-complex events and maximum time is ≥ 1 hour for the very complex algorithms or in case of delayed position reports.

As previously mentioned, the detection of the specific events, as well as the related alerting, depends on the presence and timeliness of the position reports and the complexity of the algorithms applied. For example, in remote areas where only infrequent LRIT or S-AIS reports are available, the related detection and reporting may require more time in comparison to the areas of high traffic density and proximity of the receivers (i.e. shore-based stations – like AIS stations). Additionally, detection of a single position report in a small area of interest is less computationally intensive than the analysis of multiple positions for the 'close encounters' or 'drifting' in large areas.

6. ABM OPERATIONAL USE CASES

As of June 2016 there are 56 different ABM instances actively running for users within the EU Member States and the EU Bodies. Due to the positive feedback from the operational users, as well as the validation in the real case scenarios, EMSA noted an increasing interest of the EU Member States and EU Bodies in the use of the ABMs. Some use cases of their operational application by

different user communities are presented further below (see also the reference made to the ABM types listed in Table 2). It is important to underline that the definition of communities is linked with the functional approach (it is independent of the governmental department/authority in which users are based) and is used by the authors for illustrating the use cases only.

6.1. Security community

'Security communities' dealing, for example, with the tobacco smuggling, drug trafficking, or population mass movements may be concerned about vessels that approach one another and remain at a close distance for a period of time. Such behaviour may indicate routine ship-to-ship operations (transhipment of goods or fuel) which are normally reported in advance to the shore-based authorities. Unreported encounters at sea may however suggest some illicit activities. Security communities profit from using the AtSeaEncounter ABM for the automatic detection of these events. In this context it is important to exclude the port areas from the analysis, in order to avoid the detection and reporting on the routine arrivals or departures, which in turn may be detected by other, existing ABM type (AtPortAtSea).

6.1. Safety community

Typical use case scenario for the maritime 'safety community' may be related to the monitoring of the areas of interest, like: sensitive or protected areas, vulnerable ecosystems or its own flag ships. In such cases, operations of vessels may be restricted or regulated by the responsible authorities. ABMs support the related monitoring activities, for example, by providing alerting for ships passing at a specific distance (DistanceToShore; DistancetoArea) or simply entering the area (InArea). Additional factors may be considered in the automatic analysis, such as: entries to the areas temporarily closed for navigation (TimeAndPeriodOfDay) or decrease or increase of the position reporting frequencies (UnderOverReporting).

6.2. Traffic monitoring community

For the 'traffic monitoring' communities which are, for example, engaged in the management of the Mandatory Reporting Systems (MRS), recommended sea routes or traffic separation schemes (TSS) ABMs may offer detection of the events related to: sudden change of heading (SuddenChangeOfHeading), anchoring in non-designated places or locations of the underwater infrastructure (Anchorage). As for the 'safety community' mentioned before, the authorities responsible for the

traffic monitoring also profit from the simple detection of the position reports (InArea) applying specific filters per ship types (e.g. verifying only tankers) or flag of the ship (by monitoring its own fleet or fleets flying the 'high risk' flags).

6.2. Fisheries

The 'fisheries' communities may, for example, focus on specific vessels or specific types. Using the InArea ABMs combined with filters, on geographical area and vessel types, it is possible to effectively monitor presence of the specific fishing gears or activities in the fishing grounds. The 'fisheries' communities may be also interested in detecting specific behaviours that may indicate launching of the fishing gears (SuddenChangeOfSpeed, SpeedAnomallyOverPeriod).

7. NEW REQUIREMENTS

Recent developments linked with the operational experience gained by the users have led to the definition of new requirements. These reflect new situations encountered or the development of new types of activities at sea. They can be divided into two main groups: the first one expanding the existing, 'event' based ABMs and the second one applying a new, 'statistical' based approach. For the latter one, specific behaviours could be modelled based on the statistical data and later used as a reference (e.g. model usual routes, behaviours for specific ships).
The following requirements were noted, during a dialogue conducted by EMSA with users, at various forums.

I - Expanding the 'event' based ABMs
- Use of the Earth Observation (EO) data for the detection of vessels with inactive identification transponders;
- Detection of vessels spoofing (deliberately altering) their position reports or identification.
-
II- Applying the 'statistical' based approach
- Reproduction of the routes and behaviours, per type of ship, destination or cargo carried on-board and a detection of a deviation from the usual route;
- Modelling of the impact of meteorological conditions on the ship behaviour or routes;
- Profiling of the vessels (e.g. vessels prone to specific incidents) based on the past safety or security record or other available, reference data.

8. WHAT'S NEXT?

The precondition for the effective ABM operations is the availability of the ship detection techniques (using active detection sensors like radars, or passive ones like cameras); tracking data (use of the active identification transponders); as well as the additional, reference data sets (e.g. statistical record of the trading areas, cargoes carried, incidents or accidents, security issues) for the analysis and detection of specific events.

As the use of the ABM aims at easing the work of the maritime surveillance operators, and supporting an early, automatic detection of specific events, other aspects have to be considered for the future developments. These are related to the capability of processing large sets of information. There are around 90,000 vessels engaged in the international trade worldwide (out of which around 20,000 at any given time around Europe) and approximately another 100,000 equipped with the active AIS transponders. This results in over 17,000,000 AIS position reports detected/ processed on a daily basis. Consequently, ABMs should be capable of rapidly analysing big data sets, in order to detect events and notify end-users in a timely manner.

SENSORS IN NATO MARITIME SITUATIONAL AWARENESS

Lt Cdr Davide Severino

NATO Shipping Centre

ABSTRACT

NATO Maritime situation awareness is defined as the enabling capability which seeks to deliver the required information superiority in the maritime environment, to achieve a common understanding of the maritime situation, in order to increase effectiveness in the planning and conduct of the operations. NATO MSA is based on MSA Concept development plan issued in 2008 and, since then, it is drastically evolving along with technology evolution. Although MSA was initially focused on specific areas of interest, the CD plan has recognized it as a global challenge, requiring a good engagement among national, international, industry and academy players. Many coastal nations are, indeed, developing their national MSA plans, to satisfy their operational needs and positively contribute to alliance's MSA.

NATO MARCOM MSA is currently based on AIS, LRIT and the contribution from assets under NATO or national operational control. A key role is played by the satellite based AIS: companies are improving both satellite and ground based networks in order to reduce data latency, revisit time and increase satellite detection capability. Both incumbents and newcomer companies declare they will have the new network fully operational by 2nd to 4th quarter 2017. By that time the quality of S/AIS is expected to be closer to T/AIS one. Being AIS (as well as LRIT and VMS) a cooperative source it is assessed not to have the highest level of confidence among sources. AIS data should be correlated with non-cooperative sources such as satellite radar or electro-optical, in order to be validated. Satellite network provided with radar and electro-optical sensors would greatly improve data confidence level.

A third source, the most reliable, being non cooperative and non-sensor based, is the one provided by the assets in the area which can visually confirm the accuracy of data received by sensors.

Index Terms— Maritime surveillance, Anomaly detection, Movement pattern, Meetings at sea, Risk of grounding

1. INTRODUCTION

Although NATO is by definition focused on North Atlantic, NATO MSA is of course a global challenge. Indeed vessels sail at increasingly faster speeds throughout the oceans often changing flag, name and, most importantly, owners and operators; therefore no MSA can ever be effective if not under a global perspective.

According to a study conducted by a commercial company, 27% of vessels provided with class A AIS do not transmit for at least the 10% of their activity and 19% of ships "going dark" are involved in some sort of illicit activity or activities which might potentially include threats to freedom of navigation and to security of navigation or ways for funding criminal or even terrorist organizations.

Of course, most of those vessels involved in illicit activities are not even provided with transceivers, being below the 300 GT threshold and many other vessels purposely alter their transmissions not to be detectable or recognizable. Therefore a sensor based non cooperative MSA or even specific assets (aircraft, surface or submarine) might be required.

Shipping is assessed being composed by nearly 150.000 class A AIS units plus other classes, not to mention the so called "small vessels", for which each country develop a specific strategies (e.g. the SMSS small vessel security strategy in the US, estimating nearly 20 million vessels smaller than 300 GT all over the country) to prevent, disrupt and prosecute illicit activities perpetrated with small vessels (let's just think about smuggling or migrant trafficking).

NATO MSA doesn't aim to know everything about each and every single civilian vessel but to build awareness by knowing general trends for merchant vessels as well as for fishing and leisure vessels. This would help understanding maritime patterns and the relevance of each pattern on global economy, to assess the impact of maritime security related threats on maritime activities.

2. NATO MARITIME SITUATIONAL AWARENESS

NATO MSA is defined as the ***Enabling capability … to deliver the required information superiority in the marine environment, to achieve a common understanding of the maritime situation, in order to increase effectiveness in the planning and conduct of operations***.

In its role as primary advisor to merchant shipping regarding potential risks and possible interference with maritime operations NATO Shipping Centre role builds, maintains and analyses the "white" portion of MSA, composed generically of all civilian vessels, craft and boats sailing through the oceans. This way NSC also supports NATO Operations (OCEAN SHIELD and ACTIVE ENDEAVOUR) as well as national and multinational operations and exercises.

White MSA is delivered by processing sensor based data, non-sensor based data, network information and reports from assets.

Sensor based data represent the main pillar of white shipping MSA and can be classified as either cooperative or non-cooperative, depending whether any form of cooperation from target is needed (AIS, LRIT, VMS etc.) or not (e.g. radar etc.). Additionally NATO Shipping Centre relies on assets which can provide both sensor and non-sensor based data.

In general terms, sensor based MSA requires:

- a sensor (and multi-sensor)based network, adequate to maintain the appropriate level of awareness linked to a constantly updated and reliable database
- a proper database of usual patterns of behaviors (often referred to as patterns of life – POL). This is essential to recognize, based on specific areas and seasons, what should be considered "usual", what "unusual" and what "suspect"
- an analysis tool capable to process, identify and classify those "anomalous" behaviors, considered relevant for the specific needs
- a list of tailored maritime situational indicators to recognize suspicious behaviors within their areas of interest.

The main sources of data NATO Shipping Centre uses for building and managing the white shipping picture are:

2.1 AIS

Terrestrial AIS provides a fairly homogeneous coverage, limited to roughly 50 nm from the coast, extended to all AIS classes and with a virtually unlimited capability.

Each coastal nation has its own official network, mostly used for traffic monitoring, collision avoidance and MSA purposes. Although nations are not commercially marketing their data, those are shared within international community to participate in data sharing initiatives and experimentations. VOLPE MSSIS is an important example of data sharing: it is based on agreements between the fusing center and each single nation. The level of contribution is measurable to assess its quality and each contributor is also requested to provide stations lists to understand the coverage.

Additionally several private companies have established terrestrial AIS networks by means of owned stations and / or data purchased from other station owners. Most terrestrial AIS providers fuse their data with satellite AIS providers to offer more commercially valuable monitoring services on the market.

Being NATO Shipping Centre focused on broad portions of high seas, the recent developments of Satellite AIS are closely monitored to understand the level of improvement providers are achieving with regards to satellite networks, orbits and ground based stations in order to

- reduce latency to minimum
- reduce data rejection
- improve satellite passages

To achieve the required level of MSA, NATO Maritime Command receives AIS satellite and terrestrial data from commercial satellite AIS providers and from national and commercial terrestrial AIS providers.

The main concern MARCOM faces regarding AIS data is about confidentiality assessment as it requires a deep knowledge of stations' distribution along the coastline, signals' quality, coverage and status of transmission. On the other hand, as satellite AIS providers have developed their networks improvement plans, MSA team in MARCOM is constantly assessing data quality improvements in terms of latency, satellite revisiting time, orbits and passages. Still about satellite AIS, a critical issue is sensor's capacity limits with regards to the risk for it to get crammed and to start rejecting new data.

The combination of delays related to latency, satellite passages and messages rejections affect satellite AIS network reliability. However all providers MARCOM deals with (ORBCOMM, EXACTEARTH, SPIRE) state network improvements should see the light within 2017, when the quality gap between terrestrial and satellite AIS is expected to be significantly reduced.

Lastly, satellite AIS is only limited to class A and class B/SO messages, therefore its contribution to MSA is somehow limited, although MARCOM is following the development of new commercial products such as EXACTEARTH ABSEA allowing to track also vessels smaller than 300 GT.

2.2 LRIT

For operation Ocean Shield NATO gets LRIT data from compliant nations. Such data are cross-examined with other data and information available to improve data confidentiality. As expected, the correlation of two sensors based, cooperative data has marginally improved white shipping picture's quality.

2.3 Satellite radar (used for experimentation purposes)

Correlation of AIS and/ or LRIT with satellite radar is very effective in improving MSA and white picture compilation. Satellite radar is indeed a powerful system for non-shiners detection and target recognition even with some caveats: marine target recognition from satellite indeed could be more difficult than ground one. While ground targets (vehicles) are represented only on two dimensions, targets at sea are often represented on three dimensions being third dimension the vessels' height, which is affected (in imagery capturing) by pitch, yaw and roll. Vessels wakes as detected from satellite can also reveal much information about vessels' movements and conditions.

2.4 Assets as non-sensor based data

The trend in NATO MSA is of course a shift from platform (assets) to sensor based MSA, this implies a decrease in assets centrality for MSA building. Nevertheless, when enhanced posture is required, the use of assets becomes central to validate anomalies. NATO assets are indeed deployed on areas of operations and areas of interest in order to support operations and are sometime determinant in anomalies validation processes.

3. MARITIME ALLIED COMMAND MSA DOCTRINE – THE WAY AHEAD

Technology achievements have determined NATO Maritime Command to reconsider its MSA doctrine.
Although the new MSA has not been published yet, the new approach to global MSA is likely going to split the maritime domain in three postures:

- a general one based mostly on sensor cooperative data
- two enhanced postures for smaller areas, in which a deeper level of MSA is required.

The lowest posture is likely going to rely mostly on AIS while posture two and three request a variable level of awareness based on data correlation, networking information and even reports from assets.
In general terms the correlation of sensor-based cooperative with sensor-based non cooperative data (e.g. terrestrial and satellite AIS with terrestrial or satellite radar), is a form of multisensory data fusion, allowing performing inferences not achievable from a single sensor alone to enhance knowledge over surveillance areas, enabling the detection, tracking and identification of a target including target identity, activities and history.
The highest posture should be focused on even smaller areas and involves the use of assets (ships, maritime patrol aircraft, AWACS) to achieve a deep knowledge of the traffic over the area and being able to detect those behaviors considered relevant for the situation.

4. THE ANALYSIS TOOLS: BRITE and TRITON. CMRE SUPPORT

4.1 NATO

NATO has developed its own analysis tool, the BRITE (baseline for rapid iterative transformational experimentation), a dedicated software created by ACT.
The concentration of data in some areas might saturate the fusion software; to prevent this MARCOM sometimes requires the capability to throttle data refresh time. Under an operational point to view, indeed, there is no need for a real-time data refreshing. The system is capable of processing (correlating and fusing) multiple data format to compile the white shipping picture to fulfill NATO MARCOM operational requirements. The picture is then analyzed by means of smart agents to detect anomalies to expected patterns of behavior. Such agents can detect static anomalies -by comparing displayed data with available database- as well as dynamic ones –such as destination inconsistencies-.
BRITE's advantages consist in being the software fully in house built; this allows tailoring fusing criteria and smart agents on specific operational needs.

4.2 TRITON

The alliance is developing a new comprehensive MSA tool, including all display and analysis functionalities.

The project, named TRITON, is still under development and will see the light in 3 to 4 years; it is based on open architecture and will incorporate the broad experience collected into BRITE as well as many functionalities. To system implementation NATO will outsource most of system development.

4.3 CMRE SUPPORT

A key role in the development of baseline analysis is played by NATO CMRE based in La Spezia. Its support consists in developing pattern of life analysis tools considered extremely valuable under both an operational and an experimentation point to view. Particularly the port analysis and the TREAD (traffic route extraction and anomaly detection) acquire and process info and positional data defining the traffic paths, creating density maps, analyzing routes in support to operational planning and execution. Such background information are moreover useful for detecting the anomalies.

SECTION II: PRIVATE SECTOR

ANALYSIS OF VESSEL TRAJECTORIES FOR MARITIME SURVEILLANCE AND FISHERIES MANAGEMENT

Philippe Gaspar[1], Rémy Lopez[1], Marza Marzuki[2,3], Ronan Fablet[2], Philippe Gros[1], Jean-Michel Zigna[1] and Gaetan Fabritius[1]

[1]Collecte Localisation Satellites (CLS), Ramonville, France
[2]Telecom Bretagne, Department Signal and Communications, Plouzané, France
[3]Ministry of Marine Affairs and Fisheries (KKP), Jakarta, Indonesia

ABSTRACT

During the last decade, CLS, the operator of the ARGOS positioning and data collection system, has developed several tools to analyze the trajectories of satellite-tracked vessels to add value to the information provided by ARGOS but also other positioning systems (AIS/SAT-AIS, LRIT ...). In 2010, CLS started to work, as a contractor for the European Maritime Safety Agency (EMSA), on an Integrated Maritime Data Environment (IMDatE) and specifically on a module dedicated to run different algorithms to identify patterns, generate alerts, and ultimately support the maritime surveillance missions of the European Member States. Through this project and in close cooperation with EMSA, CLS has developed and continues to develop services driven by new regulations, and user communities relying on IMDatE. During the same period, CLS also collaborated with research laboratories to develop fishing vessel trajectory analysis tools designed to support fisheries monitoring and management activities. These tools focus on the identification of the different behaviours displayed by fishing vessels at sea (cruising, tracking fish, fishing, resting...). A clear-cut identification of these different activities, allows a precise estimation of the spatial and temporal distribution of the fishing effort, a main input in fish stock assessment model. Clear identification of the different activities carried at sea by fishing vessels also allows the detection of illegal activities (such as fishing in protected areas) or frauds (such as using prohibited or not properly licensed fishing gears). Results obtained for different fisheries management organisations will be presented here.

Index Terms— Automatic Identification system (AIS), Vessel Monitoring System (VMS), behavior analysis, anomaly detection.

1. INTRODUCTION

During the last decade, CLS has developed several tools to analyze the trajectories of satellite-tracked vessels to add value to the information provided by ARGOS but also other positioning systems (AIS/SAT-AIS, LRIT ...). Vessel trajectory analysis can serve multiple purposes. Here we concentrate on two major domains: maritime surveillance and fisheries management.

2. MARITIME SURVEILLANCE

The detection of abnormal behavior is a permanent demand of the administrations in charge of the Maritime Domain Awareness, with the following main concerns:

- Prevent accidents that could occur on ships carrying hazardous material or polluting cargo;
- Detect oil spills and generate alert for agencies in charge of oil spill operations;
- Support anti-piracy operations;
- Monitor maritime borders;
- Monitor fishery and detect Illegal, Unregulated and Unreported (IUU) fishing activity;
- Detect illegal trafficking and smuggling;
- Support authorities in Search and Rescue operations.

For these purposes, CLS implemented a set a algorithms operating in EMSA's IMDatE. Inputs of these algorithms are AIS, SAT-AIS, VMS and LRIT messages but also satellite images (optical and Synthetic Aperture Radar). These algorithms are designed to detect the following events:

a) Vessel entering or leaving a specific area (marine protected area, military area, piracy high risk area…);
b) At sea encounter of 2 vessels (indication of possible transhipment or pirate attack);
c) Drastic change in ETA;

   d) Vessel off track with regard to declared voyage;
   e) Under or over reporting of positions with mandatory terminals (e.g. LRIT);
   f) Sudden change of speed;
   g) Sudden change of heading;
   h) Sudden change of port of destination;
   i) Vessels in harbors: entering, at anchor or leaving.

These algorithms are currently used for day-to-day operations by EMSA. The parameters of each algorithm can be tuned by the user to account for the type of vessels monitored or the specific targeted event.Different alert broadcast strategies can be specified depending on the detected event. Alerts can be issued: "at start", "at start and at end" or "at each occurrence" of an event.

3. FISHERIES MANAGEMENT

Satellite-tracking of fishing vessels was originally imposed, in the nineties, to verify that fishing activities were carried out only during the period and within the geographic areas where they were permitted. But fisheries scientists soon recognized that fishing vessel trajectories were actually providing more information about the fishing activity than simply the area and period of fishing [1, 2].

A major goal is to precisely identify whether a fishing vessel is cruising or fishing. At first sight, this can be done using a simple speed filter (low speed = fishing; high speed = cruising). This simple approach has been extensively used, in particular for analyzing the activity of trawlers [3].

Unfortunately, this method provides rather inaccurate estimates of the fishing effort for most fishing gears. For example, Bertrand et al. [4] report that the speed-threshold method tends to overestimate the number of fishing sets by as much as 182 % in Peruvian purse seiners targeting anchovy. This overestimation is due to similarities in vessel speeds when fishing, drifting and searching. Several more elaborate methods have then been developed to refine the detection of the fishing activities with different fishing gears. Neural networks and Hidden Markov Models (HMM) have been used in various situations [2, 4]. More recently, Hidden semi-Markov models (HSMM), random forests (RF) and Support Vector Machines (SVM) have been successfully used, allowing identification of the various fishing activities with relative errors in the range 10-30 % [5]. Such levels of error can only be reached with supervised learning but obtaining learning data sets is difficult in many fisheries where very few fishing cruises are documented by on-board observers. Systematic deployment of Electronic Reporting Systems (ERS) shall help reduce this problem.

The low sampling rate of most VMS systems is another issue. With a typical 1-hour sampling period, various fishing actions are inevitably undetected or "aliased" in VMS data. The use of high-frequency AIS data will undoubtedly help improve the situation.

Another potential use of VMS data is the detection of quite subtle frauds such as a false declaration of the used fishing gear. We recently reported results on this topic [6]. Using VMS data from the Indonesian Ministry of Marine Affairs and Fisheries (KKP), we used various data mining techniques for the automated recognition of the used fishing gear (trawl, pole and line, purse seine or longline). The different tested methods provided high rates (95 to 97.5 %) of correct classification. Interestingly a small number (near 4%) of vessels systematically displayed high misclassification rates. Such cases were further scrutinized. In some instances, the origin of the misclassification was related to discrepancies between the VMS and registration databases. In other cases, visual analysis of recorded trajectories strongly suggests an erroneous gear declaration.

Further work dedicated to the analysis of the longliners' activity is on-going and preliminary results will be shown. Pelagic longliners operate in all oceans. They are responsible for over 10 % of the worldwide tuna catches. Still, their VMS tracks have, so far, been little investigated and used for the management and control of their fishing activity.

4. REFERENCES

[1] S. Bertrand, A. Bertrand, R. Guevara-Carrasco and F. Gerlotto: Scale-invariant movements of fishermen: the same foraging strategy as natural predators. Ecological Applications, 17, 331-337, 2007.

[2] N. Bez, E. Walker, D. Gaertner, J. Rivoirard, and P. Gaspar : Fishing activity of tuna purse seiners estimated from vessel monitoring system (VMS) data. Canadian Journal of Fisheries and Aquatic Sciences. , 68, 1998-2010, 2011.

[3] N. Lee, A.B. South and S. Jennings: Developing reliable, repeatable, and accessible methods to provide high-resolution estimates of fishing-effort distributions from vessel monitoring systems (VMS) data. ICES Journal of Marine Science, doi: 10.1093/icesjms/fsq010, 2010.

[4] S. Bertrand, E. Diaz and M. Lengaigne: Patterns in the spatial distribution of Peruvian anchovy (Engraulis ringens) revealed by spatial explicit fishing data. Progress in Oceanography, vol.79,pp.379-389,2008.

[5] R. Joo, S. Bertrand, J. Tam and R. Fablet: Hidden Markov models : the best models for forager movements PLoS ONE, 8(8):e71246, doi:10.1371/journal.pone.0071246, 2013.

[6] M. I. Marzuki, R. Garello, R. Fablet, V. Kerbaol and P. Gaspar, "Fishing gear recognition from VMS data to identify illegal fishing activities in Indonesia," OCEANS 2015 - Genoa.

EXPLOITING THE POTENTIAL OF THE FUTURE "MARITIME BIG DATA"

Bernard GARNIER*, Aldo NAPOLI**

*BlueSolutions Consulting SAS, Sophia Antipolis, France
**MINES ParisTech, PSL Research University, CRC, Sophia Antipolis, France

ABSTRACT

Today, most of the operational "abnormal behaviour" detection algorithms primarily operate kinematic rules on the vessel tracks provided by the AIS [1], [2], [3]. To be more effective, they must be associated to additional "context data", however insuring this data access is today a challenge, due to the disparity of registers and the fragmentation of actors… For example, detecting suspicious "associations of ships" requires already a complex data mining to detect indirect common ownership through the myriad of cascaded legal entities used for formal ownership and registration; as another example, maritime security actors know the importance of environmental factors (sea state, fog, clouds, moon etc) when assessing the risk of illegal passages or piracy attacks at night – but gathering the right local weather forecast data in association with abnormal behaviour detection algorithms for maritime radar systems is also a challenge.

While many more data and metadata should be browsed from all the existing maritime reporting systems and data repositories to cross-check systematically the declared versus actual behaviour of commercial, fishing and leisure ships, we shall start developing a new data access thinking to benefit from the progressive deployment of the EU-wide CISE which is approaching its pre-operational validation milestone and should be largely mature by 2020, materializing a break-through in terms of data access for the maritime security communities. In parallel, another key enabler is the capacity to collect the "local picture" gathered by genuinely cooperating shipping (sightings and nav radar) with the "big picture" (VMS, AIS, S-AIS, LRIT, satellite imaging…). The VDES will provide a very effective data uplink as an alternative to broadband maritime SatComs at the same 2020 horizon. Other planned technological gap-fillers deserve to be integrated in future data processing strategies: new space projects aim at solving the data synchronicity challenge by co-locating SAR, S-AIS and VDES payloads for specialized maritime surveillance constellations; EDRS allows downloading LEO maritime surveillance data streams in near real-time from anywhere on Earth; smart and fast embarked data processing will downsize the "rising tide" of data, extracting and tagging straight away the mere fraction of data requiring prompt human attention…

This paper will aim at delivering a sort of "wake-up call" to integrate this new data access paradigm in the current research on maritime knowledge discovery associated to the detection of safety and security threats: 2020 is tomorrow, we shall think, develop and test our toolbox at the whole scale of this "Big Data".

Index Terms— Maritime surveillance, early detection, heterogeneous correlation, CISE, weak signals analysis

1. CURRENT STATE OF PLAY

While maritime surveillance has been radically transformed by the introduction of the Automatic Identification System (AIS) in 2002 through the IMO SOLAS Agreement – suddenly populating the screen of the vessel traffic management systems (VTMS) well beyond the range of the coastal radars, the operational maritime surveillance capabilities have not much evolved since. Voluntary reporting systems (mainly AIS, VMS for fishery vessels and LRIT in distant sea lanes) remain the essential source of vessel monitoring, leaving in the shade the smaller boats… and the deliberately cheating ones. Furthermore, non-cooperative ship detection provided by maritime radars (on board ships and on the coast) is now automatically fused with AIS, no more supported by additional VHF voice contact and binoculars to confirm the vessel identity and its planned route.

The recent development of commercial satellite payloads designed to collect AIS signals from ships well beyond coastal VHF horizon (S-AIS) is a welcomed "plus" to overcome the deficient cover of coastal AIS receivers in some regions, but remains overall a moderate contribution to the VTMS operation as S-AIS largely recoups LRIT.

International cooperation has become routine, but again most if not all maritime traffic data exchange agreements relate to the data of these voluntary reporting systems; as they are often faulty and sometimes cheated, this means building the common operational maritime traffic picture on sand!

Space observation systems have been promoted as a new way to ascertain the maritime traffic data. Indeed, medium and high resolution synthetic aperture radar (SAR) on low Earth orbit (LEO) satellites provide a theoretical capability of ship detection anywhere in high seas, but its use as a daily maritime traffic monitoring tool remains problematic

(no persistence, limited refresh, significant cost, latency of several hours). It is technically impossible to acquire synchronously SAR radar and S-AIS, rendering the correlation of these data tedious and often uncertain. As a consequence, its operational use is limited to specific fishing grounds and trafficking areas (where and what to look are known ahead of data collection and processing).

With these limitations, the blue borders remain largely porous to all sorts of trafficking (drugs, arms, migrants…) while endangered fishing species are still poached at high scale (IUU fishing remains as high as 25 to 30% of all catches).

In the field of Defence, Intelligence Agencies are actively seeking for illegal arms trade, intrusions in territorial waters and security threats of all sorts; however cross-border information exchanges (e.g. under the auspices of NATO) are most often limited to share a "list of usual suspects" designating about 2000 vessels of specific interest to be jointly monitored. In parallel, anti-drug operations are also most of the time driven by human intelligence (HUMINT), leaving 90% of the traffic undetected. In short, the challenge relate to the large number of "unknown unknown" threats.

To overcome the incapacity of the current state-of-play to anticipate the creativity and flexibility of criminal schemes, there is a clear need for changing the maritime surveillance paradigm: monitoring ship tracks on big screens is not enough!

2. LOOKING FOR WEAK SIGNALS

Time is long gone where seas appeared as the ultimate area of freedom, where the Master was invested of every power… after God. All maritime activities are today explicitly regulated, even in High Seas, as a result of international treaties and agreements (IMO…), regional agreements (Baltic…), national and local regulations. The respective authority of Flag States, Port States, Coastal States etc. is internationally agreed and results into massive data collection from all operators: every ship voyage generates dozens of massive files on the ship itself, the voyage, the cargo and the people on board.

Each of these files is directed to a particular Maritime Authority which screens the documents, clears the corresponding ship operation and triggers possible controls.

Criminal gangs are thus used to provide "clean" documents to avoid controls, e.g. cargo or fish catch declarations that will look "business as usual" for the custom officer or fishery inspector respectively. In the same time, these data are not today available in parallel to the serious crime investigators that could detect inconsistencies or possible correlations with their own investigations.

This "fragmentation" of the State controls of maritime activities is inherited from the absence of an holistic vision of the maritime economy common to almost all States: a comprehensive survey undertaken by DG Mare confirmed a split of the maritime authority prerogatives between more than 10 different administrations all across the 21 EU maritime nations, with many different Ministries involved (Transport, Energy, Environment, Agriculture, Interior, Economy, Defence…). Furthermore, this organizational mix differs significantly form a country to the next, with hardly a cross-border match between mandates and legal prerogatives, hence making inter-administration cooperation furthermore complex. This results into what is usually called "data silos", each of them only exploited under a single angle.

In essence, maritime surveillance operations are not distinct from any business, and the general approach of "Strategic Early Warning Systems" theorized from 1975 ref [4, 5] to provide on-time strategic reaction capabilities is perfectly applicable. The central element is that disruptions do not emerge without warning, however these warnings remain most often undetected as they don't come from the expected channels of business information. These warning signs are described as "weak signals" [4], a concept aimed at early detection of those signals which could lead to strategic surprises -- events which have the potential to jeopardise an organization's strategy. Brison and Wybo [6] represent the life cycle of weak signals as four successive steps associated with barriers that the weak signal has to overcome. These four steps are: Detection, Interpretation, Transmission and Priority setting. The extraction of such weak signals from the massive data and meta-data collected on Internet by the GAFA turns to be potentially extremely profitable – currently turning as the 21th century gold rush… Everyone has experienced already how effectively e-advertising can be targeted by processing the heterogeneous navigation data and metadata of your internet browser.

There are already demonstrative contributions of Open Source data mining and weak signals analysis in the maritime security domain, such as the ConTraffic web-service of the JRC able to alert Custom Authorities on particular containers associated with "abnormal" voyage histories (https://contraffic.jrc.ec.europa.eu/).

The largest potential relate to the application of weak signals detection over widely heterogeneous data possibly correlated. Ref [7] proposes an interesting application of this approach to the detection of cyber-intrusions, which is not dissimilar to our own preoccupation. Proper "Features Detection" comes as a cornerstone of efficient heterogeneous correlation. (http://journalofbigdata.springeropen.com/articles/10.1186/s40537-015-0013-4).

As another inspiring example, heterogeneous correlation will soon offer a totally secure substitute to traditional passwords: a very clear signal has been given by Google at its annual I/O conference 2016, announcing the

availability of a "Authentication APS developer kit" by the end of 2016 based upon "behavioural biometrics" (Abacus project). This component of Chrome will allow elaborating a "trust score" to enable the user login, achieving its authentication through a comprehensive pattern of behavioural features currently captured by the smartphone own sensors: how you type, where you are, how fast you move, your voice intonations etc. - none of them "mediated" by an explicit identification request (https://www.newscientist.com/article/2091203-google-plans-to-replace-smartphone-passwords-with-trust-scores/).

The transposition of these advanced IT concepts to cross-correlate the data respectively collected by Port Authorities, Customs, VTMS, fishery control agencies, Defence, Law enforcement agencies etc. seems straightforward: this shall allow directing the operator's focus on few "abnormal/suspicious" seafarers trying to hide in the global maritime traffic while clearing without any further investigation most of the tracked vessels.

3. THE REVOLUTION TO COME: EASING DATA ACCESS

The key point to enable weak signal analysis is to access as many data as possible without any prior selection: searching the "unknown unknown" means that the data owner has no clues to pre-select what is worth being shared with its partnering maritime authorities – so it is a totally distinct approach from current "need to know" (and even the emerging "dare to share") the data he has already identified as suspicious.

The second characteristic of this activity is to process all sorts of data collected in the global framework of "maritime management", including the associated meta-data. This is totally distinct from building a "common maritime picture" by fusing all the ship tracks collected across the community of maritime administrations: instead of aggregating every possible data of the same nature (ship tracks), the purpose is to browse with pre-determined search strategies (e.g. to build a confidence index) all possible layers of data (e.g. ship owner, previous ports of call, container numbers, crew list, average speed, mix of cargo, berthing records, occurrence of encountering with ship Y etc etc)

The conjunction of the total dematerialization of all the shipping documents (e-maritime, single national window…) and of the go-ahead for the Common Information Sharing Environment (CISE) is creating the framework of a massive "maritime Big Data" which is the pre-requisite for deploying advanced data mining tools underlying the weak signal analysis approach.

This requires however building effectively a CISE with all the features of the original vision of DG Mare in terms of

seamless access to all relevant national/sectoral data repositories.

Fig.1 is a familiar conceptual view of CISE (excerpt from the Deloitte report ref [8]) showing the various "User Community Layers" expected to rally the common exchange environment. On this graphic, developing heterogeneous correlations would come as achieving a seamless permeability between any layers, to conduct the correlation by picking data of all 7 colours and detect anomalies that no layer would ever suspect.
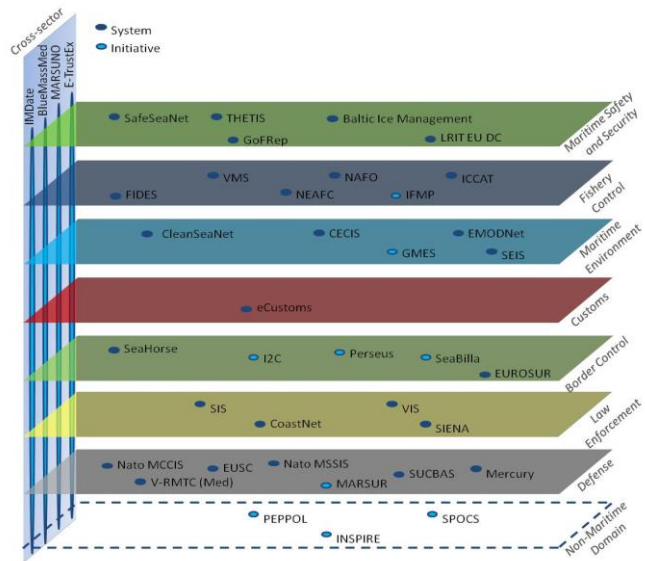

Figure 1 "CISE Landscape", from ref [8] p.189

There is currently a risk that a number of User Communities (UCs) still consider the horizontal permeability as the principal scope for CISE, materializing into a collection of "common sectoral operational picture" built from the data considered by each data owner as "interesting to share" within the same UC for improving cross-border cooperation. At a time where the Pre-Operational Validation project CISE-2020 is launching the procurement of critical IT software bricks of the future CISE, opening this discussion seems critical.

4. THE VDES OPPORTUNITY

The AIS is currently under revision at international level (IALA, IMO) to incorporate the capability of broadband data transfer (Very high frequency Data Exchange System, VDES) while improving as well the capture of AIS signals by satellites (S-AIS).

Planned to enter into service by 2020, as for CISE, the VDES will provide all reporting vessels with a capability to contribute to the global maritime surveillance picture. It shall be seen having the potential of a Copernican

revolution: moving from the era of unilateral reporting toward VTMS operators with little if no feedback, ship masters will be able to exchange all sorts of maritime safety and security notices with the neighbouring ships (via VHF) and with the whole community (via S-AIS) at no cost (compared to the SatCom broadband links currently needed). EU Maritime Authorities should monitor more closely and possibly influence the current phase of standard VDES messaging definition to secure the effective contribution of every cooperative ship to report its local environment as a contribution to the grand picture currently compiled by National Authorities, Regional Commissions, EMSA and NATO. Early reporting of the sighting by a cargo or a ferry of "strange" ships around her (fishing vessels out of fishing grounds, old cargo much too low over the water, towed pateras or RHIBs, unusual routes, apparent rendez-vous at sea, low flying plane etc) could help directing patrols well before incidents might trigger alerts. VDES has the potential to turn every cooperative ship as an "in-situ" maritime surveillance sensor, able to transmit messages, pictures, radar screenshots, open comments etc.

5. RECOMMENDATIONS

Maritime authorities will not transform their data sharing and data access policies overnight. In the same time, major enablers of a new way to think the maritime surveillance data analysis are at stake now depending on short term decisions at EU level (CISE) or UN/IMO (VDES) to freeze the technical requirements of these new systems.

Our R&D community has the duty to launch now very imaginative and convincing "vertical" data mining experiments (wrt Fig.1) to demonstrate the power of weak signal analysis, the way to build unprecedented "trust scores" and the consequence of this transformation of the notion of "abnormal behaviour detection" on the requirements (including at some stage underlying legal agreements) of both CISE and VDES. Without offering attractive use-cases, we might miss this challenging 2020 milestone, with the risk of not meeting again before long such opportunity.

6. REFERENCES

[1] Pallotta G., Vespe M. and Bryan K. (2013), "Vessel pattern knowledge discovery from AIS data: a framework for anomaly detection and route prediction", Entropy 2013, 15, 22218-2245.

[2] Vandecasteele A., Devillers R. and Napoli A. (2014), "From Movement Data to Objects Behavior Using Semantic Trajectory and Semantic Events", Marine Geodesy, Taylor & Francis, 2014, 37 (2 - Special Issue: Special Issue on Coastal and Marine Geographic Information Systems), pp.126-144.

[3] Idiri B. and Napoli A. (2012), "The automatic identification system of maritime accident risk using rule-based reasoning", 7th International Conference on System Of Systems Engineering - IEEE SOSE 2012, Jul 2012, Genoa, Italy. pp.125-130.

[4] Ansoff, H. I. (1975), "Managing Strategic Surprise by Response to Weak Signals", California Management Review, vol. XVIII no. 2, pp. 21–33.

[5] Gilad, B. (2003), "Early Warning: Using Competitive Intelligence to Anticipate Market Shifts, Control Risk, and Create Powerful Strategies", AMACOM.

[6] Brizon, A. and Wybo, J-L. (2009), "The life cycle of weak signals related to safety", Int. J. Emergency Management, Vol. 6, No. 2, pp.117–135

[7] Zuech R., Taghi M Khoshgoftaar and Randall Wald (2015), "Intrusion detection and Big Heterogeneous Data: a Survey", Journal of Big Data, Springer 2015.

[8] Deloitte Consulting (2012), "Study on the current surveillance IT landscape and the resulting options for the Common Information Sharing Environment for Surveillance in the Maritime Domain", ISA/DG Mare/DIGIT.

GENERATING AND EVALUATING LONG-TERM COMPLEX MARITIME TRAFFIC RELATIONSHIPS FOR RISK ASSESSMENT AND MISSION PLANNING VIA NEAR-REAL-TIME BIG-DATA ANALYTICS

Hugo José P. B. Paulino Pinto

Inovaworks Command & Control, Lisbon, Portugal

ABSTRACT

Detailed real-time analysis of a large-scale (continental-scale) operational maritime pictures can nowadays be achieved via commercial-off-the-shelf hardware and software components with minimal investment in both time and engineering effort. However, establishing the de facto relationships between the entities present in the scenario and deriving meaningful information from them so that it can be used in operational contexts such as route risk assessment and mission planning and forecasting requires both the evaluation of the instant maritime picture and its correlation with past events and movement patterns.

The research herein presented used latest-generation big data processing and automated deep learning techniques to analyze 5 years' worth of terrestrial AIS (Automatic Identification System) movement data and derive meaningful information in an experimental information system that continuously evaluates the current maritime picture against historical trends, matching relevant events and allowing a trained operator (either automated or in real time) to further interrogate the system for deeper extraction of both past trends and future probabilistic evaluations. The research is being pursued under Inovaworks Command and Control's private R&D center, and preliminarily demonstrates how historical information consulted and further enriched in real-time provides predictive value to a mission-planning system and is crucial for meaningful data analytics. The work presented also provides insights into the best direction for future work in this area.

Index Terms— Maritime Traffic, Anomaly detection, risk assessment

1. INTRODUCTION

Performing mission planning and risk assessment activities in large-scale, complex endeavors over vast geographical territories implicitly inhibits human-scale situational awareness analysis, while at the same time greatly amplifying the margin for error of most uncorrected automated analytics approaches. Crucial to creating a reliable, self-validating Consolidated Operational Picture is the reliance on multi-method validation of both input data and consolidated picture results, and in the correct identification of anomaly events and their significance for a decision maker's sense making.

As unassisted construction of a Consolidated Operational Picture is paramount for the establishment of valid Situational Awareness, so is unassisted detection of any given environment's abnormal vessel behaviors. Nonetheless, a major challenge in detecting automated anomalous vessel behavior in is the high rate of false alarms (due to the use of mainly geospatial – implicitly kinetical – information from indirect vessel data acquisition).

However, manually modeling what is and is not abnormal in a large-scale scenario with dozens of thousands of moving entities is not only humanly impossible but also heavily limiting, as the derived heuristics would only cover a subset of the potential real-world use cases.

For such purpose, we started exploring using vessel traffic history information as a training baseline for deriving abnormal cases and then using the trained system to detect vessel traffic anomalies on a control set. Moreover, such history traffic information could be used to derive and establish the *de facto* relationships between vessels present in a given scenario and deriving meaningful information from them so that it can be used in operational contexts such as association assessment for risk and mission planning.

2. INPUT DATA SET

In order to support the algorithms being developed, we used a large data set containing 5 years' worth of terrestrial AIS traffic around the European maritime shores for 2011 to 2015. This data set included non-downsampled AIS data frames in approximately 6 minute intervals per vessel. These data packets identity their target vessel via the ITU's Vessel MMSI number.

As such, and to additionally be able to further infer anomalies based on the vessel's own context and physical features (and not exclusively on movement data), IMO-provided data for a vessel's particulars (DWT, GT, Service Speed, MCR, etc.) was fused into the AIS traffic as it was loaded onto the system via our own internal systems Fusion and sense making capabilities:
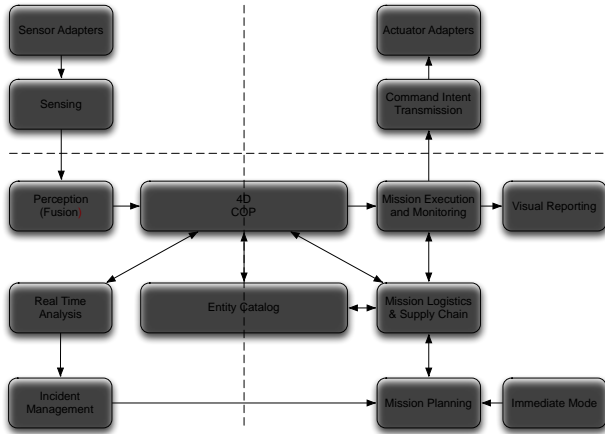
Figure 1 The Data Ingestion pipeline on the left

The system received every AIS movement data tick and processed it against well-known databased for IMO Number – MMSI Number mapping, as well as third-party vessel particulars enrichment sources. Then, each movement was stored in a fourth-dimensional spatiotemporal database for later retrieval and calculation.

In total, the data set is comprised of 10.929.973.310 vessel AIS movement data points, of which we correctly attributed 7.196.639.922 to valid IMO numbers that correspond to 78.055 distinct MMSI vessels. This averages to just under 6 million AIS movement data points per day of consolidated Situational Awareness data.

The data set was split in two: odd years (2011/2013/2015) for training, even years (2012, 2014) for validation.

2. ANOMALIES AND CLASSIFICATION

Shipping vessels involved in commercial business tend to follow set patterns of behavior depending on the activities in which they are engaged. If a vessel exhibits anomalous behavior, this could indicate it is being used for abnormal and/or illicit activities. With the wide availability of automatic identification system (AIS) data it is possible to systematically search and detect some of these behavioral

patterns using algorithms appropriate for the target detection problem.

In [1], then further consolidated in [2], an Anomaly Taxonomy is suggested for maritime events derived from movement (kinetic) observations. Based on either Motion or Location information, it classifies maritime anomalies based on the evaluation of motion against its speed and track, and, based on its Location, it suggests classifications evaluation the vessels' data against history information, specific geospatial areas, or other vessels.
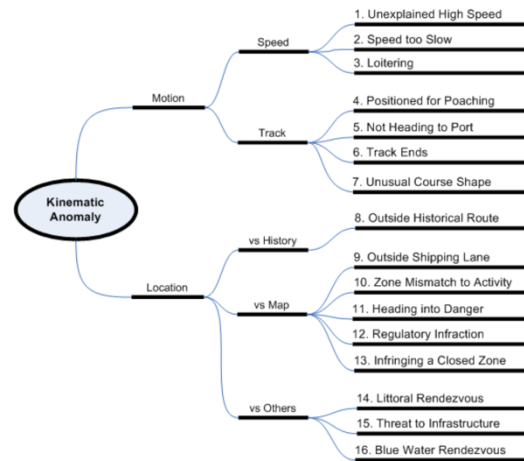
Figure 2 Anomaly Taxonomy [1]

In our research, we focused of first-order and second-order events that could be directly or indirectly derived from the vessel's Speed or Location.

For each of the focus areas, a modified machine learning detection algorithm was developed; for each potential detection, we determine the probability that it is indeed anomalous; finally, for complex events the probabilities are combined using a Bayesian network to calculate the aggregated probability for the event.

We then use elastic, big data processing techniques to process the input data set and try to derive meaningful information in an experimental information system that continuously evaluates the current maritime picture against historical trends, matching relevant events (candidate abnormalities) and allowing for a trained operator (either automated or in real time) to further interrogate the system for deeper extraction of the probabilistic evaluation.

5. RESULTS AND ONGOING WORK

Work is still ongoing regarding long-term insights to be taken from the input data being processed with the system presented herein. Still, can preliminarily demonstrate how

historical information consulted and further enriched in real-time provides predictive value for mission-planners and is crucial for meaningful large-scale data analytics.
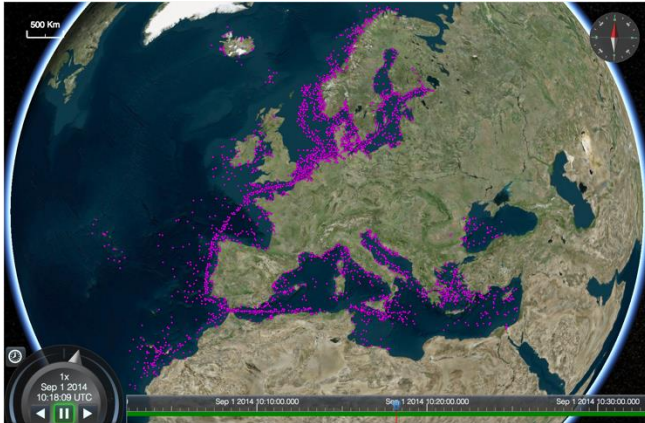
Figure 3 Inovaworks' running prototype

In our running prototype, the system is now configured to detect and validate:

- Unusual unexplained high speed
- Unusual unexplained slow speed
- Unusual unexplained turn
- Unusual course region
- Vessel Loitering
- Vessel outside historical route
- Vessel outside traffic lanes
- High-seas Vessel Rendezvous
- Littoral proximity Rendezvous
- Recurrent proximity with other Vessel(s)

6. FUTURE WORK

Inovaworks is now working on second-level inferences regarding vessel kinematic information that will further deepen the analysis possibilities for the dataset provided, which should be further enriched accordingly with correlatable data to allow for such questioning.

As an example, such analysis will allow for our technology to answer complex, derived questions such as "which distinct-type vessels came together for near littoral Rendezvous and are for whom the Captains were already previously part of the same crew?"

Also, our team will be complementing the system's probabilistic capabilities in order to allow of questioning regarding the probability of a future event (e.g., a piracy act) to occur for a given cargo on a given route, based not only on history movements, but more so on the association of historic data with concrete contributive vessels on the give route's area at the projected timeframe.

7. REFERENCES

[1] Davenport, M., Kinematic Behaviour Anomaly Detection (KBAD) – Final Report, MacDonald Dettwiler and Associates Ltd, DRDC CORA CR 2008-002, DRDC CORA, 2008.

[2] E. Martineau and J. Roy, "Maritime anomaly detection: Domain introduction and review of selected literature," Defence R&D Canada Valcartier, Tech. Rep., 2011.

SEA SURFACE CURRENTS CALCULATION USING VESSEL TRACKING DATA

Yann Guichoux, Marc Lennon, Nicolas Thomas

e-Odyn

ABSTRACT

The first charts showing information on surface oceanic currents were based on logs of both military and merchant ships. At the time, ships navigated through dead reckoning. Once or twice a day, a ship noted its position based on celestial navigation, and recorded its speed, and compass direction. If currents are present, they will likely push the ship off course and alter its speed. One can estimate the direction and speed of these currents by subtracting the predicted vector based on dead reckoning from the vector representing the ships actual speed and direction. Now, merchant ships transmit the position, the compass direction and the speed through AIS (Automatic Identification System) messages. Therefore it is potentially possible to compute surface current at finer scales. Preliminary experiments show that this approach is able to reveal mesoscale structures as eddies or filaments that can escape to satellite altimetry techniques. This paper aims to provide an overview of results in the Mediterranean area, showing the good correlation between AIS surface currents and chlorophyll concentration.

1. INTRODUCTION

Near-surface ocean currents play a variety of roles in the marine environment and are considered as a key parameter for many applications. Search and rescue, ship routing, global warming analysis: all these domains and many others require to get information related to ocean surface currents.

Therefore, complex and heavy systems are deployed to measure or estimate currents in coastal areas and high sea regions. Unfortunately, conventional methods for measuring near-surface currents may be subject to problems. While a surface drifter is uncontrollable in its spatial and temporal coverage, making such a system difficult to use to caracterize the ocean circulation in wide areas, especially in convergent and divergent flow regimes, HF radars are very complex systems which require substantial maintenance work to estimate ocean surface currents in coastal zones only and in small areas (up to 200 km² for the more efficient systems). Other conventional techniques such as Vessel

Mounted Adcp and gliders have also limitations related to their deployment and maintenance complexity, spatial coverage and service life. Altimetry satellites such as the Jason series can also be used to approximate geostrophic currents at global scales. However, a limitation of the nadir altimetry from space, is the 200- to 300-kilometer spacing between satellite orbital tracks, which is unable to resolve small-scale features in oceanography.

From an historical point of view the first charts showing information on surface oceanic currents were based on logs of both military and merchant ships. At the time, ships navigated through dead reckoning. Once or twice a day, a ship noted its position based on celestial navigation, and recorded its speed, and compass direction. If currents are present, they will likely push the ship off course and alter its speed. One can estimate the direction and speed of these currents by subtracting the predicted vector based on dead reckoning from the vector representing the ships actual speed and direction. Nowadays, merchant ships transmit the position, the compass direction and the speed through AIS (Automatic Identification System) messages. Therefore taking advantage of the data about ship navigation of the AIS system an innovative algorithm called e-Motion has been developed by e-Odyn to derive surface currents. Our preliminary experiments [1] shew that this approach is able to reveal mesoscale structures as eddies or filaments that can escape the altimetry techniques.

AIS[2] is a communication system based on a protocol using the VHF maritime mobile band, for the exchange of navigation data. AIS uses an open protocol and is not intended for secure communications. It enables the automatic exchange of shipboard information from the vessels' sensors (dynamic data), as well as manually entered static and voyage related data, between one vessel and another or a shore station. AIS devices are required internationally on most commercial vessels as identified by the International Maritime Organization (IMO) in the Safety of Life at Sea Convention (SOLAS), Chapter V. [3]

AIS receivers are subject to line-of-sight limitations where range is depending on height of the antenna. In normal weather conditions, one can expect to collect AIS messages transmitted from ship located about 40 Nm from the receiver , while sometimes, due to duct effects , the range can increase up to several hundreds of Nm.

The subject of this study starts with the observation of meso-scale and sub-mesocale features along the south and east coast of Sicily by using AIS data processed using the e-Motion algorithm. The position and the size and of these observed features are compared, from a qualitative point of view only, with one satellite observation dataset used as surface tracers : Aqua/Modis Chlorophyll concentration. Moreover, the analysis of the bathymetry in the area reveals other particulars of the surface circulation which can be related to e-Motion surface currents.

2. STUDY AREA
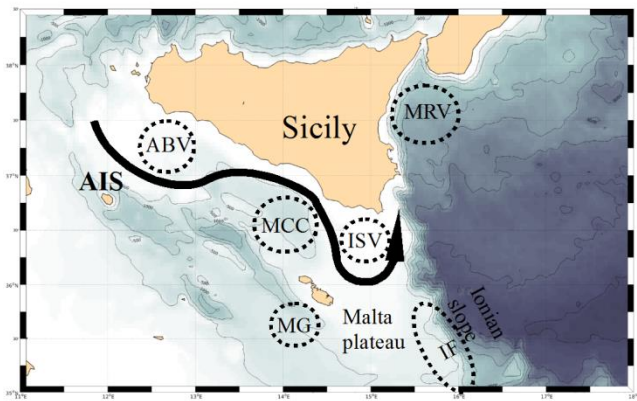
Figure 1 A simplified vue of the summer circulation in the Sicily Chanel (SC) Omrani et al. 2016. The main features are represented : Atlantic Ionian Stream (AIS), Adventure Bank Vortex (ABV), Maltese Channel Crest (MCC), Ionian Shelf Break Vortex (ISV) , Medina Gear (MG), Messina Rise Vortex (MRV), Ionian Front (IF).

The proposed method used to calculate ocean surface currents using AIS messages could be used in any area where ships are navigating, including areas where the tide effect is important. However, tide currents are nowadays well known and numerical models are quite efficient to restitute the currents in regions where this type of signal is prominent. Moreover, preliminary results from e-Odyn already shown the relevance of e-Motion to estimate tidal ocean surface currents [1]. Therefore, it is more interesting to analyze the method by comparing our results with other datasets, especially in micro-tidal area and where altimetry satellites fail in detecting eddies (near the coast for instance). This type of area can illustrate the potential of the proposed method as a complement to other techniques to observe ocean surface currents at a global scale.

The study area is mainly located south and east to the Sicily and is represented on figure 1. It was chosen mainly because of the great variety of circulation features. From a marine traffic point of view, the Sicily Channel (SC) is an intensively used area and the main gateway for ships which

are navigating between the strait of Gibraltar and the Suez Canal. That area is then very valuable to analyze the currents estimated from AIS data using e-Motion. The SC connects the Mediterranean's eastern and western sub-bassins and represents a key area for the general Mediterranean sea circulation. This strait has a very irregular bottom topography characterized in the southwest by the Tunisian continental shelf and in the northeast by the Sicilian shelf. The circulation in the area is governed by density gradients [4]. An eastward surface flow if formed by the Algerian current [5]. This flow is modulated by permanent mesoscale features, which could be related, amongst other, to bathymetry effects, upwellings and baroclinic instabilities [6]. Along the southeastern Sicilian Coast, on the downstream of the Malta plateau is an upwelling site. Due to the AIS vein a mesoscale anticyclonic eddy (Maltese Channel Crest - MCC) formation can come into action and tends to reverse the flow to a North-West direction closer to the coast.[7]

3. DATA AND METHOD
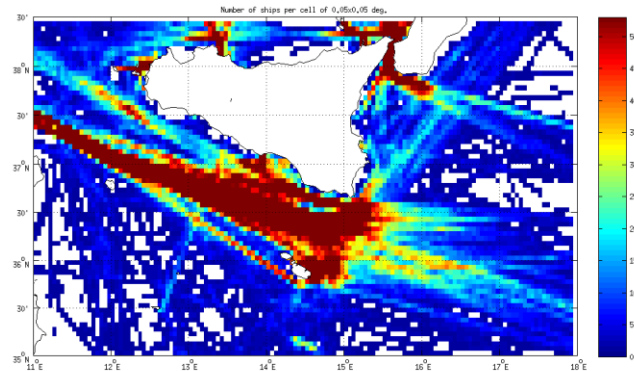
Figure 2 Density plot showing the number of ships per cell used during the 10 days period of the study to calculate ocean surface currents with e-Motion. The main ship routes can be observed (red) and correspond to the area with the highest number of gathered AIS messages.

The AIS data used in this study were gathered by e-Odyn in April 2016, using several AIS receivers located along the Sicily south and east coastline. Figure 2 presents the traffic density in the area and an overview of the range of the AIS receivers. These data were gathered at a one minute sampling rate. For the study, we selected AIS messages of merchant ships with a speed over ground superior to 6 knots in order to exclude the impact of voluntary ship maneuvers on our results, taking into account that voluntary ships maneuvers change in speed and heading create strong bias in e-Motion results.

We gathered ships AIS messages during 10 days starting from 10th, April 2016 to 19th, April 2016. This period of time corresponds to good VHF signal propagation conditions, allowing us to collect a maximum of AIS messages in the area of the study despite low performance AIS receivers.

Ocean surface currents calculated along each ship tracks using e-Motion have been bin averaged (0,05x0,05 degrees). No other processing technique has been used to enhance the results as horizontal non-divergence of surface flux. The implicit only one assumption derive from the time window of 10 days: we focus on persistent mesoscale structures at this time scale. The following figures only present raw ocean surface currents binned means.
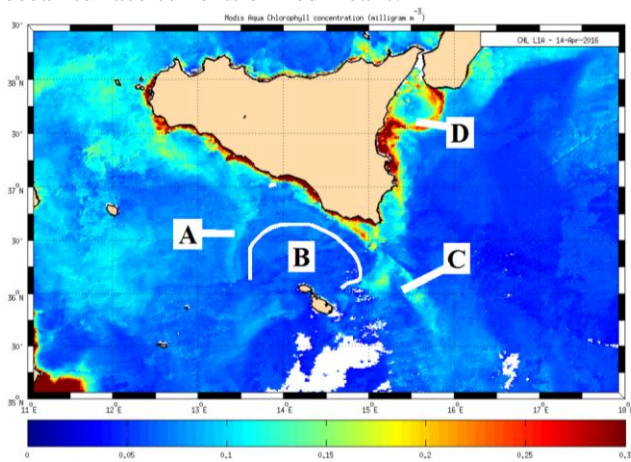
Figure 3 Modis/Aqua chlorophyll concentration from Copernicus (8 days mean – 14th, April 2016). CHL concentrations used as surface tracers reveal different types of features: a north/south stream (A), an envelop which could be related to eddies (B), an upwelling (C) and an eddy (D). Some of these features can also be linked to the simplified circulation shown on figure 1. Upwelling regions are characterized by high chlorophyll concentrations (>0.15 mg.m- 3) found along the coast, along the Malta shelf-break, and at the boundaries of MRV.

Since surface currents interact with waters rich in chlorophyll provoking the detachment of filaments useful for identifying the coastal circulation, the other used material is an optical satellite image derived from MODIS (Moderate Resolution Imaging Spectroradiometer) and provided by Copernicus: Aqua *dataset-oc-med-chl-modis_a-l4-chl_1km_8days-rt-v01_1464718499335* was selected for this study to visualize the chlorophyll gradients and e-Motion outputs at the same date.

4. RESULTS AND DISCUSSION

Near-surface mesoscale eddies having a diameter down-to 100 km can be observed using altimetry techniques.

However, altimetry often fail in detecting smaller features and have difficulties to detect turbulences located close to the coast : difficulties in estimating the mean sea level around the shelf break and issues of land contamination in the altimeter and radiometer footprints are the main encountered problems [8]. Nonetheless, eddies with horizontal scales below 50 km can be observed from space using optical sensors. [9]

The CHL map presented on figure 3 and derived from the Modis dataset shows coherent features that are easily regognizable. A very well delimited eddy can be observed north-east to the Sicilian coast (D, figure 3). This eddy is known as the Messina Rise Vortex (MRV). The Meanders (C, figure 3) centered at about (15.25°E, 36.5°N) matches the southward flow of the Malta plateau. They indicate the core of an offshore directed filament transporting water away from the coast also related to the bottom topography and Ionian slope. These visible meanders are related to upwelling signals which are easily recognizable in terms of the color anomalies since these features results in a high level of nutrients, due to the decomposition of sinking organic matter brought to the surface and utilized by phytoplankton. These meanders and upwelling are known as Ionian shelf break vortex (ISV) and Ionian front (IF). A north/south oriented filament (A, figure 3) can be observed at about (15.25°E, 36.5°N) which is the west boundary of a low concentration chlorophyll patch (B, figure 3).
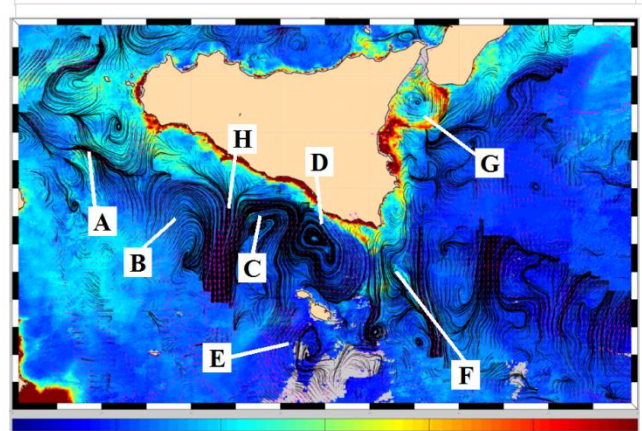
Figure 4 e-Motion streamlines computed using 10 days of AIS data from 10th, April 2016 to 19th April 2016, superimposed on Aqua/Modis chlorophyll concentration. Purple arrows are plotted to provide information related to intensity and direction of the e-Motion observed features. The main meanders, eddies and jets observed may be related to the synoptic description of the circulation shown on figure 1: A/AIS (reversed), C/ABV, D/MCC, E/MG, F/IF, G/MRV.

We superimposed e-Motion ocean surface current streamlines with CHL (figure 4) in the same area. 5 eddies (B, C, D, E, G figure 4) can be clearly derived with e-Motion algorithm. One cyclonic eddy (C) and one anticyclonic (B) are facing and conforming to the shape of the bathymetry is this area (figure 1). The position of the front (H, figure 4) between these two eddies closely resembles that of the CHL filament (A , figure 3). The flow direction observed both by CHL concentration repartition and e-Motion streamlines is mainly north/south. This mushroom feature with 2 facing eddies (B, C figure 4) and located west of Malta can be related to the pathways and transformations of the main water masses described by Lermusiaux et al [10].

A third eddy (D) is centered at (36.5° N, 15.4° E). The total envelop of eddies (C) and (D) is also conforming to the shape delimited by CHL gradients (B, figure 3). In this situation, by only observing the CHL concentration gradients, one can miss this 2 facing eddies feature. e-Motion allows to visualize the internal structure of this CHL patch (B, figure 3, C and D figure 4). Figure 6 shows e-Motion results at higher resolution.
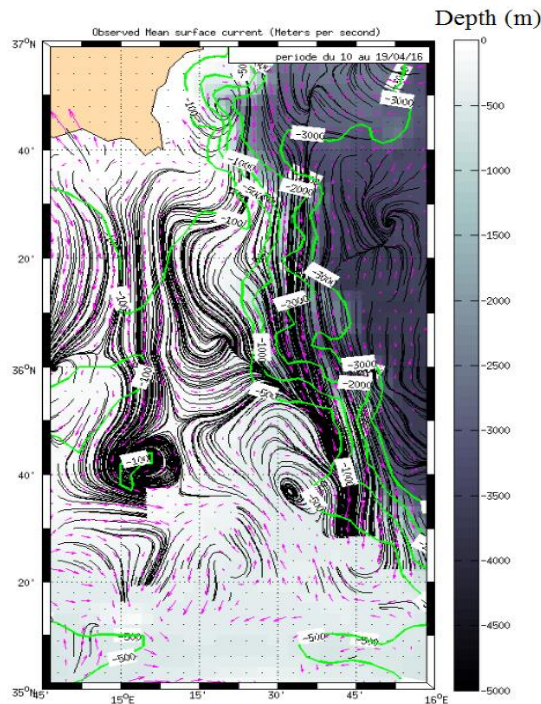
Figure 5 e-Motion streamlines (black) and vector field (purple) computed using 10 days of AIS data from 10th, April 2016 to 19th April 2016, superimposed on bathymetry contours (green).

All along the Ionian slope and on the western side of Malta plateau, the flow exhibits a component (figure 5 and F,

figure 4) parallel to bathymetry contours and CHL gradients. The position of the front is closely relatedthe 500misobaths of figure 5. An anti-cyclonically rotating eddy to the north-east of Sicily (G, figure 4) is in agreement with the shape of a patch of plankton-rich waters (D, figure 3). This eddy can be clearly related to MRV.
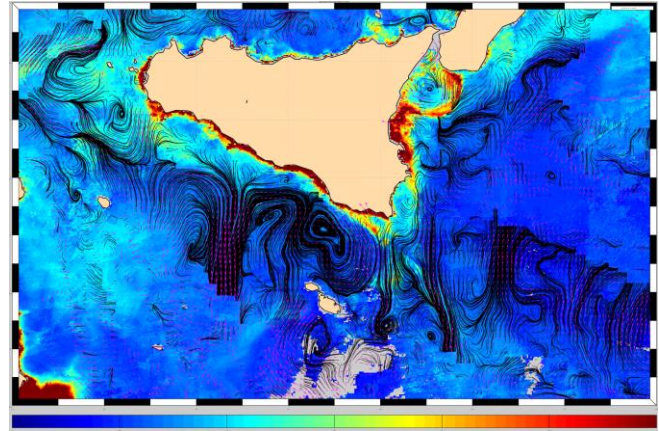
Figure 6 High resolution image showing e-Motion streamlines computed using 10 days of AIS data from 10th, April 2016 to 19th April 2016, superimposed on Aqua/Modis chlorophyll concentration. Purple arrows are plotted to provide informations related to intensity and direction of the e-Motion observed features.

5. CONCLUSION AND PERSPECTIVES

The e-Motion outputs and their comparison to CHL concentration and bottom topography have revealed several features, which were expected from previous knowledge. The Messina Rise Vortex (MRV) for example is clearly revealed by e-Motion, as well as meanders observed along the Ionian slope. Some other high resolution features are also revealed, that appear to be unfamiliar or subject to seasonal variability. They deserve to be discussed in this study and will be analyzed later from a seasonal point of view by creating e-Motion climatologies.

The preliminary results shown here suggest that the spatial coverage and high temporal resolution of the AIS data now allows a unique and detailed characterization of the surface circulation along the coastline of many countries worldwide. Previous results from e-Odyn [1] in the Iroise sea, France where the tide can produce predominant surface currents, completed with the results in the Sicily Channel now show the relevance of the method to analyze and characterize different type of ocean dynamics.

More results will be published in a near future, showing the added value of e-Motion coupled with classic techniques such as HF radars, buoys and drifters or altimetry satellites.

Those studies will include quantitative information and error estimations related to e-Motion outputs. The relevance of using satellite AIS data to calculate ocean surface currents and provide information at a global scale will be also demonstrated.

6. ACKNOWLEDGEMENT

7. DISCLAIMER

All findings of this paper are based on the analysis of a single AIS data set collected in April 2016. The situation described is only representative for this month of that particular year and it is not claimed that it represents any "mean" or "seasonal" situation of this region.

REFERENCES

[1] Guichoux, Y., Ocean dynamics 2.0 poster, *EURASC symposium*, October 2015.

[2] Recommendation, I.T.U. RM. 1371-4. *Technical characteristics for an automatic identification system using time-division multiple access in the VHF maritime mobile*, 2010.

[3] International Maritime Organization (IMO), "International Convention for the Safety of Life at Sea (SOLAS)", Retrieved 6 April 2013.

[4] Molcard, A., Gervasio, L., Griffa, A., Gasparini, G. P., Mortier, L., & Özgökmen, T. M., "Numerical investigation of the Sicily Channel dynamics: density currents and watermass advection". *Journal of Marine Systems*, *36*(3), 219-238, 2002.

[5] Millot, C., "Some features of the algerian current", *Journal of Geophysical* Research 90, 7169–7176, 1985.

[6] Omrani, H., Arsouze, T., Béranger, K., Boukthir, M., Drobinski, P., Lebeaupin-Brossier, C., & Mairech, H. "Sensitivity of the sea circulation to the atmospheric forcing in the Sicily Channel." *Progress in Oceanography*, *140*, 54-68, 2016.

[7] Drago, A., Azzopardi, J., Gauci, A., Tarasova, R., Ciraolo, G., Capodici, F., & Gacic, M. Sea surface currents by HF radar in the Malta channel. *Rapp. Comm. Int. Mer Medit*, *40*, 144, 2013.

[8] Vignudelli, S., Snaith, H. M., Cipollini, P., Venuti, F., Lyard, F., Cretaux, J. F., ... & Ginzburg, A. "Extending the use of satellite altimetry for coastal applications: the alticore project."

[9] Alpers, W., Brandt, P., Lazar, A., Dagorne, D., Sow, B., Faye, S., ...& Brehmer, P. . "A small-scale oceanic eddy off the coast of West Africa studied by multi-sensor satellite and surface drifter data." *Remote Sensing of Environment*, *129*, 132-143, 2013.

[10] Lermusiaux, P. F. J., & Robinson, A. R. "Features of dominant mesoscale variability, circulation patterns and dynamics in the Strait of Sicily". *Deep Sea Research Part I: Oceanographic Research Papers*, *48*(9), 1953-1997, 2001.

DETECTING ANOMALIES IN STREAMS OF AIS VESSEL DATA

DimitriosZissis[1,2]
[1]Dept. Product & Systems Design Engineering,
University of the Aegean
Greece
[2]MarineTraffic.com

ABSTRACT

Current state of the art techniques and technologies are struggling with the growing volumes of high-speed, loosely structured, spatiotemporal data streams, such as those produced by the vessel tracking Automatic Identification system (AIS). So as to generate actionable intelligence from these streams of data, systems are required to face challenges at a variety of levels, including fusion, processing and storage. In this paper, we report on our recent work regarding learning a vessel's "normal" behavior, so as to support situational assessment by indicating dangerous deviations from this in the future. Within this context, we report on early results, that validate the potential of a novel solution leveraging the architectural characteristics of edge (or fog) computing and employs Support Vector Machines (SVM) on the perimeter of the system, to perform low footprint unsupervised learning and analysis of sensor data for anomaly detection purposes.

Index Terms—fog computing, AIS anomaly detection, 1-SVM

1. INTRODUCTION

The International Maritime Organization (IMO) requires that all vessels over 299 Gross Tones carry an Automatic Identification System (AIS) transponder on board, which transmits data regarding their position, speed and course, amongst other static information (such as a vessel's name, dimensions, voyage details and other). Networks of coastal and satellite receivers are capable of receiving such broadcasted messages. A combination of AIS data and other spatial information can produce interactive map mashups which attempt to provide a depiction of the state at sea for port authorities, coast guards, vessel tracking services and other interested parties. For example, 'MarineTraffic.com' which is one of the most popular vessel trackers, is at any time tracking more than 80,000 vessels, while data is collected from a network of over 1,800 coastal AIS stations, located in 140 countries around the world.

Unfortunately, vessel tracking systems are vulnerable to a number of malicious attacks, as they were not originally designed with security in mind. Balduzzi presented a method of spoofing a vessel by injected invalid data into AIS gateways [1]. Ship spoofing involves creating a nonexistent vessel, assigning it all the information relevant to AIS (MMSI and call sign), and then transmitting messages as if valid, e.g. changing position, speed etc. [2]. By implementing this technique, malicious attackers, were able to trigger fake collision warning alerts, which could potentially make surrounding vessels alter their course. Another attack includes AIS hijacking, by which attackers can maliciously modify information provided by the AIS base station, eavesdropping on all transmissions (i.e. man-in-the-middle) or modifying data. This method makes it possible for attackers to alter any information broadcast by existing AIS stations regarding real vessel data (e.g., cargo, speed, location, and country). AIS transponders are also susceptible to "insider attacks", as in some occasions vessels have been reported hacking their own AIS responder. Recently an Iranian tanker was intendedly disguising itself as a smaller capacity vessel to avoid been identified [3].

Erroneous and malicious data needs to be filtered out prior to entering the database, so as not to affect data accuracy and business intelligence. In many cases, one can employ traditional approaches to filter out the data outliers in batch mode, when the data has already entered the database. But for a website such as MarineTraffic, which receives thousands of streams of vessel data, with an increase rate of approximately 5GB per day and over 1 million events triggered (port calls, collision detections etc.) it is almost impossible. In this short paper, we report on early results that validate the potential of a novel solution, which leverages the architectural characteristics of edge (or fog) computing and employs Support Vector Machines (SVM) on the perimeter of the system, to perform low footprint unsupervised learning and analysis of sensor data for anomaly detection purposes.

2. SECURITY ON THE PERIMETER OF THE SYSTEM

For streaming data, of such volume and variety, novel approaches are required for processing and storage. It is necessary to delegate an increasing number of processes to the IS itself, increasing its autonomy, while leveraging administrators and stakeholders from repetitive low level and complex intensive tasks. With the rise of the Internet of Things combined with Big Data, we are in urgent need of intelligent security mechanisms capable of anticipating, detecting, identifying, and protecting the systems autonomously. Artificial intelligence techniques have been employed in security for some time now.

An IDS is a defense system which is capable of monitoring and detecting hostile activities either across a network (Network based IDS) or on a host system (Host based IDS). In "big data" conditions a centralized IDS system would be flooded by too much data, ultimately missing hidden trends in the data. For such purposes, detection components of the IDS can be moved to the periphery of the system, delegating them with monitoring their local surrounding, while moving centralized decisions to the coordinating authority higher up in the hierarchy. Fog computing architectures, a.k.a, edge computing have recently emerged as an extension of cloud computing, offering services including storage and processing, closer to the end user, directly at the edge of the network [4]. It is a highly virtualized environment located on devices at the periphery of the network (e.g. access points), positioned for real time analytics, supporting densely distributed data collection points, low latency interactions and high geographical distribution [5]. From its infancy, researchers identified the potential benefits edge computing could bring to security in IOT and cloud environments [6]. In our work, we leverage the fog, to architect and develop a hierarchy of intelligent anomaly detection systems for IOT environments.

3. SELF-PROTECTING AIS RECEIVER STATIONS

The hypothesis of this work is that each single AIS station in a network can be viewed as a single fog node. Normal vessel traffic should be clustered around one or more specific clusters and any traffic representing anomalous behavior or suspicious behavior should potentially be positioned outside these clusters. Each fog node (e.g. AIS station), receiving only a partition of the overall dataset streaming into the application databases, can potentially learn the clusters relevant to that, which will contain clusters of vessel paths, types, positions, destinations and speed, in near or real time constraints. Any vessel data detected not falling within these clusters can be labelled as a potential anomaly, alerting a higher level centralized node, system or operator. As the node will be operating on a small portion of the overall data, only the minimum of processing and memory will be sufficient.

To validate our hypothesis we developed an intelligent fog node IDS and deploy it on an experimental AIS receiver base station located in the Aegean Sea Greece. An AIS base station can be build using simple components such as a Raspberry Pi 2 board (900MHz quad-core ARM Cortex-A7 CPU with 1GB RAM) and related sensors, which provide enough computational power and memory for successfully deploying Yocto Linux [7]. For the classification of incoming data as anomalous or not, in real time constraints, we implement a One-Class Support Vector Machine [8]. One-class SVM (1-SVM), is a one class classification unsupervised learning algorithm, which aims to find an optimal hyperplane in a feature space separating the training data (positive samples) from the origin (considered as negative samples) with maximum margin (the distance from the hyperplane to the origin). It essentially learns a decision function for novelty detection: classifying new data as similar or different to the training set. For training the machine learning algorithm, we maintain a time window of vessel data collected in the previous 12 hours. As our primary focus in this work, is to validate the architectural deployment and counter attacks such as spoofing a real vessels position data by making it to appear inland or in other anomalous location (an attack described in Balduzzi, 2014), we focus on the vessels location data (Latitude and Longitude), while ignoring other data fields.
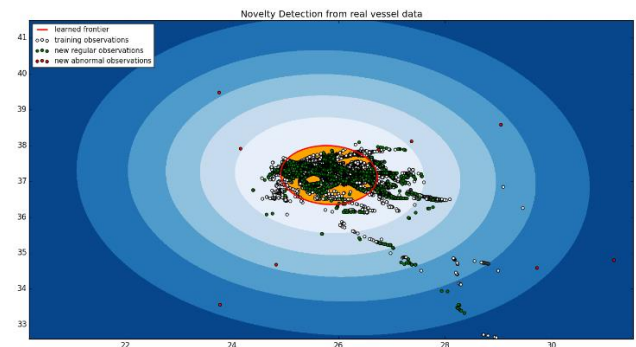
Figure 1 A visualization of received data from a single AIS base station. Each dot representing a vessel (x-axis is Latitude, while y-axis Longitude). Centre circle, represents the learned decision function by the 1-SVM depicting inliers and outliers.

The 1-SVM was trained on 24,285 instances (data received in several hours previously) on the AIS base receiver (Rasberry Pi 2 900MHz quad-core ARM Cortex-A7 CPU with 1GB RAM) running Yocto Linux in several minutes (less than 3 minutes). During training the 1-SVM

erroneously labelled 2,429 observations. After successful training, the SVM was tested on real data, both regular observations and abnormal observation such as that injected by a spoofed AIS receiver. From the 5,000 regular observations fed to the SVM, 583 were erroneously labelled as potentially anomalous, while from the 500 abnormal data injected, all were detected as anomalies. Most importantly, the SVM was capable of operating in near real time constraints, without overburdening the AIS base receiver.

4. CONCLUSION AND FUTURE WORK

Overall, results verify that based on a multivariate statistical approach, the IDS is capable of detecting abnormal vessel movements through moving temporal window of vessel measurements. In a similar fashion, a machine learning algorithm can be fed data so as to learn the most common seen destinations, vessel flags, types and more complex behaviors.

REFERENCES

[1] M. Balduzzi, AIS Exposed Understanding Vulnerabilities & Attacks 2.0, in: BlackHat Asia, 2014.

[2] M. Balduzzi, K. Wilhoit, A. Pasta, Threats at Sea: A Security Evaluation of AIS, 2014.

[3] R. Almeida, Iranian Tanker Hacks AIS to Disguise Itself Off Singapore, (2013).

[4] S. Yi, Z. Qin, Q. Li, Security and Privacy Issues of Fog Computing: A Survey, in: K. Xu, H. Zhu (Eds.), Wirel. Algorithms, Syst. Appl., Springer International Publishing, Cham, 2015. doi:10.1007/978-3-319-21837-3.

[5] Y. Wang, T. Uehara, R. Sasaki, Fog Computing: Issues and Challenges in Security and Forensics, in: 2015 IEEE 39th Annu. Comput. Softw. Appl. Conf., IEEE, 2015: pp. 53–59. doi:10.1109/COMPSAC.2015.173.

[6] K. Lee, D. Kim, D. Ha, U. Rajput, H. Oh, On security and privacy issues of fog computing supported Internet of Things environment, in: 2015 6th Int. Conf. Netw. Futur., IEEE, 2015: pp. 1–3. doi:10.1109/NOF.2015.7333287.

[7] F. Cabrera, N. Molina, M. Tichavska, V. Arana, Design of a low cost prototype of automatic identification system (AIS) receiver, in: 2015 1st URSI Atl. Radio Sci. Conf. (URSI AT-RASC), IEEE, 2015: pp. 1–1. doi:10.1109/URSI-AT-RASC.2015.7303000.

[8] B. Schölkopf, A. Smola, Support Vector Machines, in: P. Armitage, T. Colton (Eds.), Encycl. Biostat., John Wiley & Sons, Ltd, Chichester, UK, 2005. doi:10.1002/0470011815.

SECTION III: RESEARCH CENTRES & ACADEMIA

REAL TIME INTELLIGENCE OF AIS DATA

Nikitas Nikitakos
Professor
Dept. of Shipping Trade and Transport
University of the Aegean – Chios - GREECE

ABSTRACT

A conceptual framework for real time deaccessioning for AIS anomaly detection is presented. Inspired from airport electronic data real time risk assessment for resilience, a stream reasoning approach is introduced. Stream reasoning is an approach that can be used if information (in the form of assertions) arrives as a stream of (time stamped) inputs. The approach has two features that could be helpful: the knowledge base can be continuously updated and reasoning goals continuously re-evaluated as new assertions arrive, the reasoner considers events from a finite time window, and not only at a single instant

Index Terms— AIS data, stream reasoning, decision support system

1. INTRODUCTION

AIS [2,3] is now well recognized in maritime society and widely used as several systems, including class A for SOLAS vessels, class B for non-SOLAS vessels, Aids to Navigation (AtoN), Search and Rescue Transmitter (AIS-SART), Application Specific Messages (ASM). The Automatic Identification System (AIS) is a mandatory piece of navigational equipment for automatic data exchange between ships and with shore-based facilities. The overall aim of AIS is to improve safety at sea by assisting target tracking, simplifying information exchange and enhancing collision avoidance. AIS could be exploited more efficiently to improve the situational awareness both on board and ashore as well as reduce the manual workload.

In the context of information fusion and maritime surveillance the AIS data plays a critical role. Using these data an indication is derived related with anomaly detection i.e. that deviation of vessels' expected behavior and possibly further investigation is required. This is very important for achieving appropriate Situation Awareness. Several methods and algorithms [4] have been proposed to attack the issue, mainly correlating historical data with new data provided by AIS receiver. The existing methods are mainly based on neural networks using supervised and unsupervised learning or statistical/probabilistic models.

In this paper inspired by air traffic control developed in EU research project SERSCIS [1] a new concept of AIS intelligence based on complex event processing and particular on data stream reasoning is presented, where an indication of risks related with anomaly detection could be initially derived and the appropriate action initiated.

The paper is structured as follows, after the introduction a brief description of reasoning technology is presented then the proposed conceptual framework is discussed followed by conclusions and further research.

2. STREAM REASONING TECNOLOGY

Stream reasoning [5], [6] is an approach that can be used if information arrives as a stream of (time stamped) inputs. The approach has two features that could be helpful:
• the knowledge base can be continuously updated and reasoning goals continuously re-evaluated as new assertions arrive;
• the reasoner considers events from a finite time window, and not only at a single instant.

Introducing stream reasoning in AIS data processing could therefore overcome some of the current limitations by:
• allowing the concrete system model to be continuously updated, which should be faster than generating a completely new model each time we need an update;
• reducing the time lag between the evolution of the real system and that of the concrete system model, making it possible to resolve recent and rapid changes in the real system;
• representing protracted as well as instantaneously observed behaviors in the model by including information over an extended time window;
• allowing reasoning algorithms to take account of system changes during the time window, target than only the instantaneous system composition and status.

However it is important to appreciate the research on stream reasoning is still in its infant. Recent research efforts are still in early step and focus on the investigation of architecture approaches to support stream reasoning. As illustrated in Figure 1, stream reasoning consists of four main processing steps:
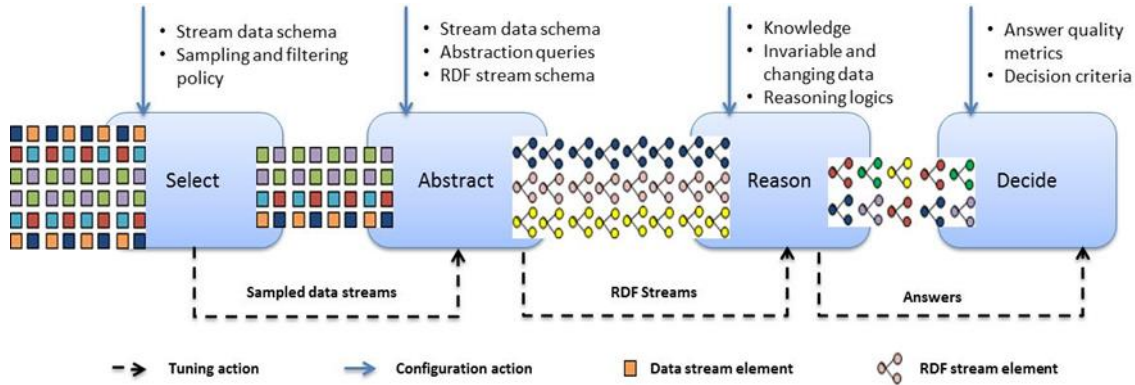
Figure 1 Information processing steps in a stream reasoner

• Select: the first step in the stream reasoning to select relevant data from input streams by exploiting load-shedding techniques by introducing sampling policies that probabilistically drop stream elements to deal with bursty streams that may have unpredictable peaks.

• Abstract: the sampled streams are fed into the abstract step that generates aggregate events by enforcing aggregation queries continuously. Outputs of the abstract step are consolidated as RDF (Resource Description Framework) streams, an unbounded bag of pairs $<\rho, \tau>$ where ρ is a RDF triple and τ is the timestamp that denotes the logical arrival time of RDF statement. This step entails the development of aggregate query language and system for query RDF data in the form of data streams. Three recent independent proposals include Streaming SPARQL [11] Continuous SPARQL (C-SPARQL) and Time-Annotated SPARQL; all extend SPARQL to handle both static RDF graphs and transient streams of RDF triples.

• Reason: RDF streams are injected into background knowledge in order to perform reasoning tasks. Given that the reasoning process is not aware of expiration time, the reasoning results remain valid until the next update. A pre-reasoning process is used to generate the current system snapshot and is responsible for maintenance of incremental materialisation of RDF snapshots. The efficient incremental materialisation of RDF snapshots is a research challenge under investigation. Recent experimental efforts include

• Decide: Before producing answers to reasoning tasks, the answering process reaches the decision step where quality metrics and decision criteria defined by application developer are used to evaluate the quality of the answer is good enough and otherwise adapt the behavior of each previous step.

After some consideration, we concluded that it is not possible to use stream reasoning in a simple way to address AIS real time intelligence implementation. However, the underlying concepts can be used to enrich the proposed run-time architecture and to provide more flexibility

3. PROPOSED REAL TIME FRAMEWORK

In this subsection we briefly overview the approach taken in conceptual framework, This is designed to exploit semantic system models to enable the use of machine reasoning to support the end user in making and implementing decisions at run-time. This translates into: · creating a semantic model of the running system based on the available monitoring data and using it to reason about the status of the system, presenting information from this model to the user, to help them understand and address current situation awareness risks.

The tools developed support machine-assisted design time system modelling, allowing its structure and properties to be described before the actual system is created by dynamic runtime composition. This model is called an abstract system model since it describes the structure of the system but not its actual composition. The proposed conceptual framework which schematically is given in Fig. 2.Then constructs a concrete system model representing a snapshot of the running system, based on monitoring data and semantic reasoning over the abstract system model. Avoiding further analysis which would be beyond the scope of this work we mention that two separate reasoning processes are taking place:

1. Semantic reasoning for potential threat of anomaly behavior classification based on whether these are addressed by the controls present in the running system

2. Bayesian inference for likelihood estimation that each threat is currently being carried out.

Within the proposed framework the user is presented with three types of information [9]:
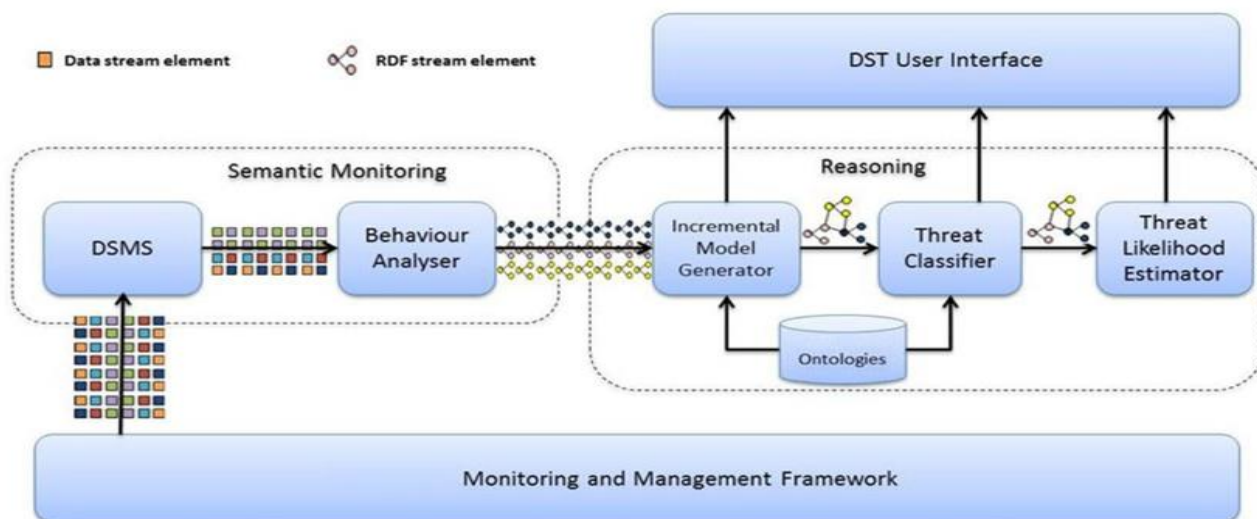
Figure 2 A proposed conceptual framework incorporating stream reasoning concepts

1. What are the system vulnerabilities, or what threats is the system unable to manage
2. What is the current likelihood probability each threat is being carried out
3. What is the threat impact on the maritime traffic.

Moreover that's classified into three classes:
Blocked threat/activity if the system has the appropriate control to prevent the abnormal behavior to create any problem Mitigated activity when the abnormal behavior cannot be prevented, but the system controls provide a response that will counteract its effect on maritime safety and security.
Vulnerability meaning the system does not have any means to prevent the abnormal behavior or counteract its effects on the targeted system asset.
The objectives of the monitoring and decision support tool are basically four.
1. Risk Classification (low, medium, high according their potential impact and blocked, mitigated, vulnerabilities depending on how well are addressed by controls)
2. Periodic assessment (the Decision Support Tool (DST) refreshes in a periodic fashion the model and dynamically reduces the involved risk factors)
3. Threat explanations (the DST provides explanation of threats which is very helpful to the operator in the loop for understanding the system and to take appropriate actions)
4. Propositions (the DST allows the operator to revert to past model versions when required allowing the user to make "what – if" tests on his model by adding controls and comparing the results with the original model). So the fault monitoring DST tool provides continuous feedback and suggests new control actions that can be useful while provides the capability to test their effect to "what – if" scenarios. Notice that the user is presented with the three vulnerability classifications: the good ones are to the left (blocked and mitigated threats) and the most troubling threats (vulnerabilities) are on the right. The core semantic language is OWL, the Web Ontology.

Language meaning that the models in the DST must be in OWL format. The version of the OWL language is OWL2 [7,10]. The support tool is built on JAVA 1.6 and SWT 3.738. Most web semantic projects are built on JAVA and this is the main reason JAVA is used in systems DST. The reasoner has a great role in the DST. The reasoner used is Hermit 1.3.5 [12]. There exit also other reasoners were used as well { but they were unable to handle real and large volumes of data. Though Hermit so far manages well with the volume data, a new reasoned is designed in order to adapt reasoning to Bayes inference used in the approach,
Conclusively semantic models have been proved very useful in the application area of security and risk management of several critical infrastructures including maritime.. The conceptual tool presented made this fact clear especially to the end users and decision makers

4. CONCLUSIONS – FUTURE RESEARCH

The concept of stream reasoning is useful for AIS data intelligence to improve current limitations. However there are still many research challenges. Some of them includes the improvement of Behavior Analyzer component using appropriate algorithms to convert raw monitoring data from AIS into RDF streams improving the knowledge about vessels adverse, the threat classifier also should be extended to handle different types of classifications, but still defined by SWRL rules and to examine the creation of specialized classifier that would be faster than general purpose reasoner and finally the Bayesian threat likelihood estimator implementation should be optimized to reduce processing time and abnormal activity hypothesis sampling should take account of secondary effects. The performance of the conceptual framework in real conditions and the implementation of potential improvement is among the objectives of future research.

REFERENCES

[1] SERSCIS 'Semantically Enhanced Resilient & Secure Critical Infrastructure Services' European Community's 7th Framework Programme, Grant Agreement No. 225336,

[2] Technical characteristics for an automatic identification system using time division multiple access in the VHF maritime mobile band, Recommendation ITU-R M.1371-3, 2007.

[3] Guidance on the application of AIS binary messages, IMO, SN/Circ.236, 2004.

[4] Michele Vespe, Giuliana Pallotta, Ingrid Visentini, Karna Bryan and Paolo Braca 'Maritime Trajectory Mining for Anomaly Detection' NATO RTO-MP-SCI-247 ,2009

[5] E. Valle, S. Ceri, D. F. Barbieri, D. Braga and A. Campi, "A First Step Towards Stream Reasoning," in Future Internet Symposium, Vienna, Austria, 2008.

[6] H. Stuckenschmidt, S. Ceri, E. D. Valle and F. V. Harmenlen, "Towards Expressive Stream Reasoning," in the Dagstuhl Seminar on Semantic Aspects of Sensor Networks, 2010.

[7] Pellet: OWL 2 Reasoner for Java. [Online] http://clarkparsia.com/pellet/.

[8] ISO/IEC 27005:2011. Information technology -- Security techniques --Information security risk management, International Organization for Standardization, 2011.

[9] D. Kostopoulos, G. Leventakis1, V. Tsoulkas1 and N. Nikitakos"An Intelligent Fault Monitoring and Risk Management Tool for Complex Critical Infrastructures: The SERSCIS Approach in Air-Traffic Surface Control," Uksim, pp.205-210, 2012 UKSim 14th International Conference on Modelling and Simulation, 2012

[10] W3C OWL Working Group. OWL 2 Web Ontology Language: Document Overview. W3C Recommendation, 27 October 2009. Available at http://www.w3.org/TR/owl2-overview/.

[11] Davide Francesco Barbieri, Daniele Braga, Stefano Ceri, Emanuele Della Valle, and Michael Grossniklaus. C-sparql: Sparql for continuous querying. In Proceedings of the 18th international conference on World wide web, WWW '09, pages 1061–1062, New York, NY, USA, 2009. ACM.

VISUAL ANALYSIS OF VESSEL TRAFFIC SAFETY BY EXTRACTING EVENTS AND ORCHESTRATING INTERACTIVE FILTERS

Gennady Andrienko[1, 2], Natalia Andrienko[1,2], Christophe Claramunt[3], Georg Fuchs[1], Cyril Ray[3]

[1]Fraunhofer IAIS, Sankt Augustin, Germany
[2]City University London, UK
[3]Naval Academy Research Institute (IRENav) Brest, France

ABSTRACT

Safety and security are constant concerns of maritime navigation, especially when considering the continuous growth of maritime traffic around the world and persistent decrease of crews on-board. This favored and led to the development of automated monitoring systems such as AIS (Automatic Identification System).Beyond its position, an AIS device also transmits navigation data such as ship identification, course, speed, and destination. However, the availability of this information does not by itself ensure the safety of the maritime traffic. Officers on the watch and monitoring authorities require the development of decision-aid solutions that will take advantage of these communication systems. Detection and analysis of anomalous events occurring in movement of vessels is a crucial asset for improving the security of vessel traffic. This paper shows an example of interactive visual analysis in which we extract anomalous events from vessel trajectories and explore the spatial distribution of these events.

Index Terms— Visual Analytics, trajectory analysis, event detection, maritime situational awareness, AIS

1. INTRODUCTION

Safety and security are constant concerns of maritime navigation, especially when considering the continuous growth of maritime traffic around the world and persistent decrease of crews on-board. This favored and led to the development of automated monitoring systems such as AIS (Automatic Identification System). AIS was created in order to provide real-time positioning of a vessel to other vessels and to shore stations located in its radio range. The International Maritime Organization requires AIS to be installed aboard international voyaging ships with gross tonnage of 300 or more and all passenger ships regardless of the size. Beyond its position, an AIS device also transmits navigation data such as ship identification, course, speed, and destination. However, the availability of this information does not by itself ensure the safety of the

maritime traffic. Officers on the watch and monitoring authorities require the development of decision-aid solutions that will take advantage of these communication systems [1]. Detection and analysis of anomalous events occurring in movement of vessels is a crucial asset for improving the security of vessel traffic [2]. The range of possible events of interest is very large from collision at sea to illegal fishing and illicit activities. This paper shows an example of interactive visual analysis in which we extract anomalous events from vessel trajectories and explore the spatial distribution of these events. Our example AIS-collected dataset consists of 5,244 trajectories of vessels that moved in the bay of Brest (France) in the time period of 313 days from the 11th of February till 21st of December, 2009. The data are available not for all days within this time period. Due to the large amount of data, we apply spatial aggregation. We combine two approaches to spatial aggregation of trajectories: discrete and continuous [3]. Continuous aggregation [4] can better preserve spatial patterns by avoiding indispensable position distortions due to space discretization. However, discrete aggregation provides accurate numeric measures of aggregated movements. Fig. 1, left, shows the study area and the trajectories aggregated into a continuous density surface. The density is represented by color variation from light blue (low density) through yellow to dark red (high density). The expressiveness is enhanced by adding illumination effects (hill shading).

2. ANALYSIS EXAMPLE

Our analysis focuses on those vessels that moved through the strait (1.8 km length) either into or out of the bay.
Using an interactive spatial filter, we select 2,411 trajectories of these vessels. The resulting density map is shown on the right of Fig. 1 (the original density map has been automatically updated according to the current filter).
We see that there are two nearly parallel lanes along the strait in which the vessels mostly move.
In the context of traffic safety analysis, we want to detect events when two vessels come too close to each other.
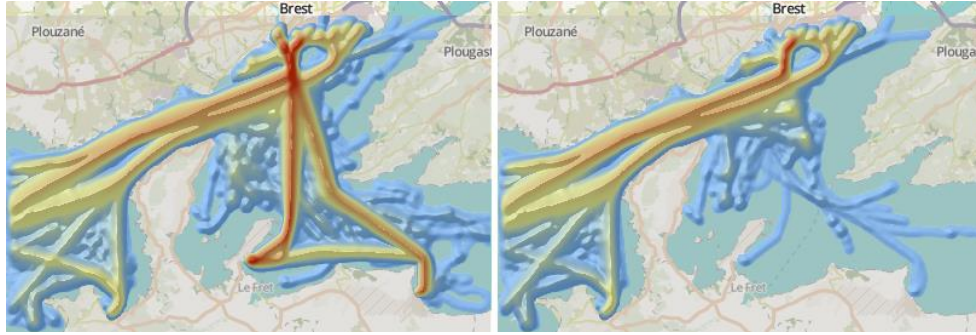
Figure 1 The study area and the density of vessel trajectories. Left: all trajectories; right: trajectories going through the strait, which are analyzed in the paper.

Instances of close approach may indicate near-collisions but also other events of interest, such as tugging, boarding, or smuggling. A near-location is commonly known as a situation in which a closest point of approach (CPA) between two vessels is identified or predicted.

Different approaches have been so far developed to evaluate such situations such as a collision diameter [5] and critical situations [6].

Our approach is based on a search of a spatio-temporal nearest neighbor for each point in the trajectory of each vessel: given the position p of the vessel at moment t, the tool determines the positions of all other vessels within the time interval $[t - \Delta_t, t + \Delta_t]$, measures the distances from p to all these positions, and takes the minimum of the distances. Here, Δ_t is a temporal tolerance threshold that compensates for possible differences in the time references of the position records in different trajectories; we set it to 30 seconds. Then, we extract those trajectory segments where the distance to the nearest neighbor is under 100 meters (these temporal and spatial thresholds are relatively representative of aforementioned events). These extracted segments, treated as independent spatio-temporal objects [3, 7], are further called *near-location events*. Some of the events occurred in the harbor or in areas outside the main traffic lanes. By applying spatial filtering to the events, we select only those that happened within or near the lanes (1,601 events out of 2,237).

Figure 2 Left: The traffic through the strait at the times of occurrence of the near-location events. Right: The traffic in the remaining times.

In the second step, we investigate the traffic at the times when the near-location events happened in order to detect any relevant pattern. The times of event occurrences are dispersed over the period of almost a year. To select all time intervals containing near-location events and only these intervals, we apply a special kind of temporal filter, called *time mask*. In response, only the parts of the trajectories that took place within the selected 303 time intervals are extracted. The trajectories that happened beyond the selected intervals are completely filtered out. There are 681 trajectories that fully or partly satisfy the combination of the spatial filter and time mask filter. The density map is automatically updated to show only these trajectories and parts (Fig. 2, left). The spatial pattern looks somewhat different from that of the overall traffic (Fig. 1 right). To better understand the differences, we invert the time mask filter and look also at the traffic pattern in the times when there were no near-location events (Fig. 2, right).

The image in Fig. 2, left, differs from that on the right in relatively high density of trajectories that switched from one lane to another. The occurrences of near-location events may be related to this lane switching.
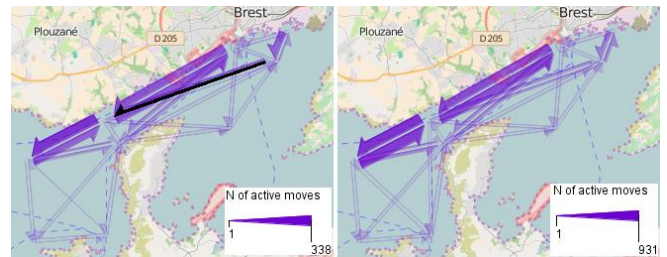
Figure 3 Discrete aggregation of the same data subsets as in Fig. 2.

Applying discrete aggregation (Fig.3) allows us to see the directions of the traffic flows and obtain numeric information concerning the flow volumes. In Fig. 3, right, we see that in the times when no near-locations happened the total incoming and outgoing traffic flows are symmetric (i.e., have approximately equal volumes). At the times of

near-locations (Fig. 3, left), outgoing flows from the Brest bay exceed the incoming flows. This is coherent as ships often leave together, especially fishing ships, this being not often the case when coming back to the harbor. In the eastern part of the Brest harbor, we observe especially high asymmetry between the incoming and outgoing traffic. There were only 65 incoming ships and 202 outgoing, out of which 152 switched from the southern to the northern traffic lane. The arrow representing the aggregated movement of these 152 vessels is highlighted in black in Fig. 3, left.
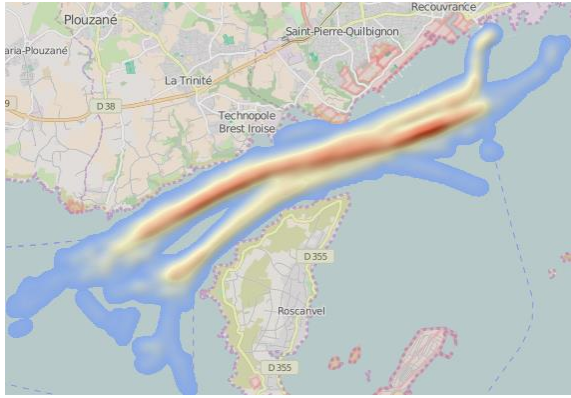
Figure 4 Density of the parts of trajectories where the distance to the nearest vessel is under 100 meters.

In Fig. 4, we applied a *filter of trajectory segments*[3] to select the segments of trajectories where the distances to the nearest neighbors were under 100 m. Such segments exist in 504 trajectories. The density map shows us that a major part of these segments are related to lane switching, which corresponds to a common trend in maritime navigation.

Considering safety reasons and navigation constraints (sea currents and depth in the strait), vessels should generally move straight within the traffic lanes. To check whether it was so, we computed for trajectory positions the sinuosity within the time window of 5 minutes (the sinuosity is the ratio of the path length to the distance between the first and last points). For straight movement, the sinuosity is close to 1. From the movements that happened at the times of near-locations, we extract events of curved movement where the sinuosity was greater than 2. We will call them sinuosity events. We exclude the events that occurred within the harbor or away from the major traffic flows. 334 sinuosity events from 187 trajectories occurred in or near the major traffic lanes, this being a bad news for traffic safety. In Fig. 5, the sinuosity events are represented by black dot symbols drawn with high transparency (97%).

The detected deviations from straight movement may be related to the earlier detected near-location events. Vessels might have to deviate from their course in order to avoid collisions with other vessels, as required by maritime

Figure 5 Dots represent events of high sinuosity that occurred in or near the major traffic lanes.

navigation rules. We apply *filtering of related object sets*[3] to select, first, those 504 trajectories where the near-location events happened and, second, the sinuosity events that occurred in these trajectories. We find out that 326 out of the 334 sinuosity events occurred in the trajectories that also had near-location events.

In Fig. 6, we again applied the trajectory segment filter to select the parts of the trajectories were the distances to the nearest vessels were under 100 meters, as in Fig. 4. For these trajectory parts, we have built a weighted density surface using the sinuosity values as the weights. This means that trajectory segments contribute to the calculated densities proportionally to their sinuosity values. We see that the highest density of sinuous movements is reached inside the strait, mostly in the northern traffic lane, and between the strait and the harbor in the southern lane. We also see a spot of relatively high density at the harbor in the northern lane (a port entrance of 300m width creates a bottleneck favoring near-location events). Judging from the spatial configuration of the dense area, it has also to do with the vessels that moved from the western part of the harbor and wanted to go to the southern traffic lane, as well as with the passenger ships that travel within the Brest bay. Evidently, sinuosity events occurred at the location where the flows coming from the western and eastern part of the harbor conjoin. Also, relatively high sinuosity was reached at the intersection of the two traffic lanes.

Hence, we can conclude that the anomalous events can be attributed to intersecting traffic flows at the times of increased amounts of outgoing traffic from the Brest harbor.

3. DISCUSSION AND CONCLUSION

Having a large temporally extended set of trajectories, we were interested in detecting and analyzing events of anomalous movement that may be potentially dangerous to the safety of sea traffic, as well as in identifying common navigation behaviors. We considered events of two types:
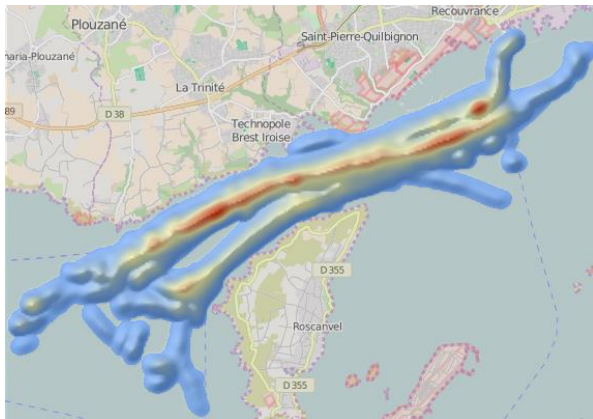
Figure 6 Weighted density of the trajectory segments where the distances to the nearest vessels are below 100 meters. Sinuosity values are used as the weights.

vessels coming too close to one another (near-locations) and sinuous movements in the areas of major traffic flows. We applied computational tools to calculate movement attributes the values of which might be indicative of such events, namely, the distance to the nearest neighbor and the path sinuosity within a selected time window. Using an interactive query tool, we extracted the events of interest based on the values of these attributes.

To investigate where and under what traffic conditions the extracted events happened, we used a variety of filters separately and in combinations. To have an overall view of the spatial distribution of the movements and events of interest, we used visual spatial summaries (aggregations) in the form of continuous density maps and discrete flow maps. We have gained the following findings:

- The near-location events most often occurred at the times when the outgoing traffic from the Brest harbor exceeded the incoming traffic.
- A major part of the near-location events happened to vessels that moved out of the harbor in the southern traffic lane and then switched to the northern lane before entering the strait, this reflecting some navigation routes predefined in the area.
- The sinuosity events are closely related to the near-location events.
- Both types of anomalous events are related to intersecting traffic flows between the harbour and the strait and, possibly, narrow space and high traffic density inside the strait, where the vessels need to go in two parallel lanes.

In our analysis, we used the following types of filtering performed by means of interactive tools:

- Spatial filtering for selecting data within an area of interest and for excluding analysis-irrelevant data (e.g., events that occurred inside the harbor).
- Time mask filter, which selects multiple disjoint time intervals based on given conditions and excludes the remaining time intervals. We used it for selecting the times when near-location events occurred.
- Filter of trajectory segments, which selects parts of trajectories based on movement attributes, either pre-existing or derived, such as the distance to the nearest neighbor and path sinuosity in a time window.
- Filter of related object sets, which allowed us to select the trajectories in which near-location events happened and then the sinuosity events that occurred in the selected trajectories.

This combination of computation-supported extraction of features of interest (events), spatial aggregation of data and visual representation of the spatial summaries, and interactive application and combination of various filters allowed us to detect and investigate particular anomalies in vessel movement. Similar approaches might be applied to identify other maritime navigation events of interests.

REFERENCES

[1] C Claramunt, T Devogele, S Fournier, V Noyon, M Petit, and C Ray, "Maritime GIS : From monitoring to simulation systems," in Information Fusion and GIS, LNCS, pp. 34–44. Springer, 2007.

[2] T Devogele, L Etienne, and C Ray, "Maritime Monitoring," in Mobility Data: Modelling, Management, and Understanding, pp. 224–243. Cambridge University Press, Aug 2013.

[3] G Andrienko, N Andrienko, P Bak, D Keim, and S Wrobel, Visual Analytics of Movement, Springer, 2013.

[4] N Willems, H Van De Wetering, and J Van Wijk, "Visualization of vessel movements," Computer Graphics Forum, vol. 28, no. 3, pp. 959–966, 2009.

[5] Y Fujii, H Yamanouchi, and N Mizuki, "On the fundamentals of marine traffic control. Part 1, probabilities of collision and evasive actions," Electronic Navigation Research Institute Papers, vol. 2, pp. 1–16, 1970.

[6] P Pedersen, "Collision and grounding mechanics," Proceedings of WEMT, vol. 95, no. 1995, pp. 125–157, 1995.

[7] G Andrienko, N Andrienko, Ch Hurter, S Rinzivillo, and S Wrobel, "Scalable Analysis of Movement Data for Extracting and Exploring Significant Places," IEEE Transactions on Visualization and Computer Graphics, vol. 19, no. 7, pp. 1078–1094, 2013.

SCALABLE ESTIMATION OF PORT AREAS FROM AIS DATA

Leonardo M. Millefiori, Luca Cazzanti, Dimitris Zissis, Gianfranco Arcieri

NATO STO Centre for Maritime Research and Experimentation La Spezia, Italy

ABSTRACT

This paper discusses work in progress to estimate port locations and operational areas in a scalable, data-driven, unsupervised way. Knowing the extent of port areas is an important component of larger maritime traffic analysis systems that inform stakeholders and decision makers in the maritime industry, governmental agencies, and international organizations. The proposed approach uses Kernel Density Estimator (KDE) and exploits the large volume of Automatic Identification System (AIS) data to learn the extent of port areas in a data-driven way. Example results for the port of La Spezia, Italy, demonstrate the approach for real data.

Index Terms— KDE, port location estimation, AIS, map reduce, big data

1. INTRODUCTION

The Mediterranean hosts one of the most complex and dense port networks in the world, a gateway to European commerce and industry. A recent report published by the European Commission calculated that 74% of goods imported and exported and 37% of exchanges within the European Union transit through the roughly 1200 seaports along its 70,000 km of coastline [1, 2]. Decision makers, policy advisors, trade partners, security experts, safety agencies, international organizations, and vessel operators are becoming more reliant on benchmark metrics of port activities to carry out their duties. Examples of such metrics include maritime and intermodal connectivity indicators, volume of cargo throughput, proportion of different types of goods transported, and fishing activity indicators. In addition, stakeholders are becoming more reliant on summary statistics and representative Patterns of Life (PoLS) to characterize the ports according to their local and regional traffic patterns and operational capabilities.

Generating valid and reliable measurements though, is a complex task. We often overlook the fact that maritime networks operate as "small worlds", where content and size vary over space and time, under the influence of the trade and carrier patterns. In particular, port region, port system, and port range are spatial entities that evolve over time [3],

yet their clear definitions are essential for obtaining accurate metrics on port activities.

Manually collating and curating port area definitions is not a realistic approach: subjective definitions of port areas and system maintenance costs make it unreliable and infeasible. Thus, the stepping stone for any useful port analysis is an automatic, unsupervised, data-driven approach to defining seaport locations and operational boundaries. While in the past, sea transport surveillance had suffered from a lack of data, current tracking technology such as Automatic Identification System (AIS) [4] has transformed the problem into one of extracting interpretable information from an overabundance of maritime data. This introduces the additional requirement that the algorithmic approaches must be scalable to big data regimes.

The major challenge faced today, is developing the ability to identify patterns emerging within these huge datasets, fused from a variety of sources and generated from monitoring a large number of vessels on a day-to-day basis. The extraction of implicit and often unknown information from these datasets belongs to the field of data mining and data science. Progressively huge amounts of structured and unstructured data, tracking vessels during their voyages across the seas, have become available. These datasets provide detailed insights into the patterns vessels follow, while they can operate as benchmarking tools for port authorities regarding the effectiveness and efficiency of their ports.

To address the big data challenge in the maritime domain, researchers have developed computational and statistical approaches that rely on (AIS) data to automatically monitor vessel activities and extract their behavioral patterns [5, 6, 7, 8]. Previous work at the NATO Science and Technology Organization Centre for Maritime Research and Experimentation (STO-CMRE) has explored how to extract stationary areas from (AIS) data based on the spatial clustering algorithm DBSCAN [9, 10]. Building on that initial work, this paper presents work-in-progress to estimate port areas in a scalable, unsupervised, data-driven way. Instead of DBSCAN, the approach relies on the Kernel Density Estimator (KDE) to form density-based estimates of port locations and operational areas from the location and velocity data contained in the (AIS) messages transmitted by the vessels. The approach is scalable because the operations underlying (KDE) are decomposable into MapReduce

primitives [11, 12], which enables distributing the computational load across different computing nodes and across distributed storage.
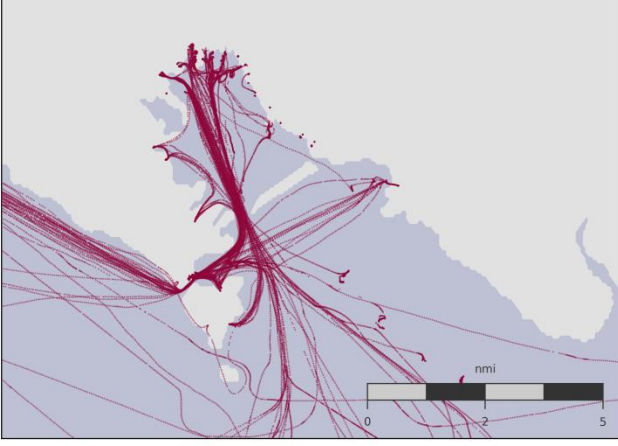
Figure 1 Maritime traffic in the port of La Spezia in a 24-hour period during August 2015. The ship positions are received by CMRE's local AIS receiver.

2. KERNEL DENSITY ESTIMATION

Let us assume that $x_i \in R^k$, with $i = 1, \dots, n$, are a set of observations from a probability density f. Initially introduced by Rosenblatt [13], a basic KDE of f has the form [14]:

$$f_n(\mathbf{x}) = \frac{1}{nh^k} \sum_{i=1}^{n} K_h(\mathbf{x}, \mathbf{x}_i), \tag{1}$$

where K_h is the kernel function, and h denotes the bandwidth (or window width), which is a smoothing parameter. The choice of h has a strong influence on the estimate, because different values highlight different features of the data, depending on the density under consideration. The choice of a kernel function, on the other hand, is not crucial to the statistical performance, and a widely adopted choice is the Gaussian kernel, defined as below

$$K_h(\boldsymbol{p}, \boldsymbol{q}) = \frac{1}{(2\pi)^{\frac{k}{2}} \sqrt{|\boldsymbol{\Sigma}|}} e^{\frac{(\boldsymbol{p}-\boldsymbol{q})^T \boldsymbol{\Sigma}^{-1}(\boldsymbol{p}-\boldsymbol{q})}{2h^2}} \tag{2}$$

2.1. Convolution

Apart from a scaling factor, the KDE formula (1) can also be seen as a convolution (which we denote with the * operator) between the empirical Probability Density Function (PDF) and the kernel function [15], that is

$$\begin{aligned}
\phi_n * K_h &= \int_{\mathbf{D}} \left(\frac{1}{n} \sum_{i=1}^{n} \delta(\xi - \boldsymbol{x}_i) \right) K_h(\boldsymbol{x} - \xi) \, d^k \xi \\
&= \frac{1}{n} \sum_{i=1}^{n} K_h(\boldsymbol{x} - \boldsymbol{x}_i) = h^k f_n(\boldsymbol{x}),
\end{aligned} \tag{3}$$

where ϕ_n is the empirical PDF, expressed as a sum of n Dirac delta functions $\delta(\cdot)$ centered in the data samples. A computationally efficient variant of this formulation bins the data samples into k-dimensional histograms, and convolves the histogram with the kernels instead of the individual delta functions. This variant is appealing when the data size increases, because it produces an essentially identical result at a fraction of the computational cost.

2.2. Adaptive KDE

Both the KDE in (1) and the KDE by convolution (3) employ a fixed kernel bandwidth for all the observed data points. An intuitive improvement is to weight observations non uniformly; that is, extreme observations in the tails of the distribution should have their mass spread in a broader region than those in the body of the distribution. Specifically, instead of having a single value for h, in the adaptive KDE approach h_i, for $i = 1, \dots, n$, is the bandwidth of the kernel centered in the i-th observation.

The first challenge is *how* to decide if an observation belongs to a region of high or low density. The adaptive approach [15] relies in fact on a two-stage procedure: combining (1) with (2), a pilot estimate is first computed to identify low-density regions coarsely, using a fixed bandwidth factor. Since only a coarse idea of how the density is distributed in the area of interest, here we can use the convolved histogram (3), which comes at a fraction of the computational cost required to compute (1).

2.2.1. Local bandwidth factors

Under the assumption that the underlying distribution is k-variate normal, the optimum (fixed) window can be written as [15]:

$$h^* = \left(\frac{4}{n(k+2)} \right)^{\frac{1}{k+4}}. \tag{4}$$

The *local bandwidth* factors λ_i, for $i = 1, \dots, n$ are then given by

$$\lambda_i = \left(\frac{f_n(\boldsymbol{x}_i)}{g} \right)^{-\alpha}, \tag{5}$$

where $0 \le \alpha \le 1$ is the sensitivity parameter and g is the geometric mean of the fixed-bandwidth density estimate $f_n(\boldsymbol{x}_i)$ evaluated in the data points

$$\log g = \frac{1}{n} \sum_{i=1}^{n} \log f_n(x_i). \qquad (6)$$

The adaptive KDE of *f* can be finally expressed as

$$\hat{f}_n(\boldsymbol{x}) = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{(h^* \lambda_i)^k} K_{h^* \lambda_i}(\boldsymbol{x}, \boldsymbol{x}_i). \qquad (7)$$

3. IMPLEMENTATION AND RESULTS

Let us indicate the *full* kinematic state of a vessel at a generic time with $\chi_i = [a_i, b_i, v_i]^T \in R^3$, where *a* and *b* represent the longitude and latitude coordinates, respectively, of the ship in a geographic coordinate system, and $v \geq 0$ is the instantaneous speed of the vessel. We introduce also a *reduced* vessel kinematic state that doesn't include the instantaneous speed $x_i = [a_i, b_i] \in R^2$. Finally, we observe the ship traffic in the neighborhood of a port in the time interval $[0, T]$, where *T* can be hours, days or even months, depending on the application.

Our objective is to determine the area of the port given the set AIS of observations *X* that can be made up either by the full or reduced kinematic states of the ships observed in the area of interest. Assuming that the samples *X* are drawn from a probability density function *f*, the proposed approach consists of applying the KDE to the data samples, and determining the port extent using horizontal cuts of the resulting estimated probability density function.

Unfortunately, the direct computation of the fixed KDE (1) is highly inefficient, especially for large or highly dimensional data sets. In fact several approaches have been proposed in the past to reduce the computational burden [16, 17, 18]. However, as the data set size and its dimensionality increase, even the aforementioned approaches can easily become computationally prohibitive and therefore distributed approaches are necessary. Zheng et al. [12] have recently proposed randomized and deterministic distributed algorithms for efficient KDE with quality guarantees, adapting them to the popular MapReduce programming model. As in [12], our approach is to take advantage of the linearity of the KDE to distribute the computation among many different nodes using the *MapReduce* [11] distributed programming model.

For our purposes, we consider the port as the *extended* location where ships exhibit a very low speed. Consequently, there are two possible approaches for estimating the density function. The first one is to compute the KDE in R^3 at a very high computational cost using the complete kinematic states χ_i including also the ship speed, and then compute the spatial density estimate $\bar{f}_n(\boldsymbol{x})$ by marginalization of $\bar{f}_n(\chi)$

$$\bar{f}_n(\boldsymbol{x}) = \int_0^{v_T} f_n(\chi) \, dv$$

where v_T is the speed threshold that discriminates the stationary ships from those under way.

The second approach is to form the KDE in R^2 using only the positional information x_i of the ships that can be considered stationary. In other words, given the set of all the observations, we can build a subset of the positional states of only those ships whose speed is below a desired threshold v_T, and compute the KDE on this subset. This second approach can be also seen as an approximation to the first one that trades some result accuracy for a more affordable computational cost.

We applied these two approaches and the adaptive KDE (7) to the data set shown in Fig. 1, which is made up by all the AIS messages received by CMRE's local station during a 24-hour period in August 2015. The resulting kernel density estimates are shown in Fig. 2, where we report: on the left side, the fixed-bandwidth KDE computed in R^3 using the kinematic states χ_i and marginalized on v; in the middle and on the right side, the fixed-bandwidth and adaptive KDE, respectively, both computed in R^2 and discarding all kinematic states whose instantaneous speed was greater than the threshold v_T, that was set, in all three cases, to 1 kn.

4. CONCLUSIONS AND FUTURE WORKS

Estimating port locations and operational areas is an essential component for achieving MSA. The large volume of AIS data imposes algorithmic approaches that require minimal human intervention and scale with the increasing data volumes. The KDE-based approaches presented here address these challenges by combining MapReduce with fixed or adaptive kernel bandwidths. The results presented on the single port of La Spezia could be extended to other ports worldwide, and a port analysis platform could be developed that learns the port areas worldwide in an unsupervised way. The proposed approach can be extended to other types of areas besides ports: off-shore platforms, anchorage areas, and fishing grounds can be detected automatically and their extent estimated in a data-driven, unsupervised fashion.
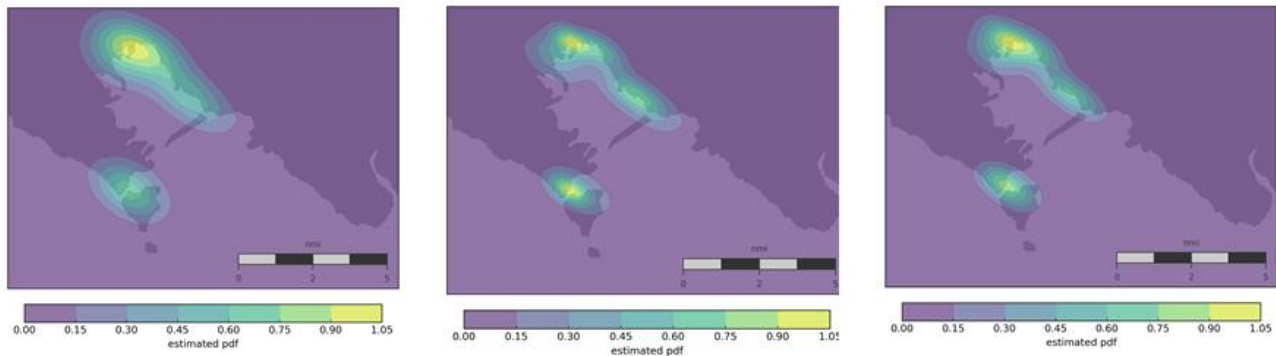
Figure 2 Comparison of kernel density estimates computed with different approaches: fixed bandwidth with $x_i \in R^3$ (left) and $x_i \in R^2$ (middle), and adaptive bandwidth with $x_i \in R^2$. The fixed R^3 version produces the smoothest result, but is unable to deal satisfactory with the low-density estimate regions, and has the highest computational cost. The fixed approach in R^2 is computationally more affordable, but is equally not able to produce satisfactory results in low-density regions. Finally, the adaptive KDE in R^2 on the right has a higher computational cost than the fixed KDE, but it is the only one that produces a *spikier* estimate on low-density regions. All the three estimates have been computed on the AIS messages received by CMRE's local base station in a 24-hour time span during August 2015, shown in Fig 1. The speed threshold that discriminates stationary from non-stationary targets is set to 1 knot.

REFERENCES

[1] E. Commission, "Ports 2030 – Gateway for the trans European transport network," Tech. Rep., 2014.

[2] E. Commission, "Ports: an engine for growth, Com (2013) 295 Final," Tech. Rep., 2013.

[3] C. Ducruet, C. Rozenblat, F. Zaidi, "Ports in multi-level maritime networks: evidence from the Atlantic (1996–2006)," in *Journal of Transport Geography*, Vol. 18, Issue 4, pp. 508-518 ,July 2010.

[4] International Communication Union, "Technical characteristics for an automatic identification system using time division multiple access in the VHF maritime mobile band (Rec. ITU-R M.1371-4)", 2012.

[5] M. Tichavska, F. Cabrera, B. Tovar, V. Arana, "Use of the Automatic Identification System in Academic Research," in *EUROCAST 2015: 15th International Conference*, Las Palmas de Gran Canaria, Spain, February 8-13, 2015, Revised Selected Papers, pp. 33-40.

[6] G. Pallotta, M. Vespe, and K. Bryan, "Article Vessel Pattern Knowledge Discovery from AIS Data: A Framework for Anomaly Detection and Route Prediction," in *Entropy,* vol. 15, no. 6, pp. 2218-2245, Jun 2013.

[7]B. Ristic, B. La Scala, M. Morelande and N. Gordon, "Statistical analysis of motion patterns in AIS Data: Anomaly detection and motion prediction," in *11th International Conference on Information Fusion*, 2008, Cologne, 2008, pp. 1-7.

[8] F. Mazzarella, M. Vespe, D. Damalas and G. Osio, "Discovering vessel activities at sea using AIS data: Mapping of fishing footprints," in *17th International Conference on Information Fusion*, 2014, Salamanca.

[9] L. Cazzanti and G. Pallotta, "Mining Maritime Vessel Traffic: Promises, challenges, techniques," in *OCEANS IEEE/MTS*, Genoa, 2015.

[10] M. Ester, H. Kriegel, J. Sander, and X. Xu, "A density-based algorithm for discovering clusters in large spatial databases with noise," in *Second International Conference on Knowledge Discovery and Data Mining*, Portland, 1996.

[11]J. Dean, and S. Ghemawat, "MapReduce: Simplified Data Processing on Large Clusters," in *Communications of ACM*, vol. 51, no. 1, pp. 107-113, 2008.

[12] Y. Zheng, J. Jestes, J. M. Phillips, and F. Li, "Quality and efficiency for kernel density estimates in large data," in *Proceedings of the 2013 ACM SIGMOD International Conference on Management of Data (SIGMOD '13).*ACM, New York, NY, USA, 433-444.

[13] M. Rosenblatt et al., "remarks on some nonparametric estimates of a density function," in *The Annals of Mathematical Statistics*,vol. 27, no. 3, pp. 832-837, 1956.

[14] D.W. Scott, "Multivariate Density estimation: theory, practice and visualisation," in *John Wiley and Sons,* 2015.

[15] B. W. Silverman, "Density Estimation for Statistics and Data Analysis," in *CRC press*, vol. 26, 1986.

[16] B. W. Silverman, "Algorithm AS 176: Kernel Density Estimation using the Fast Fourier Transform," in *Journal of the Royal Statistical Society. Series C (Applied Statistics)*, vol. 31, no. 1, pp. 93-99, 1982.

[17] Y. Chen, M. welling, and A. Smola, "Super-samples from kernel herding ," in *arXiv preprint arXiv:1203.3472*, 2012.

[18] J. M. Phillips, B. Wang, and Y. Zheng, "Geometric inference on kernel density estimates," in *CoRR, vol. abs/1307.7760,* 2013.

DATA REQUIREMENTS FOR ANOMALY DETECTION

Steven Horn*, Cheryl Eisler*, Dr. Peter Dobias*, Lt(N) Joe Collins†

* Defence Research and Development Canada, † Canadian Department of National Defence

ABSTRACT

New processing techniques are being developed to extract and highlight anomalous maritime behaviour by leveraging the abundance of open source and/or commercially available information on a global scale. This common approach to data science relies on the exploitation of large datasets through methods such as data analytics and data mining. In the reverse aspect, one can instead explicitly consider the definition and types of anomalies that a maritime security operator would desire to know about to derive the quantity of data required to achieve a given level of confidence in detection. The requirements gap between the available information and the desired effect can be identified by working the problem of anomaly detection from both ends: exploiting the data available, and quantifying the desired end state. This work presents a framework for the definition of data requirements for a set of operationally relevant anomalies. By formally quantifying the data gaps, resource investment for additional data can be better directed in order to improve operational utility of the dataset.

Index Terms— Maritime, Surveillance, Anomaly Detection, Requirements, Fusion, Information, Knowledge.

1. INTRODUCTION

The quantification of requirements for data which may be used for multiple decision-making purposes is a challenging task, which is further complicated if there is a wide spectrum of available data. First, several concepts and definitions are required to describe and conceptualize the process from data to decision. This process is described herein as a chain of derived utility, building on lower level data in order to achieve higher-level awareness, and has been previously described using multiple models such the Data Fusion Information Group (DFIG) model [1], and the Data, Information, Knowledge, Wisdom (DIKW) model [2]. In this paper, the concepts of data, information, and knowledge from the latter model will be adopted, acknowledging that the specific definition of each of these elements often varies throughout the literature [3]. However, it is noted here that there is generally a difference between the concepts of data, information, and knowledge; wherein information is something of value derived from data, and knowledge is a yet higher level cognitive situational understanding.

When considering the practical use of data, while it can be argued that more data and, therefore, information is desirable, it is not necessarily achievable if the cost to extract useful information from the data increases with the data volume faster than the actual information value of these data. Consideration of these diminishing returns is of crucial importance when resource costs are associated with data collection.

Due to the volume and associated costs of both data acquisition and data processing, it is highly desirable to know what is the right amount of data that will enable detection of anomalies with a desired confidence. In other words, what is the minimum volume of data that will give the operators a minimum desired confidence in their surveillance and anomaly detection capabilities? This is the question that this paper strives to answer.

The paper is organized as follows: First, the nature of various types of anomalies and the data types and information necessary to detect an anomaly are discussed in Section 2. Then the detection algorithms are presented in Section 3, followed by the description of the quantification of the operational requirements in Section 4. Finally, the methodology and results are given in Section 5, and a brief summary is provided in Section 6.

2. TYPES OF ANOMALIES AND DATA REQUIREMENTS

In this section, a review and description of types of maritime anomalies is presented with the objective of characterizing several fundamental properties of the anomalies. It is important to note here that the objective is to describe anomalies in the context of the ships[2] that are being described by the data, and not in the data itself, i.e., behavioural anomalies vice data anomalies. Maritime anomalies are divided here into two categories: kinematic,

---

[2] In the maritime environment, data are most commonly collected on surface ships, although data may also include submarines, aircraft, and any unmanned forms of the aforementioned vessel types.

meaning the anomaly is exhibited in the motion of a ship (such as unusual maneuvering); and static, meaning that the anomaly is exhibited by the properties of a ship (such as with unusual crew or cargo). For the purposes of this paper, the data requirements analysis will focus on the ability to detect kinematic-type anomalies.

To be able to detect an anomaly, it is necessary to collect both positional data and classification (ship type) or identifying (ship name) data. Some information, if not directly observed, can be estimated through classical statistical filtering and estimation techniques, such as Kalman filtering [7]. Previous work on the development of maritime anomaly taxonomies [4]-[5], provides a foundation for the classification of anomalies herein. The various sub-types of anomalies are grouped into three general categories.

Maneuvering: Anomalies that involve the velocity vector of a ship, such as an unexpected change of direction, stopping or loitering, or travel at a speed unusual given the type of ship or area. This includes maneuvering such as change of direction inconsistent with expected pattern, or change or lack of change of speed (stop/resume inconsistent with expected pattern) over time observed. Examples of anomalies in maneuver are grab and dash fishing [6] or pickup of illicit cargo.

Location: Anomalies related to where a ship is located, which include entering exclusion zones or restricted areas, travelling outside of vessel traffic management schemes, or travelling outside of normal historical routes. Governments can have a variety of reasons to establish restricted areas, for example security, environmental, or navigational concerns, where vessels are not allowed to enter. Some examples include operating: at trawling speed in a closed zone, in proximity to critical infrastructure, in a closed zone, in non-navigable waters, or in a zone inconsistent with the claimed activity for the given ship type.

Interaction: Anomalies related to the unusual or illicit interaction between ships or with other infrastructure. Examples could include ship rendezvous in both open-ocean and littoral waters. While there are potentially benign reasons for ships to rendezvous at sea, it is a fairly rare activity that could indicate illegal cross-transfer of resources or personnel. Requirements for detecting rendezvous could vary in the cluttered and more disordered littoral waters versus open-ocean.

3. DETECTION OF ANOMALIES

Since there are many techniques described in the literature for maritime anomaly detection [8], it is vital to consider the performance and efficiency of the algorithm used operationally. This leads to the question of where to invest additional resources: should one invest in improving the computational performance to detect anomalies using less data or information, or should one invest in additional sensors to collect more data to facilitate the anomaly detection. Since the objective of the framework is to be agnostic with regards to the type of processing that is being used to detect the anomaly, the description of how to detect the anomaly is presented from a fundamentals of detection perspective.

Given a model for an anomaly one wishes to detect, numerous sequential testing algorithms exist in the literature which can be applied to test against an anomaly hypothesis. It has been reported that good performance for target maneuver detection (a type of anomaly) is achieved using the classical cumulative sum algorithm first described by Page [9], and the Shiryayev Sequential Probability Ratio Test algorithm [10].

The set of data requirements for real-time anomaly detection is not directly investigated in this paper. Nonetheless, it is expected that the requirements for real-time detection versus batch mode will be similar but with added constraints due to the timeliness (latency) of the data, and the effect of out-of-sequence observations.

For detections that are not time-critical, such as regulatory enforcement or generation of intelligence cues, a batch mode processing approach can be used. Some examples of anomalies which are suitable for batch mode processing include: the detection of ships which have left an oil slick, or detecting ships which have entered an environmental exclusion zone. Additionally, latency in the reception of the data and out-of-sequence observations have minimal impact on the ability to detect anomalies in batch mode. For each of the three main categories of anomalies identified in Section 2, a model is created to describe the kinematics of the anomaly in the following subsections.

3.1. Detection of a ship stopping and loitering

The model for detecting a ship which stops, loiters, and resumes course is illustrated in Figure 1 as model I. This same model can be applied to the change of course anomaly if the magnitude of course change is large, which is reasonable since a small change of course is difficult to declare as anomalous given that course changes are normal events for ships, depending on the area they are in. The anomalous pattern is shown in the upper set of arrows. A ship at point **a** is moving at some initial velocity v_i and decelerates to a stop at point **b**. The ship loiters at point **b** for a time period $t_{stopped}$, and then accelerates at a_{ship} to maximum velocity v_{max} to point **c**, travelling to point **d** at v_{max} until resuming normal speed at point **e**. The non-anomalous route is shown below, where the ship moves from point **a** to **e**, maintaining constant velocity v_i.
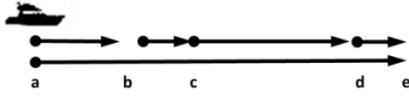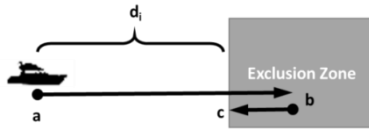
Figure 1 Diagram of model I.

Instead of describing the ability to positively detect this maneuver, the approach proposed here is to identify when it would not be possible to detect the maneuver. The primary driver for non-detection is if there are no observations of the ship in the time between points **a** and **e**. Then, given a specific time between detections, one can calculate (assuming v_i, v_{max} and a_{ship}) the maximum time ($t_{stopped}$) which would not be detectable.

3.2. Detection of a ship entering/crossing exclusion zone

The model for detecting a ship which enters and then leaves an exclusion zone is illustrated in Figure 2 as model II. A ship starts from point **a** some distance d_i from an exclusion zone travelling at some initial velocity v_i. The ship enters the exclusion zone at point **b**, and stops for some length of time ($t_{stopped}$) before accelerating at a_{ship} to leave the exclusion zone at point **c**. As in the previous model, given a specific time between detections, one can calculate the maximum time which would not be detectable.

Figure 2 Diagram of model II.

3.3. Detection of the rendezvous of two ships

The model for detecting a rendezvous between two ships of similar capability is illustrated in Figure 3 as model III. The anomalous pattern is shown by the interaction of the two arrows' paths (non-anomalous behaviour would be for the two ships to continue on a straight path with no change in speed or proximity – not shown here). A ship at point a_1 is moving at some initial velocity v_i and decelerates to a stop at point **b**. A ship at point a_2, which is moving at the same initial velocity v_i, decelerates to a stop at the same point. The ships loiter at point **b** for a time period $t_{stopped}$, and then accelerate at a_{ship} to maximum velocity v_{max} to point **c**, travelling to point **d** until resuming normal speed at point **e**.
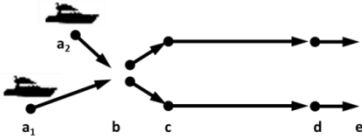
Figure 3 Diagram of model III.

This is similar to model I, but involves the ability to detect two ships at the same time and confirm their proximity at point **b**. Then, given a specific time between detections, one can calculate (knowing v_i, v_{max} and a_{ship} for each ship), the maximum $t_{stopped}$ which would not be detectable.

4. QUANTIFICATION OF REQUIREMENTS

This section presents the metric for ship inter-detection times in a data feed against which required standards of performance can be established. The required standards for this metric will be established by considering a simulated nominal data stream, and then evaluating these metrics against the models presented in Section 3. Other metrics which could be considered include quantity and latency. The concept of data quantity, as measured by the combination of unique vessels to be detected, and the number of detections achieved on each of those vessels is somewhat related to the inter-detection metric. Data latency a major concern for decision-makers as they have to be able to know that they are acting on up-to-date information to be able to form an appropriate response with the assets they have available. As previously mentioned in 3.1, latency primarily impacts real-time detection but not historical batch-mode.
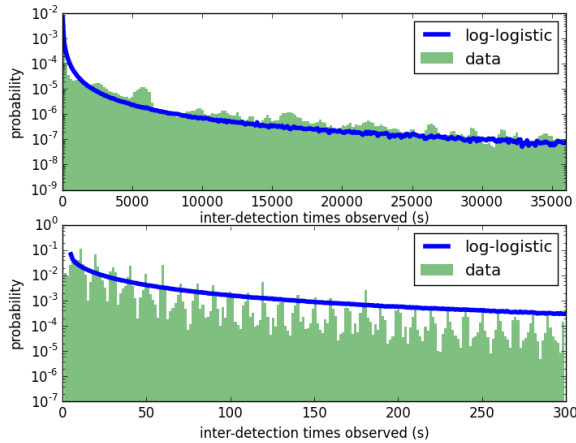
4.1. Inter-detection times

The refresh rate of data on a unique vessel is defined here as the inter-detection time. Over the collected dataset, there is a distribution associated with the refresh rates for all vessels. For example, the probability of achieving a given inter-detection time for satellite-based Automatic Identification System (AIS) dataset derived from a constellation of 8 satellites is illustrated in Figure 4. The top figure shows a 10 hour timespan, and the bottom shows a 300 second timespan. Periodic spikes observed in the data are due to the fixed transmission intervals of AIS for varying ship maneuvering states [11]. The most common transmission rates are 2, 6 and 10 seconds, and so one observes harmonics these times, with the most prominent at 10 second intervals. The inter-detection time envelope for this distribution, however, is representative of the sensor system's ability to re-detect ships.

To model the shape of this envelope, one can look to the theory in reliability engineering [12]. The likelihood of any given inter-detection time will have a non-uniform distribution, with a potentially long tail (increasingly long for low performance sensors requiring multiple looks or integration time), with some most likely detection time (approximately 6 seconds in the case of AIS). The probability distribution in Figure 4 for inter-detection times shows a good fit with a log-logistic function. Similar to latency, a minimum threshold value with a confidence

interval is necessary to ensure that the data requirements are being met for the majority of the data.

A hypothetical sensor system can then be modelled using the log-logistic distribution by choosing the shape parameters such that the mean of the distribution is equal to some objective value. This is a straightforward task since the log-logistic distribution is well described in closed form.

Figure 4 Log-logistic model for the inter-detection times of satellite-based AIS detections over two time frames.

5. RESULTS

The data requirements for the three types of kinematic anomalies are presented. Note here that the metrics have been applied to positional data, which are common to all anomaly types discussed. Also note that sensor false alarm rates, depending on the performance of the data fusion process, will also impact the data requirements. These results, however, are still widely applicable to maritime surveillance data from sources such as AIS.

5.1. Detection under models I, III, and III

In Figure 5, each subfigure consists of data for a total of 5 million Monte Carlo (MC) simulation runs consisting of 100,000 iterations for each of 50 distribution shapes chosen by varying the mean inter-detection time. The upper plot in each figure pair presents the distribution of the occurrences where the anomaly could not be detected ($t_{stopped}$) in the y-axis for an inter-detection time with a mean shown in the x-axis. The lower plot presents the same information, but with the x-axis being the 95th percentile for data in the log-logistic sensor model inter-detection times. The curves represent the frequency of occurrence where the anomaly would not be detectable in 99.7%, 95%, on average, or in 50% of the MC evaluations. The visible blip on the on the right end of the figures (most visible for the 50% line) is due

(a) Model I

(b) Model II, d_i=20 nautical miles


(c) Model III
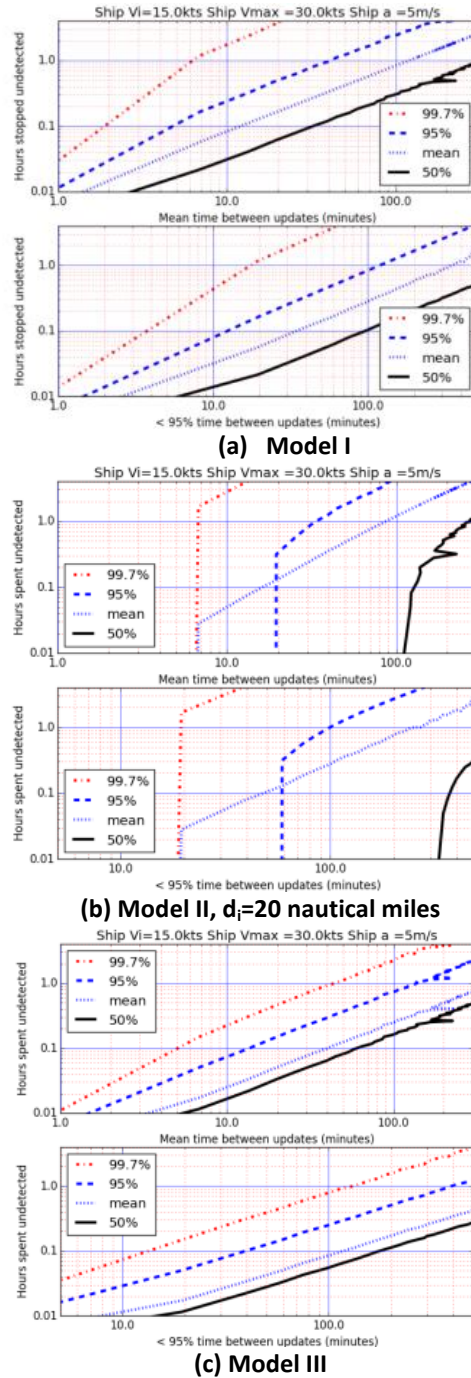
Figure 5 Plot of simulated bounds as a function of inter-detection time distribution.

to the relatively small quantity of runs that populated that region of the results.

5.2. Joint requirements

For each of the models presented in Figure 5, the maximum undetected time (worst case) is selected for each MC run and plotted in Figure 6. This represents the requirements to achieve detection of all three anomalies investigated. Given some operational requirements, such as being able to detect a ship which is loitering for longer than T_s hours, being able to detect a ship spending longer than T_z hours in an exclusion zone, or to detect a potential rendezvous which lasted longer than T_r hours, one can extract the minimum required inter-detection times. By choosing a desired level of detection, the corresponding acceptable mean and upper tail for a required sensor performance can be directly chosen (x-axes) from the upper and lower plot in the figure pair. For example, given an objective of the maximum T_s, T_z, or T_r being 1 hour, for 95% of inter-detection times, then the mean time between updates must be less than 28 minutes, and no more than 5% of updates should exceed 80 minutes.
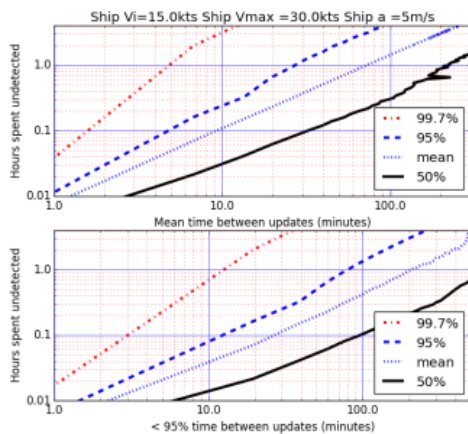
Figure 6 Combined simulated bounds for models I-III.

6. SUMMARY

A framework for quantifying data requirements based on operational processes has been presented. This method enables identification of operational requirements for data acquisition in a robust, objective, and repeatable manner. Notably, it supports the optimization of the quantity of data to meet operator requirements under constraints, thereby preventing over-expenditure in procurement costs while maximizing operational benefits. The results, when considered in comparison to the data being collected, can also be used to identify if there are any gaps in data collection, which can then be directed to the investment of additional data collection resources. In addition, this approach helps to identify the confidence level that the operators can achieve in the anomaly detections, and thus provides an indicator of the associated risks.

Future work includes investigation of real-time anomaly detection requirements, and the formalization of the data and information requirements process which can be generally applied for tasks such as the procurement of data and information.

REFERENCES

[1] Blasch, E., Steinberg, A., Das, S., Llinas, J., Chong, C., Kessler, O., Waltz, E., White, F., "Revisiting the JDL model for information Exploitation," in Information Fusion (FUSION), 2013 16th International Conference on, pp. 129-136. IEEE, 2013.

[2] Rowley, J. E., "The wisdom hierarchy: representations of the DIKW hierarchy," Journal of information science, 2007.

[3] Zins, C., "Conceptual approaches for defining data, information, and knowledge," Journal of the American society for information science and technology, 58.4, pp. 479-493, 2007.

[4] Roy, J., Davenport, M., "Categorization of maritime anomalies for notification and alerting purpose," NATO workshop on data fusion and anomaly detection for maritime situational awareness, La Spezia, Italy, 2009.

[5] Martineau, E., Roy, J., "Maritime anomaly detection: Domain introduction and review of selected literature," DRDC-VALCARTIER-TM-2010-460, Defence Research and Development Canada, 2011.

[6] Food and Agriculture Organization of the United Nations, "Code of conduct for responsible fisheries," 1995.

[7] Bar-Shalom, Y., Willet, P. K, Tian, X., "Tracking and data fusion: a handbook of algorithms," 2012.

[8] Pallotta, G., Vespe, M., Bryan, K., "Vessel pattern knowledge discovery from ais data: A framework for anomaly detection and route prediction." Entropy vol. 15 no. 6 pp. 2218-2245, 2013.

[9] Page, E. S. "Continuous Inspection Schemes," Biometrika 41, no. 1/2, pp. 100-115, 1954.

[10] Ru, J., Jilkov, V. P., Li, X. R., Bashi, A., "Detection of Target Maneuver Onset," in IEEE Transactions on Aerospace and Electronic Systems, vol. 45, no. 2, pp. 536-554, April 2009.

[11] ITU-R M.1371-5, "Technical Characteristics for an automatic identification system using time division multiple access in the VHF maritime mobile band," 2014.

[12] Kapur, P. K., Pham, H., Gupta, A., Jha, P. C., "Software reliability assessment with OR applications," London: Springer, 2011.

A FISHING MONITORING USE CASE IN SUPPORT TO COLLABORATIVE RESEARCH

A.-L. Jousselme[1], E. Camossi[1], M. Hadzagic[1], C. Ray[2], C. Claramunt[2], E. Reardon[1], K. Bryan[1], M. Ilteris[1]
[1]NATO STO Centre for Maritime Research and Experimentation La Spezia, Italy
[2]Naval Academy Research Institute (IRENav) Brest, France

ABSTRACT

This work reports on the design of a Maritime Use Case in support to the *Big Data Analytics for Time Critical Mobility Forecasting (datAcron)* project funded by the European Union Horizon 2020 Programme, which aims to develop novel methods to detect threats and abnormal activity among a very large number of moving entities in large aerial and maritime areas. The use case aligns with the European Union Maritime Security Strategy (EUMSS) and both scientists and operational partners participated in its design. It focuses on the monitoring of fishing activities, which encompass several maritime scenarios such as preventing environmental destruction and degradation, maritime accidents, Illegal, Unreported, and Unregulated (IUU) fishing, Illegal migrations, as well as suspicious vessel tracking.

Index Terms— Big spatio-temporal data, Maritime Moving Objects, Maritime Situational Awareness, Vessel Trajectories, Fishing Use case

1. INTRODUCTION

Reaching appropriate *Maritime Situation Awareness (MSA)* for the decision maker requires monitoring the real time maritime traffic and assessing it against contextual information such as maritime routes or loitering areas inferred from the analysis of historical data (e.g., [1]). This requires not only detecting, tracking and classifying vessels but also detecting, classifying and predicting their behaviour.

Sensor networks mixing cooperative self-identification systems (e.g., Automatic Identification System - AIS) and non-cooperative systems (e.g., coastal radars or satellite imagery) provide the necessary complementarity and redundancy of information to help overcome signals deception (e.g., GPS manipulation and spoofing are frequent for AIS [2]) in order to increase the clarity and accuracy of the maritime picture. In many cases, intelligence reports or expert opinions can also be helpful in refining and guiding the search in the huge amount of data to be processed, filtered and analysed, as well as representing the contextual information for decision support systems in MSA applications [3].

Facing the huge *volume* of *various* information with high *velocity* which often lacks *veracity*, a system to automatically process both historical and timely information would greatly support the Vessel Traffic System (VTS) operator such as the in monitoring and analysis tasks. This is the aim of the three-year *Big Data Analytics for Time Critical Mobility Forecasting (datAcron)* project[3] that has started in January 2016 and whose main research objectives address the development of highly scalable methods for advancing:

Obj.1 Spatio-temporal data integration and management solutions;

Obj.2 Real-time detection and forecasting accuracy of moving entities' trajectories;

Obj.3 Real-time recognition and prediction of important events concerning these entities;

Obj.4 General visual analytics infrastructure supporting all steps of the analysis through appropriate interactive visualisations;

Obj.5 Producing streaming data synopses at a high-rate of compression.

datAcron addresses two critical domains: maritime and aerial traffic, which will guide the research and development and will drive the assessment of the *datAcron* approach.

In this paper, we present the maritime use case of *datAcron*, which describes possible operational uses of *datAcron* for *Fishing Activity Monitoring* focusing on relevant practical challenges and operational questions. It emphasises a human-centric automatic processing of data, stressing the role of the user (or decision maker) in his/her interaction with the system.

The paper is organised as follows. In Section 2, the methodology adopted to develop the use case is presented. In particular, the use case requirements and how the use case is aligned with the *datAcron* objectives and challenges are described. In Section 3, the fishing monitoring use case and six operative scenarios are described, discussing the operational relevance of *datAcron* and how user and operative information needs are formalised through a list of relevant Maritime Situational Indicators (MSIs). In Section 4, the use case driven validation and assessment of

---

[3] datAcron project website: http://www.datacron-project.eu

*datAcron*is also presented. Finally, Section 5 concludes the paper highlighting future directions.

2. USE CASE DESIGN

The methodology used to develop the use case described herein relies on the previous experience of some of the authors, where use cases were designed to support collaborative research project on context-based reasoning in high-level information fusion [4, 5], and adopts the definition of use case given by McBreen et al. in [6], where a *use case* describes the interaction of a user with a system to be designed, to achieve a specific goal or accomplish a specific task. The system requirements can then be derived enabling the user to achieve his/her objectives in different scenarios. The *scenarios* illustrate different usages of the system, and eventually define success (if the goal is achieved) or failure (if the goal is not achieved).

The resulting use case provides a tool to address different aspects of a large research problem, describing users' needs, operational problems and underlying challenges. Illustrating research findings on a common use case, sharing the same datasets, and utilising outputs from other teams are all benefits of having an integrated picture of the general research problem.

As such, the *datAcron* use case has to satisfy the following requirements, which drove the design of the use case:

Req.1 Address challenging problems deemed of interest for the maritime operational community in general;

Req.2 Be aligned with the European Union maritime policies and needs in particular;

Req.3 Be aligned with *datAcron* research objectives and expected outcomes such that the use case challenges the *datAcron*'s technical solutions to be developed, while accommodating the research interests of the different partners;

Req.4 Describe the problem in a simple way as a kind of "skeleton", flexible enough to allow further evolution and developments as possibly requested by partners' interests;

Req.5 Provide the necessary information to understand the user's goal, from which the corresponding sub-goals, associated levels of granularity required, the information needs and the desired output quality can be deduced;

Req.6 Act as an ``integrator'' for the different aspects to be pursued so that teams can illustrate their findings within a common story;

Req.7 Provide a background and support for close interactions between the different work packages and teams involved with the team in charge of the maritime use case;

Req.8 Rely on the available datasets (unclassified, shareable) among the teams and others of interest in the research community (e.g., AIS data, radar datasets, databases of past events, intelligence reports, etc).
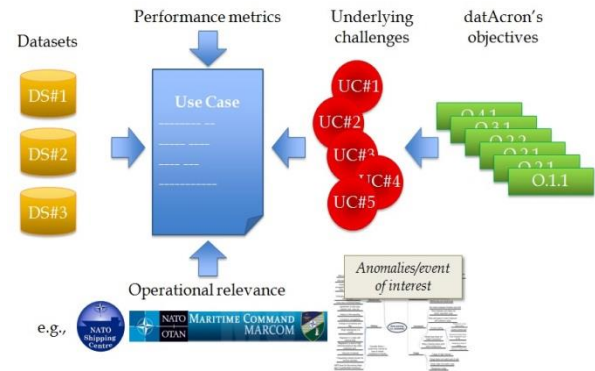
Figure 1 Methodology for the maritime use case development

The diagram displayed in Fig. 1 illustrates the idea behind the methodology. The *datAcron* objectives (cf. Obj.1 to Obj.5 in the previous Section) describe the general goals for the algorithms to be designed. They involve several underlying challenges and may drive specific research foci of interest for the project partners.

In particular, the design of systems supporting an enhanced MSA needs to tackle Big Data challenges: it requires processing in real-time a *voluminous* and high *velocity* information of different nature (numerical, natural language statements, objective or subjective assessments, …), originating from a *variety* of sources (sensors and humans - hard and soft), which often lacks *veracity* (data are either uncertain, or imprecise, vague, ambiguous, incomplete, conflicting, incorrect).

The *datAcron* Maritime Use Case comprises multiple scenarios that describe how actors in the use case perform a set of operations in order to achieve a specific goal. Scenarios describe the current operations that will serve as a basis for understanding and validating the *datAcron* technology, while demonstrating how it can be effectively used in the maritime domain.

The collaboration with the operational partners ensures that the use case is operationally relevant. In particular, the use case describes the general context of use of *datAcron* algorithms. The operational information needs are captured by relevant Maritime Situational Indicators (MSI), which formalise events of interest for the operator and the information required to detect them (cf. Table 1 in the next Section). Operational performance criteria will need to be defined to specify user expectations and to drive the assessment of the *datAcron* prototype, closely tying the experimental plan to the use case development (cf. Section 4). The use case requirements (Req.1-Req.8) may also be used as qualitative system performance metrics, while, at the implementation level, they may act as result validation measures.

3. MONITORING FISHING ACTIVITIES

The *datAcron* Maritime Use Case focuses on fishing activity monitoring, which is a complex maritime surveillance mission that encompasses several maritime risks and environmental issues such as environmental destruction and degradation but also maritime accidents, Illegal, Unreported, and Unregulated (IUU) fishing and trafficking problems, which will be addressed in different scenarios.

Ensuring *security* and *control* of fishing activities is one of the most important aspect of the European Union Maritime Security Strategy (EUMSS) - Action Plan[4], published in December 2014}, which defines several strategic interests for the European Union and the Member States in terms of maritime security. Europe, as the world's biggest market for seafood wants to promote better international governance across the world's seas and oceans to keep them clean, safe and secure. Since fishing is an activity that exploits common natural resources, it needs to be regulated to safeguard fair access, sustainability and profitability for all.

In particular, IUU fishing is a global threat to the marine environment and honest fishermen alike, whose global cost is estimated in about 10 Billion Euros per year. The European Union, in collaboration with International organisations, is committed to fighting IUU fishing worldwide.

Besides the detection of IUU fishing activities, another core issue of the EUMSS is safety. Fishing, in peace situation, is known as one of most dangerous activity. An issue here is that fishing vessels are intentionally switching off their AIS devices while fishing. Therefore, ensuring fishing safety requires processing and predicting fishing trajectories in real-time, detecting fishing events, identifying movement patterns, predicting possible collisions between surrounding ships, within a typical time scale of 5 to 15 minutes.

datAcron will support the European Union's control and enforcement strategy, providing the necessary scientific support for processing, analysis and visualisation of fishing vessels at the European scale, together with the capability of predicting the movement of maritime objects and the identification of patterns of movement and navigational events that shall improve existing solutions to monitor the compliance to the European common fisheries policy.

In order to support *datAcron*'s challenges within the fishing monitoring use case six scenarios have been considered.

All scenarios highlight the need for continuous (real-time) tracking of fishing vessels and surrounding traffic, as well as contextually enhanced offline data analytics. They have been elaborated in order to stress *datAcron*'s algorithms in terms of *velocity*, *veracity*, *variety* and *volume*. They should provide a complete support for trajectory and event detection, prediction and visualisation. For each scenario, the user information needs are expressed through a corresponding list of MSIs. In Table 1, scenarios are summarised with corresponding objectives, possible actions, and example MSIs.
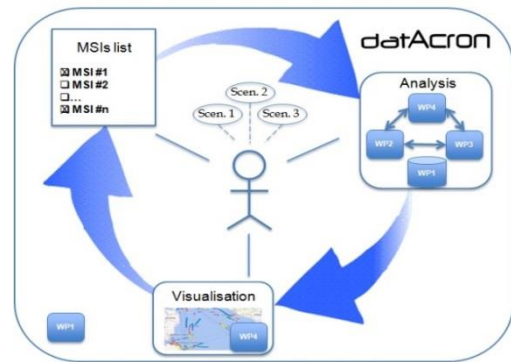
Figure 2 Operational flow of the Maritime Use Case

The MSIs defined for fishing monitoring in *datAcron* formalise the events of interest for the use case, capture the required information while formalising the goals of *datAcron* algorithms and driving the analysis. The list of the MSIs used in *datAcron* is extracted from the outcomes of different workshops held in Sweden [7], Canada [8] and a recently updated NATO standard [9], abstracted to address *datAcron* needs. Specifically, the MSIs have been filtered out considering only (1) the MSIs that *datAcron* can provide, (2) the MSIs that are relevant to the fishing monitoring scenarios.

The conceptual diagram in Fig. 2 illustrates the operational flow and the interaction of the *datAcron* software in the fishing monitoring use case. Depending on the scenario, the user may accomplish different tasks (i.e., monitoring, detecting or preventing the events described by the scenario), and may express his/her information needs through a list of MSIs of interest at a given time. He/she selects the appropriate algorithms and parametrises them accordingly to run the analysis. He/she is able to observe results of the selected algorithms using the visualisation tools and additional visual analytics, allowing to refine the analysis varying the parameters of the MSIs (e.g. change the areas of interest, speed thresholds).

Scenario		Objective		Actions	MSI examples
Secure fishing	SC11	Collision prevention	Protect fishing vessels from collision with large vessels (cargos, tankers, ferries)	Warn fishing vessels at risk, warn vessels heading to fishing areas	Vessel is: in proximity of other vessels; drifting
	SC12	Vessel in distress / MOB (SAR)	Provide early assistance to a vessel in distress	Warn the closest vessels for early assistance, provide precise location of the vessel for the SAR team	Vessel is drifting; AIS emission has interrupted
Sustainable development	SC21	Protection of ecological areas	Protect specific areas from illegal fishing activities	Send control patrol boat to suspicious vessels location	Vessel's course is not compatible with expected destination; AIS emission has interrupted
	SC22	Fishing pressure	Estimate and predict fishing pressure, identify areas at risk	No direct action, but could modify the fishing policies on the mid-term	Vessel is: engaged in fishing; within a given areas
Maritime security	SC31	Migrants and human trafficking	Detect possible human trafficking involving fishing vessels (or the like)	Communicate to security boarder control authorities, provide possible assistance (see SC12)	Vessel's course is not compatible with expected destination; AIS emission has interrupted
	SC32	Illicit activities	Detect suspicious activities involving fishing vessels	Send control boats for further checking	Vessel is on a maritime route; AIS emission has interrupted

Table 1 Scenarios objectives, user's role and actions, MSI

4. VALIDATION AND ASSESSMENT

The quality of the maritime picture can be assessed according to the five criteria of *Completeness* (ratio of detected indicators), *Accuracy* (ratio of correctly detected or classified indicators), *Clarity* (confidence degree about the detection or classification of indicators), *Continuity* (if these detections or classifications are maintained in time) and *Timeliness* (time to obtain the detection or classification result). Each criterion may be defined relatively to a given area, a given period of time, and a given MSI. Hence, for a given scenario, the user expects *datAcron* algorithms to provide answers to the relevant MSIs with a quality defined by these five dimensions. The user chooses the MSIs to detect the scenario-related events (collision, vessel in distress, smuggling, etc). Another layer of performance criteria is related to human factor tasks while dealing with scenario-events.

Fig. 3 illustrates the two levels of assessment of *datAcron*: the MSI level and the scenario level. The *datAcron* algorithms will be evaluated along both the operational and technical criteria (some may overlap). The data would be degraded to study the impact of the different Big Data dimensions on the algorithms outputs. The datasets would be controlled to provide some ground truth information to be able to assess some robustness to the *veracity* of data. The *volume* and *velocity* of data will vary to observe the impact on the timeliness of the algorithms. The *variety* of the data would vary depending on the sources selected to feed the algorithms.

5. CONCLUSIONS

In this paper, the design of the fishing activity monitoring use case of the H2020 project *datAcron*has been presented. The use case addresses operative scenarios of interest for the

European Union Maritime Security Strategy as well as Big Data challenges.

The use case will be a bridge between the operational and the scientific communities, will facilitate collaborative research work among the different project partners and work packages, and will drive the integration the different work package contributions. Future work will address the design of the experimental, which will rely on the maritime use case and associated datasets to structure the assessment and validation of *datAcron* algorithms and prototype.
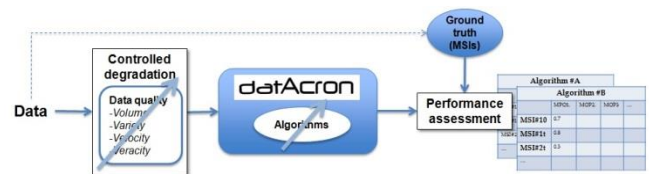
Figure 3 (a) MSI level assessment
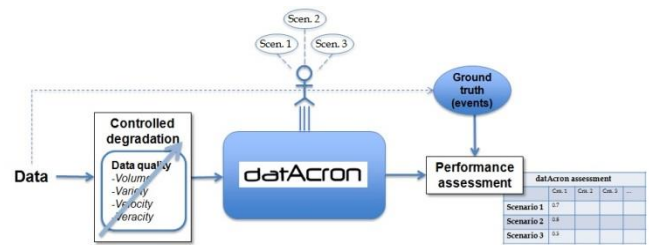
Figure 3 (b) Scenario level assessment

REFERENCES

[1] R. Laxhammar, "Anomaly detection for sea surveillance," in *11th International Conference on Information Fusion (FUSION)*, 2008 pp.1919-1926.

[2] C. Ray, C. Iphar, A. Napoli, R. Gallen, and A. Bouju, ,"DeAIS project: Detection of AIS spoofing and Resulting Risks" in *OCEANS15 MTS/IEEE, Genoa, Italy*, 2015.

[3] J. Llinas, A.L. Jousselme, and G. Gross, "Context as an Uncertain Source," in *Context Enhanced Information Fusion: Improving real world performance with domain knowledge*, Springer, 2015.

[4]A. L. Jousselme, K. Bryan, Karna, M. Ilteris, and E. Reardon, Eric,"Selection of use cases to support Maritime Situation Awareness algorithmic development," in*Technical Memorandum*, *NATO Centre for Maritime Research and Experimentation (CMRE),* 2016, to be published.

[5] L. Snidaro, L.Vaci, J. Garcia, E. D. Marti, A: L. Jousselme, K. Bryan, D. D. Bloisi, and D. Nardi, "A framework for dynamic context exploitation," in *18 th International Conference on Information Fusion (FUSION)*, Washington D.C. (USA), July 2015.

[6] P. McBreen, "Using Use Cases for requirements capture," in *www.mcbreen.ab.ca,* McBree Consulting, 1998.

[7] S. Andler, M. Fredin, F. Gustafsson, J. va Laere, m. Nilsson, and P. Svenson , "SMARTracIn - A concept for spoof resistant tracking of vessel and detection of adverse intentions," in *SPIE Defense, Security, and Sensing*,Orlando, FL, 2009.

[8] J.Roy, and M. Davenport, "Exploitation of maritime domain ontologies for anomaly detection and threat analysis," in *Proc. of the IEEE int. Waterside Security Conference (WSS)*, 2010.

[9] STANAG 4162, "Identification Data Combining Process (Edition 3) - AIDPP-01 Edition 1," in *Tech. Rep.NATO Standardization Agency,* 2015. NATO UNCLASSIFIED.

CONTEXTUAL ANOMALOUS DESTINATION DETECTION FOR MARITIME SURVEILLANCE

Melita HADZAGIC and Anne-Laure JOUSSELME

NATO STO Centre for Maritime Research and Experimentation, La Spezia, Italy

ABSTRACT

The paper presents a situational analysis model for maritime anomaly detection in which we study the role of context and the impact of the imperfection of information in detecting vessel's deviation from destination. The focus is on the exploitation of non-kinematic information, contextual information in the form of previously extracted routes, and the predicted kinematic features as outputs of a vessel tracking algorithm. An uncertainty graphical model example is designed manually to represent expert knowledge and measurement uncertainty. The evaluation of the situation is performed in terms of availability and variability of contextual information, and in terms of reliability (i.e. observability and correctness) of non-kinematic information. The results of the analysis show benefits of using the position prediction algorithm, confirm the advantage of using routes as contextual information, and highlight the characteristics of AIS data in detecting the considered anomaly. These results facilitate the requirements and design specifications for the development of an efficient system for maritime anomaly detection.

Index Terms— situation analysis, maritime anomaly detection, deviation from destination, AIS, uncertainty graphical models

1. INTRODUCTION

Maritime situation awareness (MSA) requires the process of maritime situation analysis (SA) [1] commonly by maintaining the recognized maritime picture (RMP), which is compiled at different fusion levels from data acquired from possibly multiple heterogeneous sources. Its completeness and hence the MSA depend on the effectiveness of the approaches used for assessing the states of maritime situational items and their relationships with the ultimate goal to alert decision makers about potential threat and anomalous behaviour of vessels.

Vessel's anomalous behaviour is often described as a deviation of some traffic characteristic from normal trend which can be short-lived and rare event. It may be accidental and innocuous (e.g. stopping due to vessel failure, sailing at low speed due to bad weather conditions) or deliberate and harmful (e.g. vessels' rendezvous for illegal trafficking, oil spilling, or sailing off-route). In [2] several taxonomies of maritime anomalies are presented. One such anomaly is the ship's *deviation from destination*, which may be an indicator of illicit activity or distress. This anomaly is also of interest to the marine insurance industry since the policies of insurance, on both vessel and its cargo, would be void in the case of any deviation from the direct course and the destination of the voyage without necessity [3].

The significant challenges for compilation of the complete RMP are the volume and the imperfect nature of data to be processed under time-critical conditions. With the advancement of the coastal and satellite-based AIS, the internationally standardized cooperative vessel self-reporting system, there are an abundance of data to be processed in order to extract the knowledge about vessels' tracks and their behaviours, since ships using Automated Identification System (AIS) transponders automatically and continually transmit up-to-date navigational data. These include non-changing data such as ship's name, IMO and MMSI numbers, and length, which are also called "static" data, dynamic data such as current position, speed and course over ground (SOG and COG), rate of turn (ROT), and "voyage-related" data, which include destination (or next port of call (NPOC)), estimated time of arrival (ETA) and draught. The dynamic data are taken from the ship's own data being used for navigation. Position, SOG and COG are commonly taken from the ship's Global Navigation Satellite System (GNNS) such as GPS or GLONASS. However, despite their availability and large available volumes, AIS data are characterized to a great degree with uncertainty [4, 5]. In particular, the voyage related and static information may be incorrect, conflicting or missing due to remote spoofing or deliberate manipulation of the AIS unit on-board, among which obscuring the final destination in the AIS transmissions is one of the most common. With only 41% of vessels globally reporting their destinations, it is suggested that this lack of data could skew views of commodity flows worldwide [4]. Moreover, at open seas or at the border of exclusive economic zones (200nm off-shore), AIS data may be sparse or arrive hours after the observations due to either low coverage or to multi-level processing issues. Hence, crucial to an improved MSA is the ability of the maritime

surveillance system to compensate for poor quality of AIS data, their latency or variable temporal resolution by appropriate modelling of uncertainty.

Furthermore, maritime SA requires assessing and characterizing vessels' states and their relationships within a specific context. An appropriate consideration of contextual information is expected to provide the maritime surveillance system for decision support the necessary modularity and flexibility to adapt to the user's needs and limitations of sources. Formally, context can be defined as the events or circumstances that form (Context-of-*X*) or influence (Context-for-*X*) the environment, within which something exists or takes place, and where *X* represents any physical or conceptual entity and event of interest, [6]. The selection and representation of contextual variables at various times and levels of details establish the context for reasoning about a surveillance picture relevant to a specific decision maker. In the maritime domain, contextual variables may include physical contextual information directly related to the zones of interest (e.g. restricted or fishing areas, borders, harbours, shipping lanes), the previously identified traffic patterns (e.g. routes), the environmental context (e.g. sea conditions, weather) as well as the geopolitical context [7]. The estimated current or predicted future vessel kinematic or behavioral features provided by a model based tracking algorithm are also expected to be helpful.

1.1. Previous Work and Contribution

Previous works on extracting knowledge about motion patterns from the AIS data in support to maritime surveillance include numerous methods for supervised and non-supervised clustering to other data mining techniques [8, 9, 10]. Their use in maritime anomaly detection can be found, for example in [11], where they have been used as normalcy model, and in [12], where the extracted routes have been incorporated as contextual information in the form "context-for-*X*". Here, as in [12], we make use of the identified traffic patterns from the historical AIS data, the so-called ``routes'' as the outputs of the CMRE TREAD tool [10] for representing the contextual information in the reasoning model about the considered maritime anomaly. However here, we focus on the "context-of-*X*" or the additional maritime situational elements in the form of routes which add hypotheses in the chosen uncertainty modelling framework. Additionally, besides kinematic AIS information, we make use of non-kinematic information from the field NPOC as well as the outputs of the tracking and prediction algorithm from [13] in reasoning about the maritime anomaly. In particular, we study the impact of the imperfection of information and availability and variability of contextual information on the reasoning under uncertainty in the problem of detection of a vessel's deviation from destination within a probabilistic graphical

model for representing and managing uncertainty of AIS data.

2. DETECTION OF DEVIATION FROM DESTINATION

Graphical models for uncertainty representation and modelling in maritime situation analysis provide means for structuring knowledge and propagating new information, while managing the uncertainty and complexity of relations. This approach also facilitates the requirements and design specifications for the development of both an efficient model and data driven system for maritime anomaly detection by enabling inference from noisy and ambiguous measurements and their coherent global interpretation while also taking into account their spatio-temporal context, and domain-specific contextual knowledge.

In our implementation of the graphical model example we use a probabilistic graphical model, the Bayesian network. For a given area of interest (AOI) and a given time period of interest, it is assumed that there is a collection of AIS data from which we consider both kinematic and non-kinematic (i.e. voyage-related) information from AIS class A unit: longitude, latitude, COG, SOG, NPOC, and ETA. For the considered AOI, there exist information about previously identified traffic patterns, the routes between ports. Furthermore, it is assumed that the tracking algorithm is part of our surveillance system which outputs the estimated destination $\widehat{D}$ and the estimated time of arrival $\widehat{ETA}$ according to the specific motion model, the observation model, the data and the filtering algorithm from [13]. All these comprise the network input nodes. From all identified routes in the area by TREAD, we consider those which have the exit points (i.e. the physical ports) equal to the NPOC and those with the exit points equal to the estimated destination. The term destination may indicate three different entities: the NPOC field in the AIS message, the physical port in the area, also being the exit point of the route taken, and the predicted destination according to the vessel's kinematic features at a given time instant. According to the domain expert knowledge the existence of the considered anomaly may be influenced by several events: *i)* any inconsistency between the information in the NPOC field in the AIS message and the course, the sailing route information (i.e. the exit point of the route) and/or estimated destination $\widehat{D}$ by the algorithm, *ii)* missing NPOC information, *iii)* as the increase or decrease in the sailing distance calculated as the difference between the destination location and the current location, *iv)* position relative to the route for which the exit point is the estimated destination (e.g. sailing along that route or not); the chosen routes may vary depending on the inconsistency with the NPOC and the route length, or predicted destination and the route length,

and *v)* the level of the course change if off or on route to destination. The graphical model is designed so as to capture and encode this knowledge within the created nodes *Distance From Destination, Course Change*, and *Route To NPOC* which are used to test the above mentioned inconsistencies. The time slice of the Bayesian network, depicted in Fig. 1, illustrates the concept for reasoning about the presence of deviation from destination. The possible states and corresponding prior conditional probability distributions (CPDs) for each created node are defined based on the expert knowledge. The node *Distance From Destination* contains the states: *increasing, decreasing, not-changing*. The destination is by default taken as NPOC, while the predicted destination $\hat{D}$ calculated on the basis of the current motion features is used if NPOC information is missing. The node *Course Change* can have three states: *small, moderate and large*, while the node *Route To NPOC* has two states: *onRoute* and *offRoute*, where *onRoute* designates being on the route of which the exit point is the destination. The states *onRoute* and *offRoute* depend on a user defined distance threshold for the current position relative to the route. The choice of route from all the routes of interest may vary with respect to inconsistency with ETA and remaining time on the route and the predicted ETA.
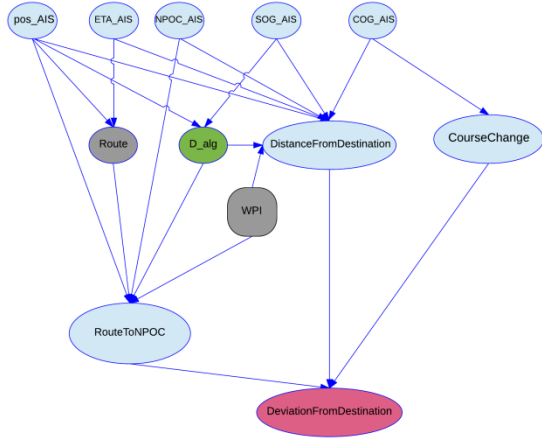
Figure 1 The model

Probability updating in the model is done using the chain rule to calculate the joint probability table of the universe U of variables (i.e. all node variables in BN), where d-separation property used to avoid using the full table, i.e.

$$P(U, e) = \prod_{A \in \mathcal{U}} P(A)|pa(A)) \prod_{i=1}^{m} \mathbf{e_i} \qquad (1)$$

$$P(A|e) = \frac{\sum_{\mathcal{U} \setminus \{A\}} P(\mathcal{U}, e)}{P(e)}, \qquad (2)$$

for $A \in U$, and where $\{\mathbf{e}_1, ..., \mathbf{e}_m\}$ are findings on A, and pa denote graphical model potentials, which in BNs are the CPD tables [14].

2.1. Results

To evaluate the impact of contextual and non-kinematic information on the inference about the considered anomaly, the Bayesian network is implemented using GeNie[5], the open source application developed by the Decision Systems Laboratory, University of Pittsburgh. This evaluation, for two time slices, is carried out with respect to the availability and the correctness of NPOC only (not ETA), the availability and the variability of route information, and the availability of information about the predicted destination by the tracking algorithm for the situation in which the deviation of the destination exists. We assume that there are two possible port destinations, Genoa (correct destination) and Livorno, for which the position coordinates in *(lon, lat)* are known from the World Port Index table [15]. The results are summarized in Table 1. The first set of results corresponds to the analysis with no input from the tracking algorithm. For example, assuming that we have the evidence $e = \{NPOC = Livorno, DistanceFromDestination = increasing, Route = BastiaGenoa\}$, $P(Deviation|e)$ is calculated by marginalizing the remaining node variables using the variable elimination method: start with the set of CPD tables S, and when marginalizing a node variable A, select all the CPD tables with A, calculate their product, marginalize A out and place the resulting table back in S. In the second part of the analysis, the outputs of the tracking algorithm are added to the inputs of the network resulting in improved results. In the absence of the NPOC information, the predicted position is used to calculate the inconsistencies regarding the motion features and the possible ports in the area alleviating the problem of having a parent node with unspecified probability when the data is not available. Another way to solve this would be to associate a so-called default potential with each input node (e.g. route information). If the route information, the predicted position and the correct NPOC are available then the model infers higher probability of anomaly while the incorrect NPOC increases the resulting posterior probability. The values $C_1(R)$ and $C_2(R)$ denote the correct and the incorrect routes, respectively, where the correct route corresponds to the route for which NPOC is the route's exit point. If the vessel is sailing along the incorrect route then the probability of anomaly is higher. The availability of route information and the predicted position improve the inference in the lack of NPOC information.

---

[5]http://genie.sis.pitt.edu

Probability of the deviation from the destination (%)						
AIS_NPOC			$\hat{D}$	Context		
correct	incorrect	not available		$C_1(R = right)$	$C_2(R = wrong)$	not available
		x		56	76	65
x				24	45	36
	x			61	84	79
		x	x	62	92	84
x			x	43	54	48
	x		x	66	96	89

Table 1 Probability of the presence of deviation from destination with respect to the availability and thevariability of route information, the availability and imperfection of Next Port of Call (NPOC), and availability of the predicted position $\widehat{\boldsymbol{D}}$.

3. CONCLUSION AND FUTURE WORK

To demonstrate some of the issues with maritime data quality, particularly AIS, and to determine the requirements for developing a model and data driven system for maritime anomaly detection, we presented the uncertainty model for detection of deviation from the destination which considers context and motion prediction when non-kinematic AIS information are imperfect. The model is evaluated in terms of influence of content in the NPOC field, the availability and variability of contextual information as routes, and the availability of the predicted destination by a tracking algorithm on the reasoning about the anomaly. The analysis shows that reasoning about the presence of deviation from destination benefits from inclusion of both the route and the prediction information, and confirms the negative impact of the imperfection of the non-kinematic information, thereby suggesting introducing source quality control strategies together with prediction and context modules as design requirements for maritime surveillance systems. The model can be extended to include ship type or additional expert knowledge, while with the Markov property assumption, also to a full dynamic BN, where the model in Fig. 1 would then illustrate a single time slice without temporal links. Since the domain knowledge is rather relational than functional, the relations can be quantified with a degree of confidence, thus other graphical models for representing uncertainty will also be considered.

4. REFERENCES

[1] M. R. Endsley, and D. J. Garland, *Situational Awareness, Analysis and Measurements*, Lawrence Erlbaum Associates Publishers, 2000.

[2] J. van Laere, and M. Nilsson, "Evaluation of a workshop to capture knowledge from subject matter experts in maritime surveillance," in *12th International Conference on Information Fusion,* 2009.

[3] E. Fitzmaurice, X. Arroyo, and Eds. Y. Belya, *The IMLI Manual on Maritime International Law, V. II: Shipping Law*, Oxford University Press, 2015.

[4] Windward, "Report on AIS," http://www.windward.com, 2014.

[5] D. Winkler, "Enhancing the Reliability of {AIS} through Vessel Identity Verification," available online at the url http://msi.nga.mil/MSISiteContent/StaticFiles/NAV_PUBS/WPI/Pub150bk.pdf

[6] A. Steinberg, and G. Rogova, "Situation and context in data fusion and natural language understanding," in *11th International Conference on Information Fusion,* 2008.

[7] L. Snidaro, L., J. Garcia, and J. Llinas, "Context-based information fusion: a survey and discussion," in *ELSEVIER Journal on Information Fusion,* 2015.

[8] Z. Feixiang, "Mining ship spatial trajectory patterns from AIS database for maritime surveillance," in *2nd Internationl Conference on Emergency Management and Management Science,* 2009.

[9] M. Hadzagic, M.-O St-Hilaire, S. Webb, and E.Shahbazian, "Maritime Traffic Data Mining Using R," in *16th International Conference on Information Fusion,* 2013.

[10] G. Pallotta, M. Vespe, M., and K. Bryan, "Vessel Pattern Knowledge Discovery from AIS Data: framework for anomaly detection and route prediction," in *Entropy V,* 2015.

[11] B. Ristic, B., B. La Scala, M. Morelande, and N. Gordon, "Statistical analysis of motion patterns in AIS data: Anomaly detection and motion prediction," in *11th International Conference on Information Fusion,* 2008.

[12] G. Pallotta, and A.-L Jousselme, "Data-driven Detection and Context-based Classification of Maritime Anomalies," in *18th International Conference on Information Fusion,* 2015.

[13] M.Hadzagic, and H. Michalska, "Linear stochastic process and genetic algorithm for ship trajectory modeling," in *SPIE Defense, Security, and Sensing, 76970V-11,* 2010.

[14] F. Jensen, and T. Nielsen, *Bayesian Networks and Decision Graphs,* Springer New York, NY, USA, 2007.

[15] USA National Geospatial Intelligence Agency, "World Port Index," *http://msi.nga.mil/MSISiteContent/StaticFiles/NAV_PUBS/WPI/Pub150bk.pdf*

AUTOMATED PROCESSING SYSTEM FOR SAR TARGET DETECTION AND IDENTIFICATION IN NEAR REAL TIME APPLICATIONS FOR MARITIME SITUATIONAL AWARENESS

Sergey Voinov, Egbert Schwarz and Detmar Krause

German Aerospace Center (DLR), German Remote Sensing Data Center (DFD), Kalkhorstweg 53, 17235 Neustrelitz, Germany

ABSTRACT

Spaceborne Synthetic Aperture Radar (SAR) systems have already proven their advantage in Maritime Situational Awareness applications, including such task as targeted vessel detection at sea. Today, involving multiple SAR missions, it is possible to reduce limitations related to the sensor's spatial coverage as well as revisit time. Complementary information from the Automatic Identification System (AIS) offers a huge benefit; regardless that AIS original was designed for collision avoidance only. In particular, it enables to identify detected targets as well as to perform AIS anomaly investigations. This paper describes completely automated processing system of deriving SAR-AIS data fusion products developed at the Maritime Security Lab Neustrelitz, part of DLR's German Remote Sensing Data Center (DFD). Presented technology has been implemented for operational use in Near Real Time (NRT) Applications at DLR's Ground Station in Neustrelitz. The current implementation supports following SAR satellites: TerraSAR-X/ TanDEM-X, Radarsat-2 and Sentinel 1. The development is still ongoing and supported by different projects, to increase the overall performance and to be compliant to the user requirements.

Index Terms— Remote sensing, Synthetic Aperture Radar (SAR), Automatic Identification System (AIS), data fusion, Maritime Surveillance, Maritime Situational Awareness.

1. INTRODUCTION

The major part of global transportation of goods is held over the sea. Safe and secure shipping at sea is a guarantee of world's sustainable development, therefore maritime surveillance applications are nowadays of global importance.

Remote Sensing technologies are widely used in different monitoring tasks including maritime situational awareness. A special place, among the others, holds Spaceborne Synthetic Aperture Radar (SAR) systems which capable to cover huge areas and provide full picture independently from time and weather conditions. Involving multiple SAR satellites the revisit time drops down and improves the efficiency of NRT-based services.

Depending on the resolution of the SAR sensors it is possible not only to detect a target (vessel) at sea, but estimate such parameters as objects width, length and heading [1]. Integrating this information with additional attributes acquired from Automatic Identification System (AIS) opens new capabilities in the context of maritime surveillances such like AIS anomaly investigations or detection of malicious actions.

This paper describes the automated processing system for SAR target detection and identification which was developed and integrated for operational use at DLR's Ground Station Neustrelitz.

2. PROCESSING SYSTEM

The Ground Station Neustrelitz supports data reception from different optical and SAR spaceborne sensors. Currently, operational SAR missions are: TerraSAR-X/TanDEM-X, Sentinel-1 and Radarsat-2.

The data processing starts automatically after its reception by the ground station. The processing chain is organized by means of the Processing System Management (PSM) [2] which schedules different processors according to predefined set of processing rules. Processors which inputs are might be independent from each other can be run in parallel order and wait till necessary steps are complete prior running the next processing action. The overall workflow of presenting system is illustrated on figure 1 and main processing steps are described in the following sub-sections.

2.1. Image Processing

Once the data has been ingested in the processing environment, the system initialises first L0/L1b processor. For every satellite a special processor transforms RAW data into the image format, performs radiometric data calibration, and extracts the L1b image metadata containing geolocation information, imaging times, satellite positions and number

of different coefficients for further calibration and validation. For TerraSAR-X data the TerraSAR Multi Mode SAR Processor (TMSP) is used for this task [3].
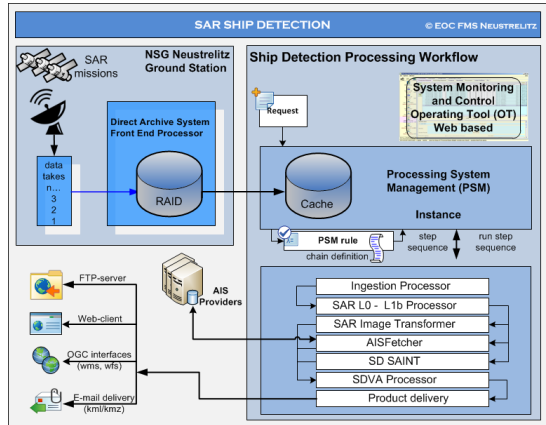
Figure 1 SAR target detection and identification workflow

The next processing step is done by SAR Image Transformer which performs automatic histogram adjustment as well as georectification of SAR images based on ground control points extracted from L1b image metadata. The processor generates several outputs: the full resolution georeferenced (GeoTIFF) image in projected(UTM) and in geographical WGS84(EPSG:4326) projections. In addition, quicklook images in .png and .kmz format (for visualization in Google Earth) can be generated.

2.2. AIS Ingestion

The processor "AIS Fetcher" collects AIS data for required time and spatial extent in accordance to the L1b image metadata. It supports querying different interfaces from several AIS providers as well as import data in RAW NMEA (National Marine Electronics Association) format. In addition, the AIS Fetcher crosschecks every sequence of AIS messages with embedded AIS Plausibility Processor [4]and marks anomalistic messages. The AIS Plausibility Processor was developed inthe DLRInstitute of Communications and Navigation.

2.3. Target detection

The SAR AIS Integrated Toolbox (SAINT) [1] is used for SAR target detection task. The detection algorithm is based on constant false alarm rate (CFAR) detector and operates with unprojected SAR L1b image. Then, extracted points are geocoded with help of L1b image metadata file and provided with lat/lon (WGS84) coordinates. The processor has been developed at the Maritime Safety and Security Lab in Bremen, part of DLR's Remote Sensing Technology Institute.

2.4. Data fusion

The next processor called by the PSM is the Ship Detection Value Adder (SDVA) which combines all the outputs from previous processing steps and generates final delivery products in different formats. The core function of SDVA is the data fusion of detected ships from SAR image with AIS reports.

At initial phase SDVA filters out static objects on sea which appeared to be oil platforms, wind parks, buoys or other man-made objects. This operation is done by crosschecking every object if it intersects with features from so-called sea-signs data base (only for Germany).

At the same time, AIS tracks are reconstructed by interpolating intermediate points using "dead reckoning" approach. The processor always tries to build a realistic track which would not intersect the coastline and will not have sharp angles on the trajectory as it shown in figure 2. The new attribute values are calculated by distance weighted interpolation.
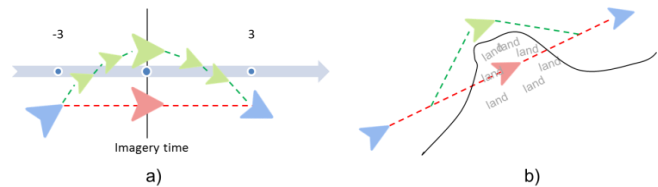

Figure 2 AIS track reconstruction

After the track has been reconstructed, coordinates at imaging time are derived. Time deviations within the image due to possible long imaging (up to 30 second or more) are considered. The L1b image metadata provides necessary information to build a time vector within the image. As the result, all extracted AIS reports at imaging time may have different timestamps (in case if the imaging process took more than 1 second).

The known problem of moving targets on SAR images is their additional Doppler shift which causes object displacement from its actual position on the image. Especially this effect is visible when object's motion trajectory is crossing the satellite track. This type of motion called across-track direction [5]. Displacement in the azimuth direction due to across-track motion can reach up to several hundred meters and depends on object's velocity. Figure 3 shows an example of azimuth displacement of detected vessels.

Number of different techniques exists in the subject of how to compensate this effect. The most efficient approaches are based on utilisation of additional auxiliary datasets, like it was described in the paper "Towards traffic monitoring with TerraSAR-X" [5].
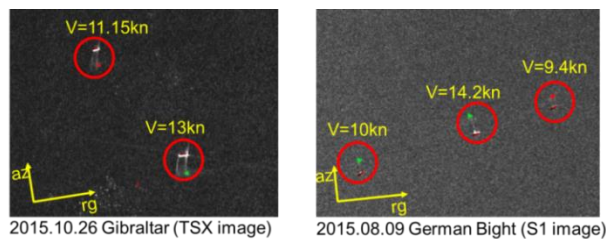
Figure 3 Azimuth displacement due to across-track movement

Here, the AIS dataset in combination with L1b image metadata provides all the necessary information to emulate objects azimuth displacement. With known satellite position at imaging time as well as vessel's velocity and course over ground it is possible to project AIS reported ships positions as they would appear on the SAR image. This method does not require high computation costs and widely used (e.g. [6] and [7]) for SAR-AIS data fusion, a therefore was implemented in SDVA.

Once prediction of azimuth displacement is done the data fusion process takes place. Correlation is done by nearest neighbour search and attributes comparison between SAR-derived target characteristics with AIS reported, which includes heading, width and length. At the end, the candidates with smaller differences will be merged together.
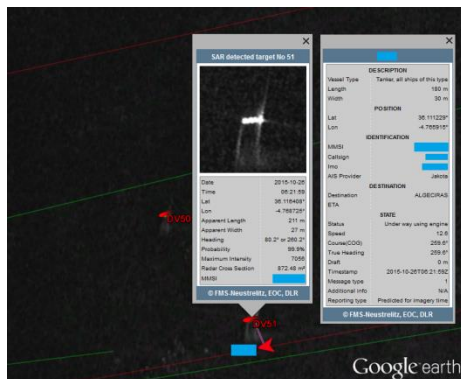
Figure 4 KMZ product output. TerraSAR-X image with overplayed ship-detection point with associated AIS report (visualised in Google Earth software)

2.5. Data dissemination

The SDVA processor generates a number of different output formats supporting different groups of users to perform data analysis. In particular, the most easy-to-use format –the KMZ file which allows data visualisation with Google Earth software. It contains such layers as AIS tracks and points, SAR Ship detections (points with thumbnails) and quick look overlay as it shown on figure 4.

Different dissemination options are supported like automatic ftp/sftp or e-mail delivery as well as giving access to the results over OGC interfaces (wms, wfs) enabling users to connect the data directly in GIS applications without having a local copy. Another user friendly option is web-mapping client which provides similar functionality as KMZ file, but requires no special software.

3. CONCLUSION

This paper presents completely automated solution for NRT maritime surveillance applications by means of data composition acquired from two different sources – spaceborne SAR sensors and AIS. Current implementation is done using parallel computation as much as possible and able to generate ship detection value added products already within 10-15 minutes after image have been received by ground station.

Presented system already integrated for operational use at Ground Station Neustrelitz and able to operate with data received from TerraSAR-X/TanDEM-X, Sentinel-1A and Radarsat-2 satellites. Involving new satellites as well as new auxiliary data such as sea routes maps would extend reliability of system and is a subject for improvement.

REFERENCES

[1] B. Tings, C. A. Bentes da Silva and S. Lehner, "Dynamically adapted ship parameter estimation on TerraSAR-X images.," *International Journal of Remote Sensing,* 2015.

[2] M. Boettcher, R. Reißig, E. Mikusch and C. Reck, "Processing Management Tools for Earth Observation Products at DLR-DFD," in *DASIA 2001 Data Systems in Aerospace*, Nice, 2001.

[3] H. Breit, B. Schättler, T. Fritz, U. Balss, H. Damerow and E. Schwarz, "TerraSAR-X Payload Data Processing: Results from Commissioning and Early Operational Phase.," in *IEEE Geoscience and Remote Sensing Symposium (IGARSS)*, Boston, USA, 2008.

[4] F. Heymann, T. Noack and P. Banyś, "Plausibility analysis of navigation related AIS parameter based on time series," in *European Navigation Conference*, Vienna, 2013.

[5] F. Meyer, S. Hinz, R. Müller, G. Palubinskas, C. Laux and H. Runge, "Towards traffic monitoring with TerraSAR-X," *Canadian Journal of Remote Sensing,* vol. 33, pp. 39-51, February 2007.

[6] Z. Zhao, K. Ji, X. Xing, H. Zou and S. Zhou, "Ship Surveillance by Integration of Space-borne SAR and AIS – Further Research," *The Journal of Navigation,* vol. 67, pp. 295-309, 2014.

[7] F. Mazzarella, M. Vespe and C. Santamaria, "SAR Ship Detection and Self-Reporting Data Fusion Based on Traffic Knowledge," *IEEE Geoscience and Remote Sensing Letters,* vol. 12, no. 8, pp. 1685-1689, August 2015.

DATA DRIVEN IDENTIFICATION OF MIGRANT VESSELS AT SEA

Chad Langford [1,2], Tao Cheng [2], Michele Vespe[3]

[1] University of Salzburg,
[2] SpaceTimeLab, Department of Civil, Environmental and Geomatic Engineering, University College London,
[3] European Commission, Joint Research Centre

ABSTRACT

There is an urgent migrant crisis in much of Europe, fueled by conflict in the Middle East. With a rise of seaborne migration from Turkey to Greece and Italy, there is a need to save lives and secure external borders. This research sets out to expand the foundation of knowledge available on migrant vessels, and by doing so aids in the intervention of migrant ships adrift at sea. This is achieved by using a data driven approach to analyze the vessels' AIS data in the eastern Mediterranean Sea. A partially unsupervised anomaly detection approach, affinity propagation clustering is first-time used to analyze the AIS data, which identifies the potential migrant vessels, and also identify when during a vessel's voyage it may be identified as a migrant vessel.

Index Terms— migrant, refugee, vessel, anomaly detection

1. INTRODUCTION

Political turmoil in parts of Africa and the Middle East, and particularly Syria, have caused the number of asylum seekers in the European Union to grow 45% from 431090 in 2013 to 625920 in 2014 [1]. Unsurprisingly the nationality with the most asylum seekers within the European Union is Syrian with 122115 or 19.5% of all asylum seekers, representing a 144.3% increase from 2013 to 2014 [1]. This sharp increase in asylum seekers is mirrored in the number of illegal border crossings that have occurred. Illegal border crossings rose 164% from 2013 to 2014 with the largest increase of 277% being via the Mediterranean Sea to Italy and Malta [2].

This research aims to identify if and when migrant vessels may be identified during their journey using vessel-specific summary statistics. This is aligned to one of the pillars of the EU Agenda on Migration on saving lives and securing the external borders [3]. The sooner the model is able to identify migrant vessels, the sooner authorities will be able to intervene and offer assistance.

The datasets used in this research are GPS track data (i.e. position, speed and course over ground) from vessels carrying AIS (Automatic Identification System) and located in the eastern Mediterranean Sea, including the Aegean, Ionian, and Marmara Seas during December 2014. The dataset includes 5804 unique vessels and over 6.75 million records. Of the 5804 unique vessels, three are known to have trafficked migrants and refugees from Turkey to the EU and their track data are analyzed in this work.

2. METHODS

By using the spatio-temporal dataset of vessel movements, existing anomaly detection methods (see e.g. [4, 5]) would identify anomalous ranges of data within each vessel's track; this would be considered a *collective* anomaly [6]. There are considerable strengths and weaknesses to this approach. The primary strength is that the approach may be able to identify the specific portion of a vessel's track that is unusual and potentially indicative of a migrant vessel. This strength is, however, overshadowed by the weaknesses that require sequential data to identify the unusual subsequences and it is unable to consider the relationships between multiple dimensions of data. Using the collective anomaly approach also assumes domain knowledge; that is, it assumes we are experts in the field of migrant vessels and definitively know there is a specific, unique subsequence that may be identified as an anomaly. This is not the case. This analysis of vessel data is preliminary to building a foundation of migrant vessel knowledge, thus collective anomaly detection methods are better suited once a better overall understanding of migrant vessels exists. Instead, a dimensionally reduced point-based anomaly detection method is applied to summary statistic vessel data.
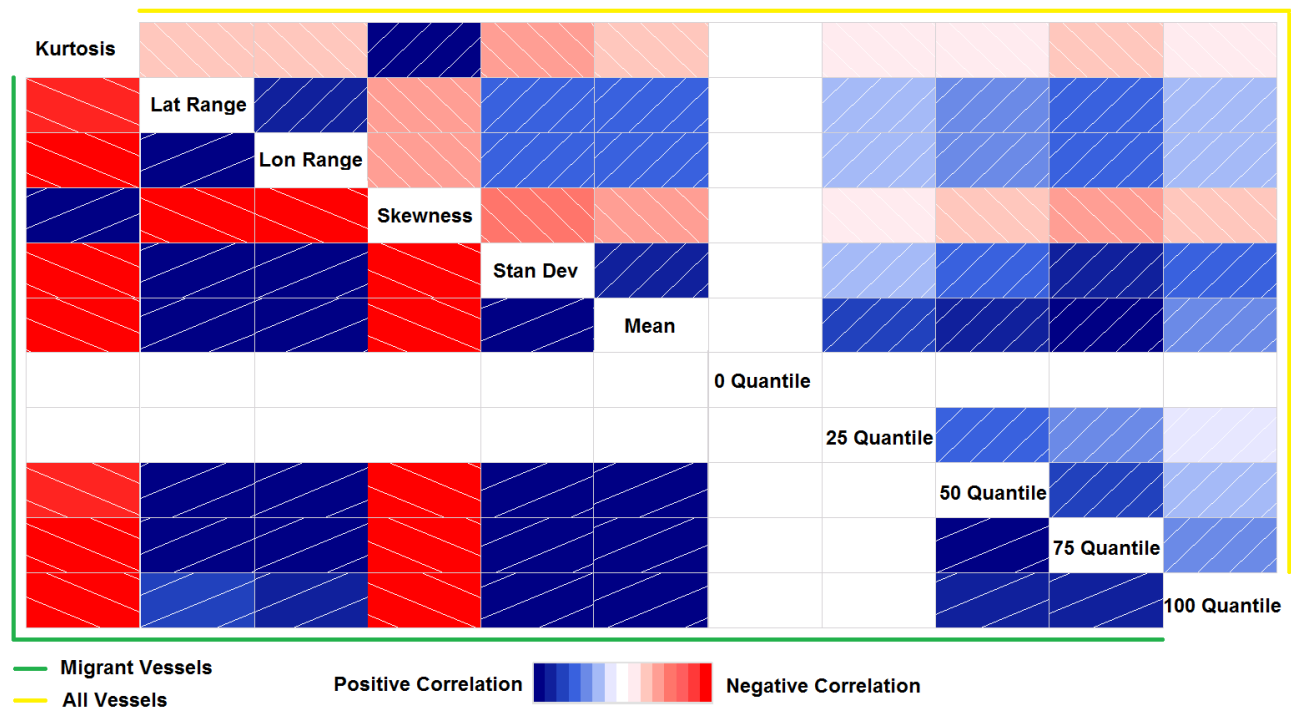
Figure 1 Correlation of variables

2.1 Variable selection

The goal in selecting variables is to maximize the dissimilarities between known migrant vessels and all other (unknown) vessels. The correlogram in Figure 1 shows that for migrant vessels all variables are highly positively or negatively correlated, with the exception of the 0th quantile break and 25th quantile break. Further exploration of the 0th and 25th quantile breaks shows that these variables each have a value of zero for all known migrant vessels. Figure 1 also shows that for most variables all other vessels are weakly correlated. The mean, standard deviation, and 75th quantile breaks SOG variables are the most highly correlated with all other variables for all vessels; these variables are omitted from further consideration. The remaining variables (SOG kurtosis; latitudinal range; longitudinal range; SOG skewness; and the 0th, 25th, 50th, and 100th SOG quantile breaks) are also evaluated to determine how information rich each variable is with respect to the classification of migrant vessels.

Mutual information is a calculation that determines how related a variable is to a label, such as migrant vessel. Mutual information is calculated as the difference between the independent entropy and conditional entropy of the vessel type. That is, the mutual information value for each variable is indicative of how much certainty is added to a label (migrant or unknown) if the variable is present. The mutual information of the remaining variables from the previous step maximizing dissimilarities shows that all variables, with the exception of the 0th, and 100th SOG quantile breaks) provide equal amounts of information with respect to the vessel label. Only the variables with the most information among them will be considered further.

The remaining variables are information rich but provide a set of variables that are biased towards representing each vessel's SOG more than the distance travelled. In order to better balance the set of variables skewness is omitted. Skewness is chosen as the omitted variable due to its redundancy with the kurtosis variable. Longitudinal and latitudinal ranges are also redundant with respect to the other variables but removing either spatial variable would once again bias the analysis towards assuming that the SOG derived variables are more important to the identification of migrant vessels. The latitudinal and longitudinal ranges derived from the original latitude and longitude variables as well as the kurtosis, 25th quantile break, and 50th quantile break derived from the original SOG variable represent a well-rounded selection of information rich variables to be used in identifying migrant vessels.
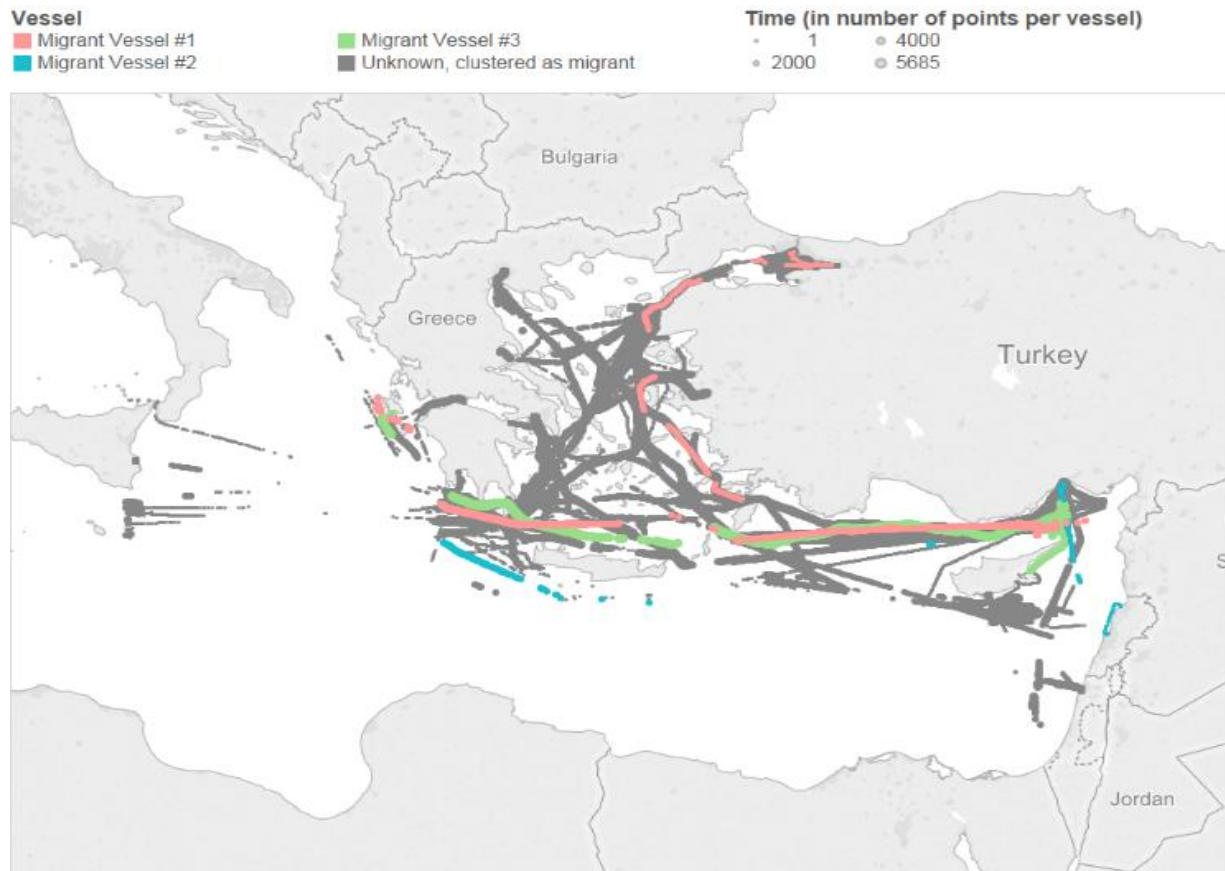
Figure 2 Potential migrant vessels, December 2014

2.2 Affinity propagation clustering

As an alternative to the commonly used *K*-means clustering methods in which the user must define *K* number of clusters, affinity propagation clustering requires no parameter determination on the part of the user. The affinity propagation algorithm has a number of advantages over *K*-means methods: it is not sensitive to initial randomly selected centroids or to the order of data, the user does not determine the number of partitions in the data, and it is generally robust with respect to noise and outliers. Affinity propagation starts by considering all points as centroids, or exemplars as they are called by this method; this is designed to intentionally avoid the random start issues commonly witnessed in K-means methods. Affinity propagation works by using pairwise similarities to exchange responsibility and availability messages between nodes (points) in a network, these messages are used by points to essentially vote for which point will be the exemplar. This data driven method of determining the appropriate number of clusters and cluster membership does not require manual input of parameters. Instead the user of this algorithm must only first create the similarity matrix from which points will be associated.

The method used to calculate pairwise similarities is the negative squared Euclidean distance, a standard method for most algorithms that require similarity values between points [7]. The matrix of similarities and the point data are the only required input for the affinity propagation model. Other parameters may be set by the user, such as maximum number of iterations, but these are not required and the default values have been shown to produce results more accurately than alternative K-means methods [4]. The default parameters and their values are: a maximum number of iterations equal to 1000, and the number of iterations required without cluster changes to terminate with convergence equal to 100. If the algorithm returns an error, that the model has not converged within 1000 iterations, then these values will be revisited and adjusted accordingly.
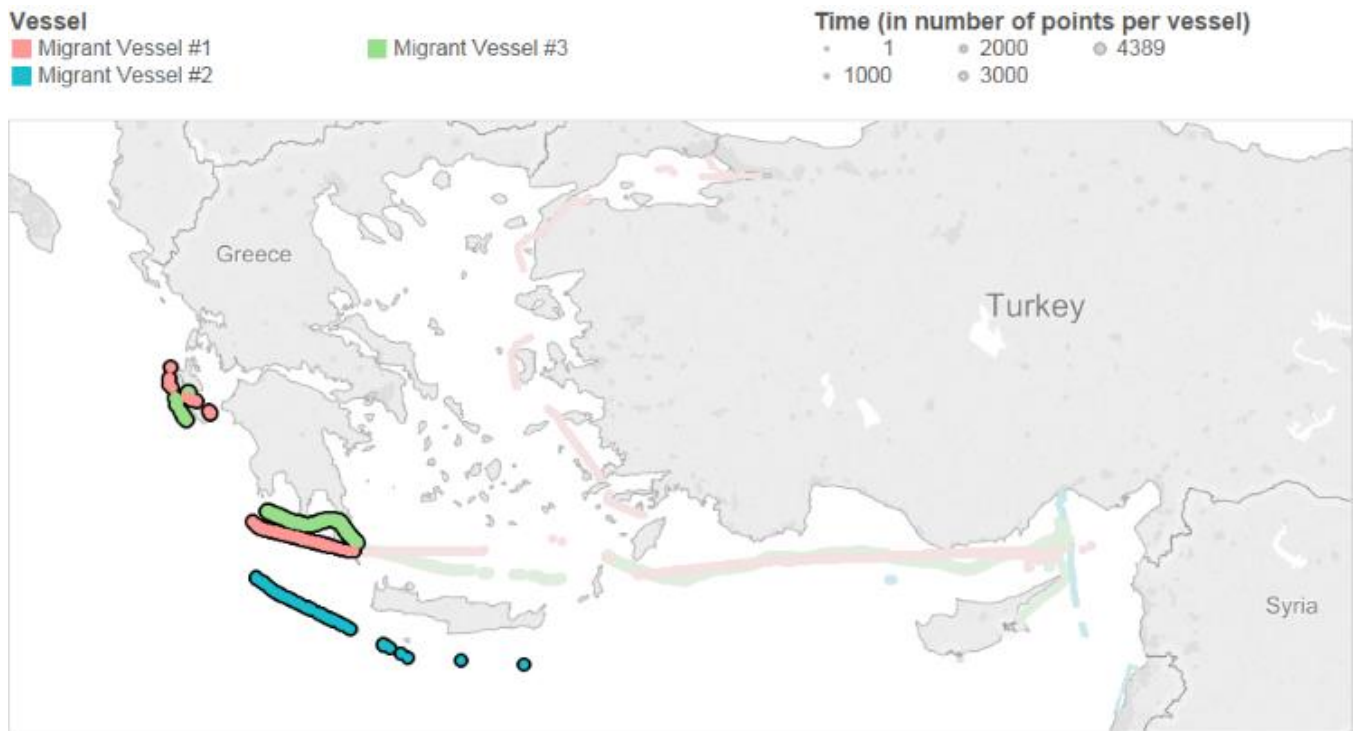
Figure 3 Portion of migrant vessel voyages clustered together

As stated previously, it is imperative that migrant vessels be identified as soon as possible in order to intervene and provide assistance to possibly stranded migrants and refugees upon drifting ships. To achieve this, the original spatio-temporal data is first manipulated to remove portions of the migrant vessel trajectory before rebuilding the point data structure with the updated speed and locational statistics. This process is completed 31 times for each known migrant vessel for a total of 93 times. The three known migrant vessels are necessarily considered separately such that the remaining two migrant vessels may serve as anchors in the migrant vessel cluster.

This results of this method show at which point (percent journey data) all three known migrant vessels are clustered together, and display how the known migrant vessels change clusters through space-time.
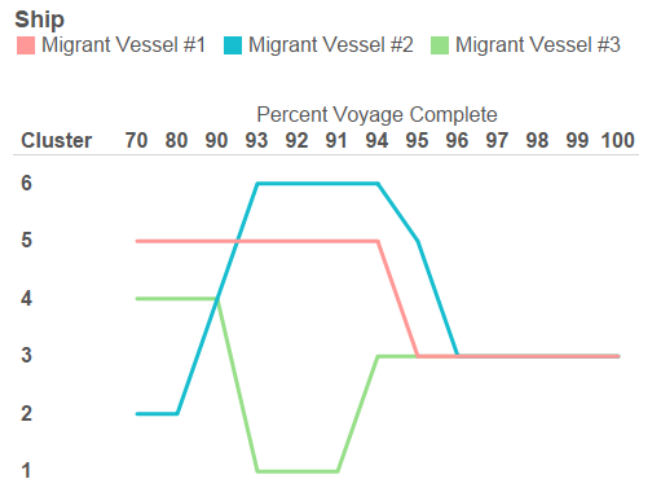
Figure 4 Change in migrant vessel clusters over time

3. RESULTS

The affinity propagation model converged with the data partitioned into 76 clusters. The three migrant vessels are clustered together with 40 other vessels, as seen in Figure 2. There are 28 clusters that have only one vessel. This means that while we may be able to claim that migrant vessels are capable of being identified in the same cluster, it cannot be said that they are considered anomalies with the variables used.

The three known migrant vessels are clustered together beginning when approximately 96 percent of their respective December 2014 data is considered. The corresponding locations may be seen in Figure 3. Figure 4 shows that the known migrant vessels do not share a common cluster history before converging into the same cluster. These results show that it may be possible to further identify potential migrant vessels while they are at sea. The verification of additional potential migrant vessels in this cluster is not practical and highlights a major limitation of this research.

The Central, Eastern and Western Mediterranean Sea feature different types of migration flows, with *modi operandi* of smugglers that change in time. The methodology presented could be implemented to adaptively detect vessels of migrants at sea. In addition, the same approach can be used on radar tracks of smaller vessels that are not broadcasting AIS messages and that are commonly used by smugglers.

REFERENCES

[1] European Commission: Employment, Social Affairs & Inclusion, "Analytical Web Note 3/2015," 02 July 2015. [Online]. Available: http://ec.europa.eu/social/BlobServlet?docId=14211&langId=en. [Accessed 12 July 2015].

[2] Frontex, "Annual Risk Analysis 2015," 27 April 2015. [Online]. Available: http://frontex.europa.eu/assets/Publications/Risk_Analysis/Annual _Risk_Analysis_2015.pdf. [Accessed 06 June 2015].

[3] Communication from the Commission to the European parliament, the Council, the European Economic and Social Committee and the Committee of the Regions - A European Agenda on Migration, COM(2015) 240 final, Brussels, 13.5.2015

[4] Chandola, V., Banerjee, A. Kumar, V., 2009. Anomaly detection: A survey. ACM computing surveys (CSUR), 41(3), p.15.

[5] Pallotta, G., Vespe, M. and Bryan, K., 2013. Vessel pattern knowledge discovery from ais data: A framework for anomaly detection and route prediction. Entropy, 15(6), pp.2218-2245.

[6] Ristic, B., La Scala, B., Morelande, M. and Gordon, N., 2008, June. Statistical analysis of motion patterns in AIS data: Anomaly detection and motion prediction. In 11th international conference on information fusion, 2008.

[7] D. D, "Affinity Propagation: Clustering Data by Passing Messages," 2009. [Online]. Available: http://www.cs.columbia.edu/~delbert/docs/DDueck-thesis_small.pdf. [Accessed 05 August 2015].

METHODOLOGY FOR REAL-TIME DETECTION OF AIS FALSIFICATION

C. Ray [(1)], C. Iphar [(2)], A. Napoli [(2)]

[(1)]Naval Academy Research Institute (IRENav), Brest, France
[(2)]MINES ParisTech, PSL Research University, CRC, Sophia Antipolis, France

ABSTRACT

The Automatic Identification System is an electronic system enabling vessels to send localization messages. Those messages are used for several uses such as fleet control, traffic control or boarding prevention. Sent messages contain errors, falsifications and undergo spoofing due to the unsecured channel of transmission, and that weakens the whole system and the safety of navigation. Beyond known errors, recent works have shown that falsification of AIS messages is easy, and therefore could mask or favor illegal actions, lead to disturbance of monitoring systems and new maritime risks. This paper presents the DEAIS project which proposes a methodological approach for modelling, analyzing and detecting such maritime events.

Index Terms— AIS Falsification, data mining, signal processing

1. INTRODUCTION

The Automatic Identification System is an electronic system enabling vessels to send localization messages. Those messages are used for several uses such as fleet control, traffic control or boarding prevention. Sent messages contain errors (unintentional), falsifications (intentional) and undergo spoofing (intentional) due to the unsecured channel of transmission, and that weakens the whole system and the safety of navigation.

This work reports on the design and first results of a methodology for the detection of AIS falsification. The objectives are the determination of the false messages in real-time and the improvement of both the effectiveness of the system as a security system and the maritime situational awareness.

As a first step, a risk analysis study of the Automatic Identification System has been done via EBIOS method. It led to the identification of circa 350 threat scenarios. A typology of anomalies has been also proposed, alongside with a methodology for anomaly detection.

Intentional broadcast of false AIS information can be understood at both the physical and logical levels. The first approach focuses on signals transmitted by transponders while the second considers information exchanged where fraud and attacks can be identified by message-based data mining methodology to identify abnormal messages (and parameters). In our approach we are considering a combination of both analyses within a single information system.

Method for the integrity assessment of messages and the discovery of anomalous data is particularly based on spatial information, which is the cornerstone of AIS messages but not only as AIS also broadcast many contextual and control information along 27 messages. Integrity assessment is done within one lone message, between messages sent by the same vessel, and between messages sent by several vessels and include MMSI-based cross verification in order to link information received by different stations.

We also studied physical characteristics of the signal which are intended to be integrated in the mining process. We currently considered five parameters. The first parameter is the power of the received signal and the four others are time-dependent and are relative to the shape of the signal. While these parameters cannot fully qualify ship's identity and presence, the regularity of these parameters can conversely help to identify inconsistent values.

2. A SYSTEM WITH WEAKNESSES

Three major cases of bad data quality can be distinguished: the errors (when false data in non-deliberately broadcasted), the falsifications (when false data is deliberately broadcasted) and the spoofing (when data is created or modified and broadcasted by an outsider) (Ray et al., 2015). Data contained in AIS messages can be erroneous, falsified or spoofed for several reasons: there is no strong verification of the transmission, the transmission is done using a non-secured channel, some pieces of information might not be well known by the crew or the crew may want to hide some data from other people's knowledge. Those operations modify and handicap the understanding of the maritime traffic.

The errors, by nature unintentional, can be caused by transponder deficiency, a wrong input of manual data, an input of manual data of poor quality, erroneous pieces of information that come from external sensors, and can have an impact on the name of the vessel, its physical characteristics, the position or the destination for instance. Those pieces of information can then be false, incomplete, impossible according to the norm or impossible according to the physics (for instance a latitude field value shall be

inferior to 90°). According to (Harati-Mokhtari et al., 2007), circa 50% of the messages contain erroneous data.

A falsification is the fact to voluntarily degrade a message by the modification of a genuine value by a false value, or by stopping the broadcast of messages, made in order to mislead the outer world. Identity theft (The Maritime Executive, 2012), the disappearances (Windward, 2014), the broadcast of false GNSS coordinates or the statement of a wrong activity (Katsilieris *et al.*, 2013) are types of falsification. According to (Harati-Mokhtari *et al.*, 2007), about 1% of the vessels broadcast falsified data.

The spoofing of messages is done by an external actor by the creation ex nihilo of false messages and their broadcast on the AIS frequencies (Balduzzi, 2014). Those spoofing activities are done in order to mislead both the outer world and the crews at sea, by the creation of ghost vessels, of false closest point of approach trigger, a false emergency message or even a false cape (in the case of a spoofed vessel).

The whole AIS data transmission system is displayed in Figure 1, where (1) is GPS data transmission, (2) is AIS-SAT transmission, (3) and (4) display VHF marine transmission, (5) shows digital transmission and (6) depicts human supervision. All the chain of AIS data transmission can be affected by one of these three problems.
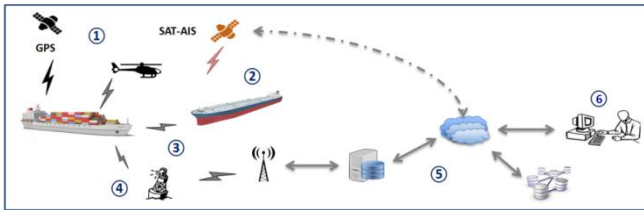
Figure 1 AIS data transmission

As mentioned, problems with the AIS can be understood at the physical and logical levels. DEAIS project considered these two levels for the identification of falsifications. Next sections summarise our risk analysis (section 3) and the methodology proposed for signal analysis (section 4) and message integrity assessment (section 5).

3. AIS EBIOS RISKS ANALYSIS

The EBIOS method (ANSSI, 2010) has been created by the ANSSI (French National Agency for the Security of Information Systems) and is used in both the public and private sectors. It is an approach of risk evaluation which clarifies the entities of the system, their vulnerabilities, the inventoried threats, and contributes in the assessment of the right level of security (compliant with ISO norms 27001, 27005 and 31000).

We conducted an EBIOS analysis of the AIS in which we compiled all known information about the system in order to obtain a complete understanding of it. The application of the EBIOS method on the AIS led to the construction of several tables that enable us to consider several risk levels and the importance to put in place security measures on certain areas which have been found out as particularly vulnerable according to threat scenarios and possible threat sources. These tables describe:

- The essential goods (e.g. dynamic AIS data)
- The essential functions (e.g. transmit AIS data)
- List of support goods (e.g. surveillance centre organisation)
- Identified threat sources (e.g. rival vessel or ship-owner)
- Dread events (e.g. position determination is impossible)
- Threats scenarios (e.g. identity data change on the transponder)

The study led to the identification of more than 350 threat scenarios. Such a study influences the choice of detection algorithms to elaborate first. In particular, it has motivated the study of the AIS signal.

4. SIGNATURE IDENTIFICATION THROUGH MAGNITUDE AND TEMPORAL CHARACTERIZATION

At the physical level, falsification can be identified by signal analysis. For instance, destination masking or disappearances which are also a kind of falsification, as ships turn off their AIS transponder in order to hide some of their activities can be studied by exploiting radar information (Katsilieris *et al.*, 2013). Another approach considers radiolocation of signals to confirm the existence of a real ship and its approximate localization (Papi *et al.*, 2014).

In order to identify a ship's signature or possible falsifications, pertinent features extracted from each frame of the input AIS signals have been studied (Ray *et al.*, 2016). An experimental campaign of reception of frame AIS was conducted in the bay of Brest. Sixteen recordings of five minutes each were collected corresponding to 10 000 usable AIS frames. Each sample is also 5 minutes with a center frequency of 162 MHz and a bandwidth of 100 kHz. It allows recording simultaneously both frequencies of the AIS.

Five features were measured for every AIS frame (Figure 2). The top graph represents the temporal evolution of the frequency modulation of the AIS signal and the down graph represents its power. The first feature is level of the received power, which will allow estimating the broadcast power knowing the distance. The four others temporal parameters are relative to the shape of the signal and are: rise time (Fig. 2-2), fall time (Fig. 2-4), and times before (Fig. 2-1) and after demodulation (Fig. 2-3).

Decoded frames, power of the received signal, and temporal characteristics of the associated signals were then gathered into a geographical database (cf. section 6) to realize a reference database of ships' id and allow statistical studies.
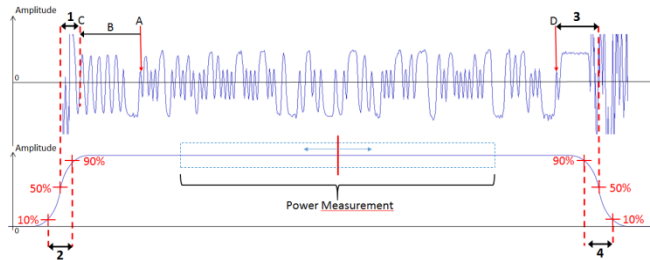
Figure 2 Analysis of a received AIS frame

The study of these different parameters highlights particular values which will allow us to relate with ships' identity signature. For example, Figure 3 proposes a representation of time before modulation in the form of box-plot. The X-Axis corresponds to the MMSI number of ships, the time before modulation being on the Y-Axis. For each ship, the values of "time before modulation" are in a given interval, values that seem different from a ship in the other one.
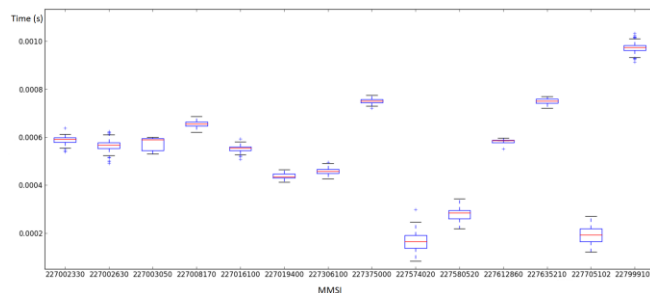
Figure 3 Box plot "Time before modulation" distribution for 'class A' AIS systems

While temporal characterization cannot fully qualify ship's identity, the regularity of these parameters can conversely help to identify inconsistent values. In addition, the study showed that repeaters exhibit specific patterns easily recognizable.

The perspective concerns the improvement of this methodology with the definition of additional signal parameters and the integration of data mining techniques combining signal features with static and dynamic information provided by AIS messages as described in the following section.

5. AIS MESSAGES INTEGRITY ASSESSMENT

At the logical level, fraud and attacks can be identified by message-based data mining methodology to identify abnormal messages and navigational behaviours (Iphar *et*

al., 2015). For instance a ship navigating with a MMSI number which is not the real one, allocated and internationally recognized, can be identified by a correlation with official ships' registry and confirmed by a real-time monitoring of AIS identities at the worldwide level.

Considering the data within the fields of the 27 AIS messages, four ways to discriminate the inner integrity of those data can be distinguished. The first way consists of the control of the integrity of each field of each message taken individually. The second way is at the scale of one single message, and assesses the integrity, in this very message, of all the fields with respect to one another. As there are 27 types of messages, message of the same type have the same fields and it is thus possible to compare them and assess their integrity, this makes the third way. Eventually, the fourth way is the comparison and integrity assessment of the fields of different messages. Indeed, although pieces of information can come from different messages, it is possible to assess their integrity as some fields are either the same or linked or comparable (i.e. MMSI-based cross verification in order to link information received by different stations). Those four ways are referred as first-order, second-order, third-order and fourth-order assessments, respectively.

Depending on the type of messages assessed and the order of assessment, the number of item to check is fixed. We established a list of 669 items for the 27 messages, and an ad-hoc nomenclature has been established so that each item can have a clear unique identifier.

An integrity coefficient is assessed by order, i.e. a coefficient is computed for first-order items, another one for second-order, and so on, depending on the type of assessment wanted. Then a global coefficient can be computed, by weighting the order-based coefficients and other results from other methods as desired.

The perspective concerns the implementation of the methodology together with first detection algorithms. Amongst current developments, we are considering black hole detection in AIS transmission in order to identify possible masking. The following section introduces the architecture designed for the detection of AIS falsification.

6. ARCHITECTURE FOR DATA PROCESSING

A synoptic diagram of the proposed architecture can be found in the Figure 4. The signal can be received from various sources, the parser provides messages parameters, the data processing of the signal provides some signal parameters and two different steps of data processing. All this architecture is built around the database in order to fill it and use it for knowledge discovery. Two implementations are currently developed in parallel; one based on a relational database (postgres/postgis) and a second one based on Flink (Salmon et al., 2015) to cope with larger volume of data.

The data processing box number two corresponds to a signal processing for the determination of aforementioned

characteristics. These data are stored in the database with the associated NMEA message and decoded AIS frame.

The data processing box number one is in charge of on-the-fly analysis of first-order and second-order data assessment, in order to have as output coefficients to store in the database. Similarly, the data processing box number three is in charge of the analysis of third-order and fourth-order data assessment, in order to have as output coefficients to be stored in the database. This part of the study, unless the previous, needs to request historical data.
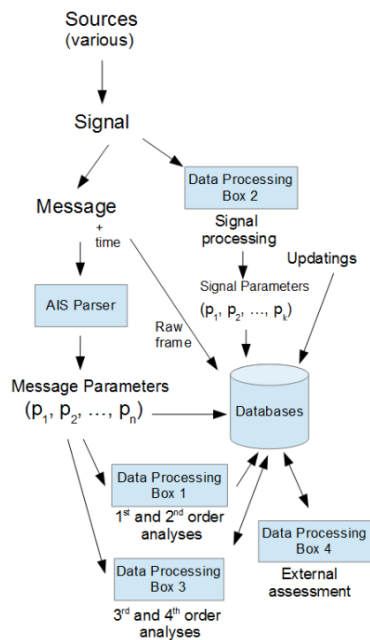
Figure 4 Proposed architecture

In the database itself, each new entry will lead to the creation of a new item (i.e. a new line), with as attributes shall have: a unique identifier, the time of reception, the raw frame, all message field values and the various coefficient obtained through assessments (the four orders and the signal parameters).

The data processing box number four will be in charge of integrity assessments between AIS data and external and aggregated data, (e.g. cartographic information, weather conditions, black hole computations). Of course, the types of processing will vary according to the type of external information available, and it is not possible to have a strictly defined process in this part. A list of assessment items can be created for each new database when its specifications are known (i.e. its fields, their precision, their source and reliability), and two similar databases (i.e. on the same subject) are likely to have two different lists of assessment items as their specifications will differ. Updating of the external databases will, in certain cases, be necessary, as to ensure information is not outdated and data quality assessment is reliable.

7. CONCLUSION

This article proposes a method for analysing AIS data using integrity of information as a key factor, with database storage of information and an assessment done on the message itself, on the message with respect to other messages, on the message with respect to external databases and on the signal itself with its physical characteristics. Such an assessment is the consequence of the defects of this system, transmitting erroneous and possibly falsified data. This method is meant to be implemented and to provide integrity-based confidence coefficient on data that will be useful for the determination of erroneous and falsified data, leading to a risk assessment and alert triggering in a decision-support system and in the end provide an additional tool for the enhancement of maritime security.

8. ACKNOWLEDGEMENT

REFERENCES

ANSSI, 2010.*http://www.ssi.gouv.fr/guide/ebios-2010-expression-des-besoins-et-identification-des-objectifs-de-securite.*

Balduzzi, M., Pasta, A. and Wilhoit, K.,A security evaluation of AIS automated identification system. In: *Proceedingsof the 30th annual computer security applications conference.* ACSAC 2014, New Orleans, USA, December 8-12, 2014.

Harati-Mokhari, A., Wall, A., Brooks, P. and Wang J., Automatic Identification System (AIS): a human factors approach. *J. Navig. Vol 60(3),* Cambridge University Press, 2007.

Iphar, C., Napoli, A., Ray, C., Data Quality Assessment For Maritime Situation Awareness, 9th ISPRS International Symposium on Spatial Data Quality (ISSDQ 2015), Volume II-3/W5, pages 291-296, La Grande Motte - France, 29-30 September 2015

Kastilieris, F., Braca, P. and Coraluppi, S., Detection of malicious AIS position spoofing by exploiting radar information. In: *proceedings of the 16th international conference on information fusion.* Istambul, 2013.

Papi, F., Tarchi, D., Vespe, M., Oliveri, F., Borghese, F., Aulicino, G., and Vollero, A., Radiolocation and tracking of automatic identification system signals for maritime situational awareness. Radar, Sonar & Navigation, IET, 9(5):568–580, 2014.

Ray, C., Iphar, C., Napoli, A., Gallen, R. and Bouju, A.. DeAIS project: Detection of AIS Spoofing and Resulting Risks In: *The proceedings of OCEANS'15.* Genova, 2015.

Salmon, L., Ray, C., Design principles of a stream-based framework for mobility analysis, Geoinformatica, Special Issue on GeoStreaming, 25 pages, April 2016 (DOI 10.1007/s10707-016-0256-z)

The Maritime Executive, Iran, Tanzania and falsifying AIS signals to trade with Syria. Published in The Maritime Executive, December 7th, 2012.

Windward, *AIS data on the high seas: an analysis of the magnitude and implications of growing data manipulation at sea*, 2014.

IMPROVING THE MARITIME TRAFFIC SITUATION ASSESSMENT FOR A SINGLE TARGET IN A MULTISENSOR ENVIRONMENT

Gregor Siegert, Paweł Banyś and Frank Heymann

Department of Nautical Systems
German Aerospace Center (DLR)
Neustrelitz, Germany

ABSTRACT

Exploiting the diversity of multiple on-board sensors is a promising approach to generate a reliable picture of the traffic situation in the vicinity of a particular vessel. This work focuses on multi-sensor fusion for single target tracking in a loosely-coupled architecture. An Interacting Multiple Model Multi-Sensor Probabilistic Data Association filter is designed to capture rapidly changing vessel dynamics in the presence of possible clutter measurements. The actual target tracking is made up of two Unscented Kalman filters each being conditioned on radar and AIS measurement updates. The benefits of the proposed method will be demonstrated on behalf of real-world measurements obtained from the Baltic Sea.

Index Terms— AIS, IMM-MSPDA filter, UKF, radar image processing, sensor fusion, single target tracking

1. INTRODUCTION

The increasing challenges of the maritime traffic domain call for advanced solutions to guarantee safety at sea. Nearly 80 % of the global trade traverses the seas and harbors worldwide (see [1]) stressing the vital economic interests in secure and efficient shipping. Key aspect to all mariners, traffic management and security authorities is a reliable and timely picture of the traffic situation not only in their close vicinity but also with respect to vessels in greater distance. For better identification and localization of maritime traffic participants the Automatic Identification System (AIS) was introduced by the International Maritime Organization (IMO) as an ITU-R recommendation [2] in 2004, yielding a mandatory standard for vessels greater than 300 GRT. AIS can be understood as additional sensor that supports the use of classical surveillance techniques for collision avoidance, e.g., radar, that are used aboard or in shore-based Vessel Traffic Service (VTS) monitoring stations. However, none of the available sensors, neither AIS or radar, can constantly provide sufficient data on their own to establish a reliable and accurate traffic picture at all times. While radar may detect vessels invisible in AIS, it is in general less accurate
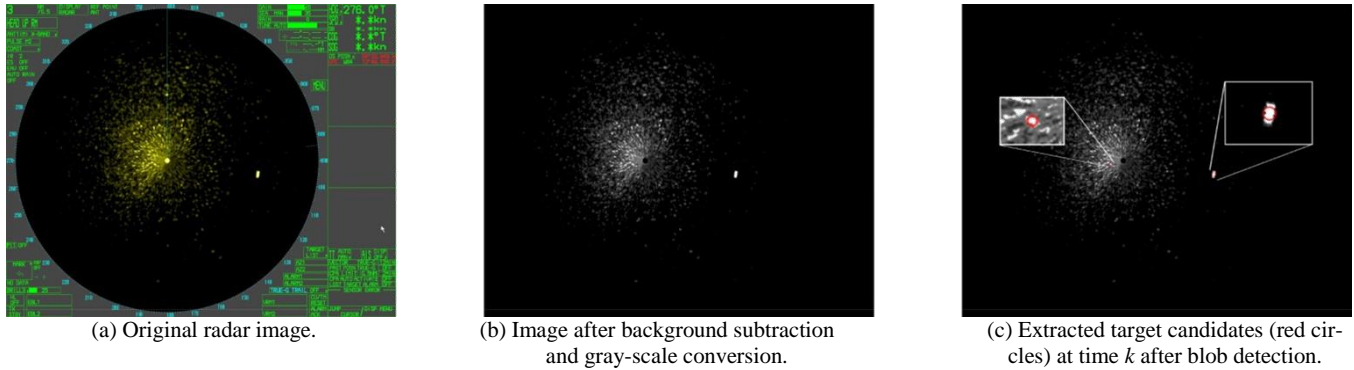
and will always be subject to external weather phenomena that may result in false echoes or clutter measurements. On the contrary, AIS yields great precision of vessel positions, but entirely relies on the cooperative nature of the system. With its open standard AIS is vulnerable to a series of threats, such as availability disruption, ship spoofing or AIS hijacking, as discussed in [3]. Apart from that, unintentional misuse or imperfect equipment may introduce additional error sources compromising the reliability of the system, as was also shown in a comprehensive AIS plausibility analysis in [4]. To encounter these shortcomings, we propose to fuse both, radar and AIS, to establish a more accurate and reliable traffic picture by exploiting the complementary nature of the two sensors. In the literature various approaches have been published to augment maritime surveillance or collision avoidance systems, mostly based on radar target fusion with additional sensors like laser in [5] or multiple radar systems for exploiting aspect diversity as in [6]. The matter of AIS and radar fusion was mainly addressed for anomaly detection, e.g., based on multi hypothesis tests in [7] or by exploiting historical traffic route knowledge for SAR/AIS fusion in [8]. In [9] an overview was given for different AIS/radar fusion techniques incorporating online covariance estimation.

The remainder of this article is structured as follows. In section 2 the general methodology for single target tracking in a radar/AIS environment will be outlined. Section 3 demonstrates the working principle of the proposed scheme w.r.t. measurement data. A conclusion is given in section 4.

2. METHODOLOGY

In this section the proposed methodology for fusing radar and AIS data for single target tracking will be presented in more detail. By designing an Interacting Multiple Model (IMM) Multi-Sensor Probabilistic Data Association (MSPDA) filter that is conditioned on asynchronous radar and AIS measurements a loosely-coupled architecture was chosen.

(a) Original radar image.

(b) Image after background subtraction and gray-scale conversion.

(c) Extracted target candidates (red circles) at time k after blob detection.

Figure 1 Processing chain for one radar image at time k to extract the target candidates.

2.1. Radar image based target extraction

In order to fuse radar with AIS position data, the target candidates need to be detected and extracted from radar first, to feed them to the filter as measurement updates. The utilized approach to extract radar target information is based on image processing instead of directly working on the radar signal level. This may introduce additional error sources originating from mapping the radar signal to image domain, but also yields the advantage of applying the proposed technique to most commercial radar systems by simply interfacing to the video output. To extract target candidates from the current radar image at time k, the following procedure is applied:

1. Masking the image eliminating static but undesired features, e.g., colored heading lines, blob in center, radar information tables.
2. Conversion of image from RGB to grayscale (weighted average from color channels).
3. Blob detection with fixed range settings for convexity, circularity, inertia, size and intensity of expected tar-gets.
4. Each detected target candidate per frame is expressed in range and bearing, relative to the radar's, i.e., ship's, position.

The key aspect in this processing chain is certainly the scale-invariant blob detection to eventually detect target candidates. This algorithm is well described in literature and finds many applications in image based target detection and tracking such as described in [10]. For this work the implementation provided by the OpenCV framework was used[1]. Figures 1a to 1c show the different radar processing stages.

2.2. AIS dynamic target data

The typical AIS data set contains numerous static and dynamic parameters, that are distributed over different

AIS message types and specified in the ITU-R recommendation [2]. The set of dynamic parameters always comprises the vessel position in longitude and latitude, course over ground (COG) and speed over ground (SOG), but may also contain true heading and rate of turn (ROT) information. The specified time intervals between successive messages range from 2 s to 180 s, depending on the dynamic state of the vessel. As was shown in [4] these reporting rates are violated in a considerable amount of cases, leading to outdated or simply missing AIS messages.

2.3. IMM-MSPDA framework for single target tracking

In this work, an IMM-MSPDA filter was designed for single target tracking in an AIS/radar environment. The IMM, being first proposed in [11], is generally applied to best capture rapidly changing motion dynamics by running a bank of interacting Kalman filters in parallel, with each filter being conditioned on a different process model. The final IMM state estimate as well as the re-initialization of the Kalman filters after each iteration is based on a weighted combination of the individual state estimates, whereas the transition between the models (or modes) is governed by an underlying Markov process. The combination with a Probabilistic Data Association (PDA) filter yields a powerful scheme for associating clutter measurements to the expected target state in a dynamically challenging scenario. The basic steps of the PDA filter are comprehensively described in [12]. Essentially, each sensor measurement gets validated based on a validation region centered around the expected state of the target. The final state update is then based on the weighted sum of the residuals between validated and expected measurements, with the weights being computed from the likelihood of the measurement to origin from the target. In contrast to the standard PDA approach in [12] we apply Unscented Kalman Filtering (UKF) (see [15]) to compensate especially for nonlinearities in the radar

---

[1] OpenCV 3.1.0: https://github.com/Itseez/opencv.git

measurement domain. An algorithm combining both approaches to form an IMM-PDA filter in a multi-sensor environment was originally proposed in [13], outlining a scheme to combine synchronous measurement updates from 2 to 3 sensors sequentially. An extension to incorporate multiple sensors providing asynchronous or delayed measurements was published in [14]. In our work, the latter is adopted to the particular scenario of observing high rate radar measurements and low rate AIS updates, both running asynchronously. In contrast to the original algorithm, in our implementation the standard IMM cycle is continued on arrival of any sensor measurement. Otherwise, if low rate AIS messages would solely trigger the update of the IMM model probabilities, the IMM could not adopt to changing motion dynamics as quickly as if radar measurements were also used for initiating the model probability update of the IMM cycle.

2.4. UKF filter design

For the actual target tracking an Unscented Kalman filter (UKF) was designed incorporating state augmentation by the process noise during state prediction and additive correction steps for each of the sensors. Details on the basic idea of the unscented transform as well as the implementation based on state augmentation can be found in [15]. In our particular application the UKF was found to outperform the Extended Kalman filter (EKF) in the presence of highly nonlinear radar measurement updates, as was already discussed in [6] and [16]. In the context of vessel dynamics two dominant motion scenarios were identified, that are nearly straight-path and turn maneuver based motion. For that reason, two process models were defined, namely the Constant Velocity (CV) and the Constant Turn Rate Velocity (CTRV), assuming the former to provide best fit to straight-path and the latter to turn maneuver motion respectively. Further details on the definition of CV and CTRV process models can be found in [17].

Within each filter hat implements one of the modes from above, the predicted state $x_{k|k-1}$ and its associated covariance will be based on measurements of sensor $s \in$ *{radar, ais}*. The corresponding measurement models are expressed as functions $h^s(x_{(k|k-1)}, \epsilon_k^s)$, with

$$h^s(\mathbf{x}_{k|k-1}, \epsilon_k^s) = \left[x_{k|k-1}, y_{k|k-1} \right]^T + \epsilon_k^s \quad (1)$$

for $s = ais$ and

$$h^s(\mathbf{x}_{k|k-1}, \epsilon_k^s) = \\ \begin{bmatrix} \sqrt{(x_{k|k-1} - x^s)^2 + (y_{k|k-1} - y^s)^2} \\ \arctan\left(\frac{y_{k|k-1} - y^s}{x_{k|k-1} - x^s}\right) \end{bmatrix} + \epsilon_k^s \quad (2)$$

for $s = radar$, mapping the target position fom state to radar measurement domain. In that context, (x^s, y^s) denotes the radar reference position and $(x_{k|k-1}, y_{k|k-1})$ the predicted position in the target's local ENU frame respectively. The vector $\epsilon_k^s \sim N(\mathbf{0}, \mathbf{R}^s)$ captures the additive sensor measurement noise. Careful attention has to be paid to the interaction of models with state spaces of different dimensions within the IMM cycle. In this work the strategy from [18] is followed, which is based on state augmentation. In this context, the extra element from the CTRV state space is essentially replicated to obtain a combined IMM state estimate.

3. RESULTS

In this section the proposed algorithm for fusing AIS with radar in an IMM-MSPDA filter shall be evaluated based on a dynamically challenging measurement scenario.

3.1. Baltic Sea experiments
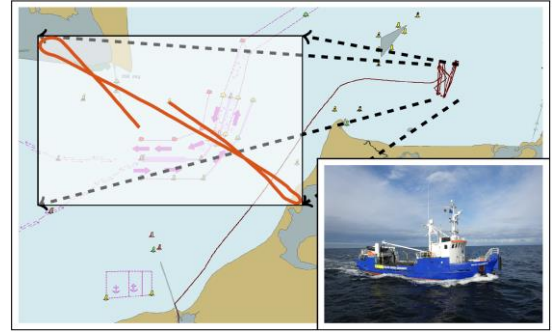
Figure 3 Nautical chart depicting the area of the measurement campaign at the Baltic Sea, zooming into the selected test trajectory. The bottom right picture shows the vessel to be tracked.

For validating the proposed method a dedicated measurement campaign with two chartered vessels was conducted in October 2015. The offshore supply ship BALTIC TAUCHER II was conducting sea trial maneuvers for two successive days in the Baltic Sea (see Fig. 3). Its transmitted AIS messages were recorded at a shore-based AIS station at the Darßer Ort Lighthouse, Germany[2]. Additionally, this ship was equipped with a multi-frequency GNSS receiver that allowed for computation of a PPP reference trajectory in post-processing. A second ship, the tug vessel AARON remained anchored in the center of the sea trial area, monitoring the scenery by radar at an interval of 1 Hz.

---

[2] Courtesy of German Federal Waterways and Shipping Administration (WSV)
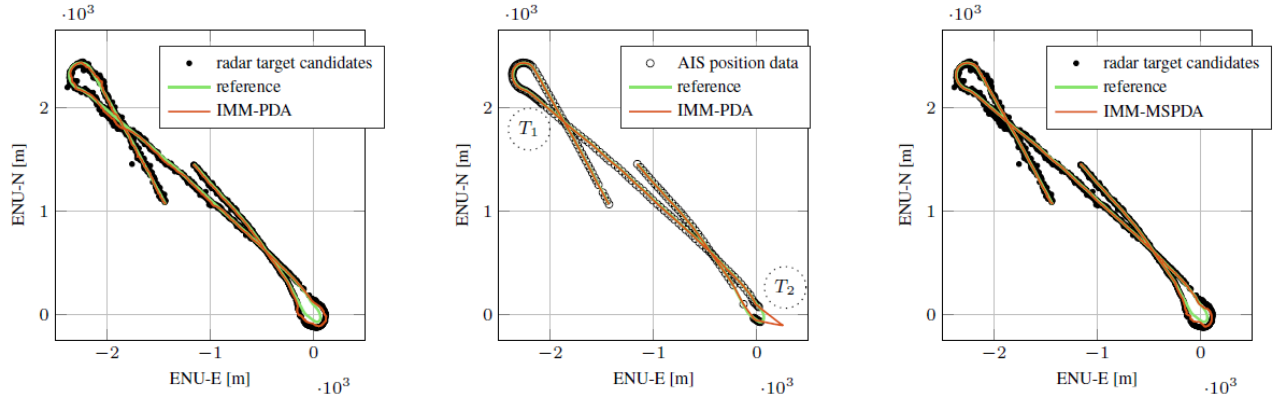
(a) Trajectory of tracked vessel based on radar data only, running an IMM-PDA only.

(b) Trajectory of tracked vessel based on AIS data only, running an IMM-PDA filter.

(c) Trajectory of tracked vessel, fusing radar and AIS data, running an IMM-MSPDA filter.

Figure 2 Comparison of filtered vessel trajectories from two IMM-PDA filters conditioned on either radar or AIS alone and an IMM-MSPDA filter fusing both sources.

With this scenario the feasibility of the proposed method for maritime situation awareness w.r.t. to a single target shall be demonstrated. For the validation of the proposed filter, the subset highlighted in Fig. 3 was selected due to its two distinct turn maneuvers, covering 1708 s or 201 valid AIS messages respectively.

3.2. Evaluation

For evaluation and to demonstrate the potential benefits of the proposed scheme, three different filters were tested. At first, an IMM-PDA filter was conditioned on plain radar target candidate data. Secondly, the AIS messages from the same track were used as sole input to this filter. Figures 2a and 2b show the filtered trajectory in comparison to the reference and original measurement updates. Thirdly, the proposed IMM-MSPDA filter was tested with both asynchronous sensor measurement updates. The trajectory obtained from this fusion process is shown in Fig. 2c. As can also be seen in Table 1, the filter being conditioned on radar image data only cannot compete in terms of accuracy to filtered AIS position data. However, while the filter running on low rate AIS messages is introducing a large position error during the second turn maneuver (at label T_2 in Fig. 2b) due to missing AIS messages radar can still be used for tracking as it provides continues measurement updates. By fusing both sensors the filtered trajectory overpasses smoothly the lack of AIS messages during the turn maneuver, while it is mainly following AIS updates otherwise. In this particular case, the maximum error in the estimated target position was drastically reduced from nearly 236 m to below 56 m.

In Table 1 prominent statistics for the three different filters are listed stressing the performance improvement from the proposed IMM-MSPDA filter in terms of maximum and RMS error. It is not surprising that the σ-value of the error distribution, i.e., the value which bounds 68.27 % of the errors, is increasing for the fused process compared to the filtered trajectory conditioned on AIS data only. Due to the high rate radar measurements more uncertainty is inferred to the filter in times where AIS messages would actually suffice.

Table 1 Statistics of the horizontal position error for the three different filters.

	mean	σ (68.27 %)	RMSE	max.
IMM-PDA AIS only	9.6 m	3.2 m	36.9 m	235.7 m
IMM-PDA Radar only	18.3 m	19.1 m	22.3 m	75.8 m
IMM-MSPDA	8.9 m	7.1 m	14.8 m	55.6 m

4. CONCLUSION

In this work, an IMM-MSPDA framework was utilized to exploit the complementary nature of radar and AIS sensors in a loosely-coupled data fusion architecture. The overall aim is to provide a more robust picture of the traffic situation in the vicinity of a particular vessel, resilient to AIS faults or anomalies. Based on real-world measurements the benefits of the proposed scheme could be visualized for cases of missing or insufficient AIS message updates. In future work this framework will be

extended for multiple target tracking including track initialization based on candidate extraction from radar.

REFERENCES

[1] United Nations, World Economic Situation and Prospects 2012, chapter 2, pp. 41–66, United Nations publication, 2012.

[2] ITU Radiocommunication Sector (ITU-R), "Technical characteristics for an automatic identification system using time division multiple access in the VHF maritime mobile band.," Recommendation M.1371-5, ITU, February 2014.

[3] Marco Balduzzi, Alessandro Pasta, and Kyle Wilhoit, "A Security Evaluation of AIS Automated Identification System," in Proceedings of the 30th annual computer security applications conference, ASAC, New Orleans, LA, USA, December 2014.

[4] Frank Heymann, Thoralf Noack, and Paweł Banyś, "Plausibility analysis of navigation related AIS parameter based on time series," in ENC, Vienna, Austria, 2013.

[5] Lokukaluge P. Perera, Victor Ferrari, Fernando P. Santos, Miguel A. Hinostroza, and Carlos Guedes Soares, "Experimental Evaluations on Ship Autonomous Navigation and Collision Avoidance by Intelligent Guidance," IEEE JOURNAL OF OCEANIC ENGINEER-ING, vol. 40, APRIL 2015.

[6] Paolo Braca, Michele Vespe, Salvatore Maresca, and Jochen Horstmann, "A Novel Approach to High Frequency Radar Ship Tracking Exploiting Aspect Diversity," Geoscience and Remote Sensing Symposium (IGARSS), 2012 IEEE International, pp. 6895 – 6898, 2012.

[7] Marco Guerriero, Peter Willett, Stefano Coraluppi, and Craig Carthel, "Radar/AIS Data Fusion and SAR tasking for Maritime Surveillance," in International Conference on Information Fusion, 2008, vol. 11th.

[8] Fabio Mazzarella and Michele Vespe, "SAR Ship Detection and Self-Reporting Data Fusion Based on Traffic Knowledge," IEEE GEOSCIENCE AND REMOTE SENSING LETTERS, April 2015.

[9] Witold Kazimierski and Andrzej Stateczny, "Radar and Automatic Identification System Track Fusion in an Electronic Chart Display and Information System,"THE JOURNAL OF NAVIGATION , no. 68, pp. 1141– 1154, 2015.

[10]Michael Isard and John MacCormick, "BraMBLe: A Bayesian multiple-blob tracker," in Eighth IEEE Inter-national Conference on Computer Vision, 2001, vol. 2, pp. 34–41.

[11]Henk A. P. Blom and Yaakov Bar-Shalom, "The Interacting Multiple Model Algorithm for Systems with Markovian Switching Coefficients," IEEE Transactions on Automatic Control, vol. 33, 1988.

[12]Yaakov Bar-Shalom, Fred Daum, and Jim Huang, "The Probabilistic Data Association Filter," IEEE CONTROL SYSTEMS MAGAZINE, December 2009.

[13]Yaakov Bar-Shalom, Fred Daum, and Jim Huang, "Multisensor Tracking of a Maneuvering Target in Clutter," IEEE TRANSACTIONS ON AEROSPACE AND ELEC-TRONIC SYSTEMS, vol. AES-25, March 1989.

[14]Soonho Jeong and Jitendra K. Tugnait, "Multisensor Tracking of a Maneuvering Target in Clutter with Asynchronous Measurements Using IMMPDA Filtering and Parallel Detection Fusion," in Proceeding of the 2004 American Control Conference, Boston, Massachusetts, 2004.

[15] Simon J. Julier and Jeffrey K. Uhlmann, "A New Extension of the Kalman Filter to Nonlinear Systems," in Proc. of AeroSense: The 11th Int. Symp. on Aerospace/Defence Sensing, Simulation and Controls., 1997, pp. 182–193.

[16]Zhansheng Duan and X. Rong Li, "Sequential Unscented Kalman Filter for Radar Target Tracking with Range Rate Measurements," in In Proc. 2005 International Conf. on Information Fusion, 2005.

[17]Gregor Siegert, Paweł Banyś, Cristina Saez Martìnez, and Frank Heymann, "EKF Based Trajectory Tracking and Integrity Monitoring of AIS Data," in IEEE/ION Position, Location and Navigation Symposium - PLANS, Savannah, GA, April 2016, IEEE.

[18]John D. Glass, W. D. Blair, and Yaakov Bar-Shalom, "IMM Estimators with Unbiased Mixing for Tracking Targets Performing Coordinated Turns," Proceedings IEEE Aerospace Conference, 2013.

A HYBRID APPROACH FOR THE ANALYSIS OF ABNORMAL SHIP BEHAVIORS

Aldo NAPOLI

MINES ParisTech, PSL Research University, CRC, Sophia Antipolis, France

ABSTRACT

Current maritime traffic monitoring systems are essentials for a maritime situational awareness. However, they are not always adapted to the identification of risky behaviours of ships. It is very difficult for operators responsible for monitoring traffic to identify which vessels are at risk among all the shipping traffic displayed on their screen [1, 2, 3].We present in this paper a hybrid approach for analysing dangerous behaviours of ships based on AIS data. This approach is based on supervised and unsupervised analyses and it was developed in the frame of PhDs. Our approach is based on three complementary methodologies: (1) data mining for knowledge and pattern extraction for behaviour modelling, (2) ontological modelling of behaviour for an unsupervised detection and (3) geovisual analysis of large volume of data for a supervised detection of threats at sea. Three prototypes were developed to test our approach.

Index Terms— Maritime Domain Awareness, Ontology, Data Mining, Geovisual Analytics

1. INTRODUCTION

The maritime surveillance centres (MRCC) integrate monitoring systems in order to have in real time a large vision of the traffic of ships. Data acquisition operates heterogeneous data like AIS data, meteorological data, bathymetry data, but all the data are not integrated in a unique interface. Moreover, the surveillance systems are in general not equipped with analysis support or decision support allowing detecting dangerous behaviours.

Since 2007, in the frame of PhD and R&D projects, our research centre focus its work on the design and the development of maritime surveillance systems and specially on automatic or supervised detection of abnormal behaviours of ships. This hybrid approach is illustrated in Fig. 1.

We can identify two kinds of behaviours:
- Known behaviours that we can model with expert knowledge [4, 5];
- Unknown behaviours or behaviours interpretable with difficulties, to be characterized with automatic methods like data mining [6].

Then, the modeled behaviours can be integrated into a real-time system of detection of abnormal or dangerous behaviours.

The hybrid approach is designed on both unsupervised and supervised analysis methods. We present in the following sections the components of the approach:
- An unsupervised method for the analysis of the abnormal behaviours, based on data mining;
- An ontological framework for the modelling of behaviours; this framework is used into a real-time detection system of abnormal behaviours, relying on case-based reasoning;
- A geovisual analytics frameworks allowing supporting the operator in his task of behaviour analysis;
- A maritime surveillance system integrating all the components of the methodology.
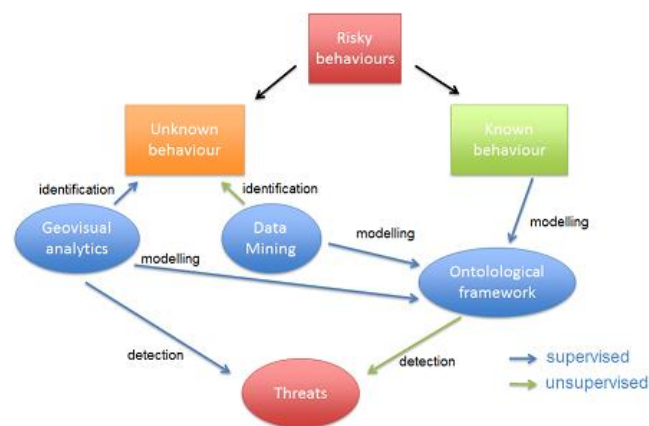
Figure 1 The hybrid approach for analysis of maritime behaviours

2. A DATA MINING SUPPORT SYSTEM

The unknown behaviours can be founded with data mining methods that can detect characteristic patterns. The patterns define a ship behaviour that can be modelled for further

analysis. In our research (PhD of Idiri), we developed a prototype of AIS data analysis system based on data mining methods [7, 8]. This system named ShipMINE (Fig. 2) is inspired by the system MoveMine [9] that integrates algorithms for the analysis of different kind of trajectories (animals, cyclones, etc.).

Different algorithms are integrated into ShipMINE for the detection of:

- Zones with a lot of accidents (algorithm DBSCAN),
- Abnormal trajectories into a group of trajectories (algorithm TROAD), (Fig. 3),
- Usual trajectories of ships (algorithm TRACLUSS),
- Parallel trajectories like trajectories of parallel fishing that is forbidden (algorithm CONVOY).

The patterns detected with ShipMINE are interpreted by experts of the domain. The useful patterns are then used for the modelling of abnormal or dangerous behaviours.
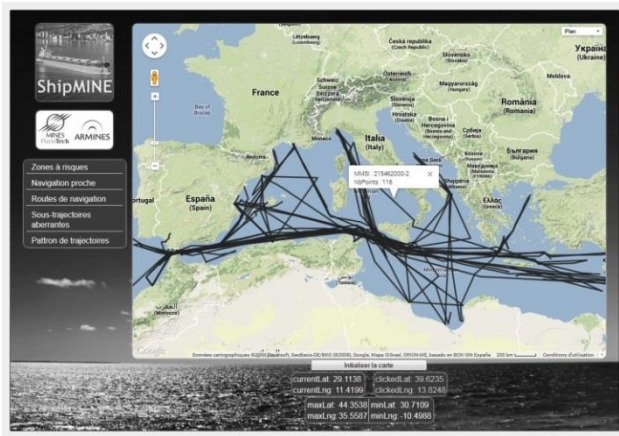
Figure 2 The prototype ShipMINE
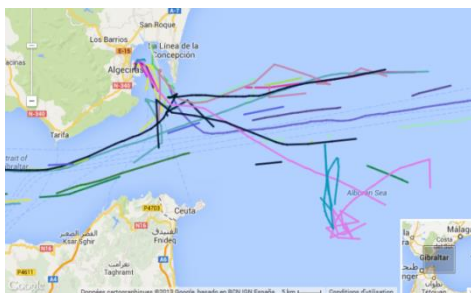
Figure 3 Extraction of abnormal trajectories with ShipMINE in [7]

3. AN ONTOLOGICAL FRAMEWORK

Ontologies and the semantic enrichment of maritime trajectories are necessary in order to characterize the sequences of the behaviours. In the frame of the PhD of

Vandecasteele [10, 11], we based our research on the extension of the ontological framework developed by Yan and his colleagues [12]. We decided to consider not only the spatio-temporal positions of the trajectory but also semantic trajectory units (e.g. begin, stop, moves, end). These semantic units can be enriched with different types of knowledge (e.g. spatio-temporal, geographic, domain) to provide end-users with high-level semantic descriptions of trajectories and a better understanding of the situation (step (a) in Fig. 4). This step allows performing further analyses of trajectories identifying potential alerts related to abnormal movement (step (b) in Fig. 4). Then, the proposed framework allows interpreting vessels' activities and behaviours (step (c) in Fig. 4), using a case-based reasoning approach to compare previous behaviours defined by operators with the current facts. Then the semantics behaviours are integrated through a specific user interface that provides a better understanding of the situation (step (d) in Fig. 4). This approach was integrated into the prototype OntoMAP (Fig. 4).
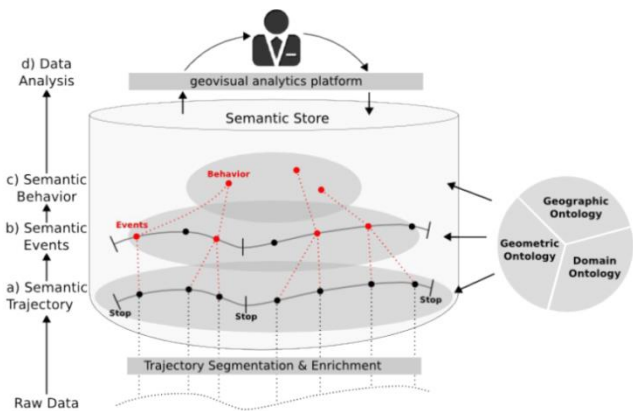
Figure 4 Conceptual architecture of the system. Raw data are extracted, enriched and then analyzed to identify potential abnormal behavior (in [11])
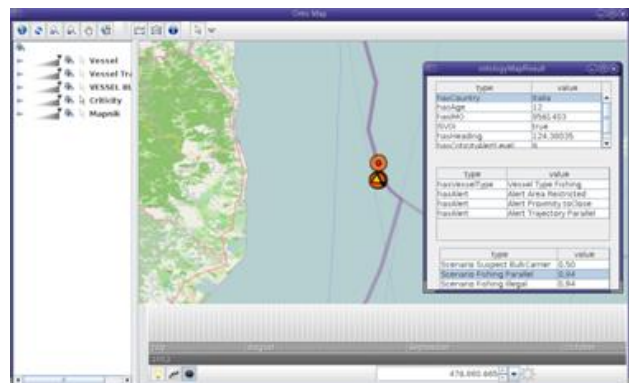

Figure 5 The prototype OntoMAP in [10]

4. A GEOVISUAL ANALYTICS SUPPORT SYSTEM

The community of geovisual analytics develops a lot of visualizing methods for geographical information [17, 18, 19, 20]. During the PhD of Vatin [13, 14, 15, 16], we developed a methodological approach of ship trajectory analysis based on geovisual analytics (Fig. 6). Our system proposes to an operator, information and visualizing method the most adapted to the analysis of risky situations. Our approach is based on (1) the modelling of the normal or abnormal situations to be analyzed, (2) the modelling of the information and the visualizing methods to be used and (3) the modelling of the profile of the operator and his capacity to handle the information and the visualizing methods. Because the operator of the MRCC is not accustomed to handling these methods, our system proposes to him, based on the analyses of his capacity and of the situation to be detected (pirate attacks, etc.), the visualizing methods the most adapted to the context.

We developed a system allowing a real-time analysis as well as delayed analysis of ship traffic. It can be adapted to every situation and every user profile. This prototype is integrated into our maritime surveillance system FishEYE.
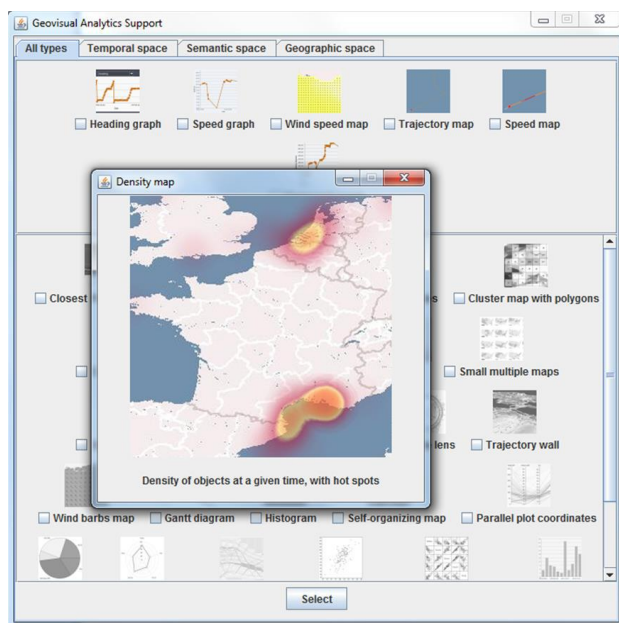
Figure 6 The Geovisual analytic interface in [13]

5. A MARITIME SURVEILLANCE SYSTEM

In order to monitor data in real time and to test the researches introduced in previous sections, we developed a prototype of maritime surveillance system named FishEYE (Fig. 7). This system integrates heterogeneous data (ship localizations, meteorological and oceanic data, bathymetry,

etc.) and different functions (analysis filters, drift models, etc.). Prototypes presented in the previous sections have been integrated as modular functions of the system. The design and the development of FishEYE are still in progress and improved continually.
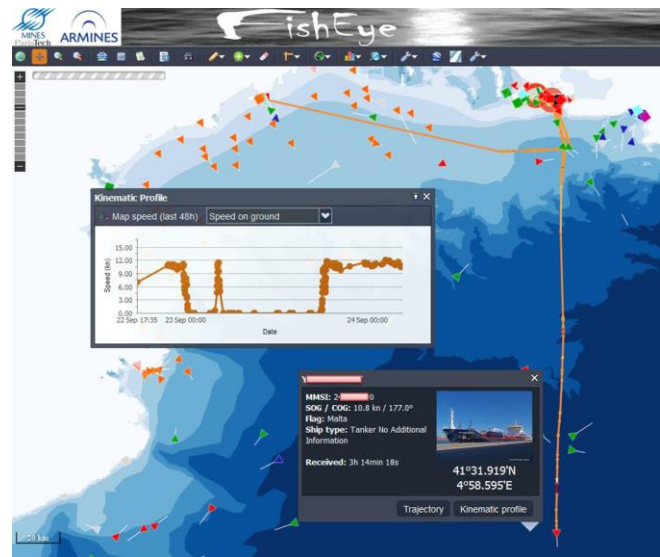
Figure 7 The prototype FishEYE

6. CONCLUSION

The proposed approach allows analyzing identified and unknown behaviours thanks to supervised and unsupervised analysis methods. Unknown behaviours are detected with unsupervised methods (data mining). Similarly to known behaviours, the detected behaviours can be interpreted with a system based on supervised methods (geovisual analytics). Then, the behaviours can be formalized within an ontological framework.

Different prototypes were developed, integrating the methods chosen (data mining, geovisual analytics, case based reasoning). Finally the maritime surveillance system FishEYE was developed to integrate all methods into a unique interface, easier to be handled by an operator.

Next step of our research will focus on a geocollaborative support system allowing supporting operators to solve a problem like a huge accident or oil spill. This framework will be integrated into FishEYE.

REFERENCES

[1] Morel M., Napoli A., George J.P., Jangal F., Giraud M.A., Botalla M., « Surveillance et contrôle des activités des navires en mer : ScanMaris ». In *Proc. ofWorkshop Interdisciplinaire sur la Sécurité Globale*, Troyes, France, 2010.

[2] Riveiro M., Falkman G., "The role of visualization and interaction in maritime anomaly detection". In *Proc. of SPIE-IS&T Electronic Imaging*, 7868:78680M, San Francisco, CA, USA: Chung Wong, P. (Eds), 2011.

[3] Vatin G. and Napoli A., "Guiding the controller in geovisual analytics to improve maritime surveillance", In *Proc. of GEOProcessing 2013: The Fifth International Conference on Advanced Geographic Information Systems*, Applications, andServices, Nice, France, 2013.

[4] Roy J., "Anomaly detection in the maritime domain" In *Proc. of Optics and Photonics in Global Homeland Security* IV; 69550W. Spie., 2008.

[5] Van Laere J. and Nilsson M., "Evaluation of a workshop to capture knowledge from subject matter experts in maritime surveillance", In Proc. of the *12th international Information Fusion Conference*, Seattle, USA, pp. 171-178, 2009.

[6] Pallotta G., Vespe M. and Bryan K., "Vessel pattern knowledge discovery from AIS data: a framework for anomaly detection and route prediction", *Entropy 2013*, 15, pp. 22218-2245, 2013.

[7] Idiri B., « Méthodologie d'extraction de connaissances spatio-temporelles par fouille de données pour l'analyse de comportements à risques – Application à la surveillance maritime », *PhD thesis, MINES ParisTech, CRC*, 2013.

[8]Idiri B. and Napoli A., "The automatic identification system of maritime accident risk using rule-based reasoning", In *Proc. of the 7th International Conference on System Of Systems Engineering - IEEE SOSE 2012*, Jul 2012, Genoa, Italy. pp.125-130, 2012.

[9] Li Z., Ji M., Lee J.G., Tang L.A. and J. Han, "MoveMine: Mining Moving Object Databases" In *Proc. ofInternational Conference On Management of data (SIGMOD)*, Indianapolis, 2010.

[10] Vandecasteele A., « Modélisation ontologique des connaissances expertes pour l'analyse de comportements à risque – Application à la surveillance maritime », *PhD thesis, MINES ParisTech, CRC*, 2012.

[11] Vandecasteele A., Devillers R. and Napoli A., "A semi-supervised learning frameworkbas ed on spatio-temporal semantic events for maritime anomaly detection and behavior analysis". In *Proc. of CoastGIS 2013 - The 11th International Symposium for GIS and Computer Cartography for Coastal Zone Management*, Jun 2013, Victoria, Canada.4 p., 2013.

[12]Yan Z., Chakraborty D., Parent C., Spaccapietra S. and Aberer K., "Semantic Trajectories: Mobility Data Computationand Annotation". *ACM Transactions on Intelligent Systems and technology*, 9:1–34, 2012.

[13] Vatin G., "Formalisation d'un environnement d'aide à l'analyse géovisuelle – Application à la sécurité et sûreté de la maritimisation de l'énergie », *PhD thesis, MINES ParisTech, CRC*, 2014.

[14] Vatin G. and Napoli A., "High-Level Taxonomy of Geovisual Analytics Tasks for Maritime Surveillance", in *Proc. 26th International Cartographic Conference*, Aug 2013, Dresde, Germany. 14 p., 2013.

[15] Vatin G., Rigaud E. and Napoli A. "Geovisual Analytics Environment for Supporting the Resilience of Maritime Surveillance System". In *Proc. ofThe Council of Engineering Systems Universities (CESUN). CESUN 2014, 4th InternationalEngineering Systems Symposium*, Jun 2014, Hoboken, NJ, United States.7 p., 2014.

[16] Vatin G. and Napoli A., "Using Ontologies for Proposing Adequate Geovisual Analytics Solutions in the Analysis of Trajectories". In *proc. iV 2014 : 18th International Conference on Information Visualisation*, Jul 2014, Paris, France.IEEE, pp.176-182, 2014.

[17] Kraak M.J., "Beyond geovisualization", *IEEE Computer Graphics and Applications* 26 (4): 6‑9, 2006

[18] Andrienko N. and Andrienko G., "Visual analytics of movement: an overview of methods, tools and procedures". *Information Visualization* 12 (1): 3‑24, 2013.

[19] Willems N., « Visualization of vessel traffic ». Technische Universiteit Eindhoven, 2011

[20] Riveiro M., "Visual analytics for maritime anomaly detection". University of Skövde, 2011.

MARITIME SITUATIONAL AWARENESS IN THE HIGH NORTH

Torkild Eriksen, Atle Ommundsen, Brita Gade, Morten Aronsen

Norwegian Defence Research Establishment (FFI), P.O. Box 25, N-2027 Kjeller, Norway

ABSTRACT

Analyses of long-term satellite AIS data provide information about the activity in the High North back to July 2010. In this paper the distribution of ships per month is shown, illustrating the variations in the activity and which flags that are present. A multiple hypothesis tracker (MHT) algorithm and Smart Agents are also presented; these are important tools for multi-sensor fusion of data from maritime surveillance assets and mandatory reporting systems enabling a comprehensive current maritime picture and end-user support in the detection of anomalous behaviour.

Index Terms— Knowledge discovery, AIS, anomaly detection, data fusion

1. INTRODUCTION

FFI carry out research to obtain the best possible Maritime Situational Awareness (MSA) in the High North, and are involved in developing all aspects of the data collection, processing and information production chain. Key components in the R&D activity are fusion of data from a heterogeneous mix of platforms, sensors and information systems that facilitate anomaly detection, user friendly presentation and information exchange.

2. SHIPPING INTENSITY

The Norwegian AIS satellites are instrumental in developing Norway's maritime surveillance capacity. In addition to providing updates of ship positions in the Arctic every 45 – 90 minutes, the long-term data provide information about ship positions and activities since July 2010. Density plots may be used to represent the normal situation in terms of shipping intensities that may be used for trend analyses as well as anomaly detection.

Figure 1 shows the monthly shipping intensity in a part of the Norwegian area of interest in November 2015, for which the current maritime picture is shown in Chapter 3.2. The AIS data used are position reports from both Class A and Class B Automatic Identification System (AIS) transponders [1]. A rainbow colour scale is used to show the ship counts on a 1°x1° grid; from red for

low numbers to violet for 48 ships per grid cell during the month, and black for 49 and higher numbers.
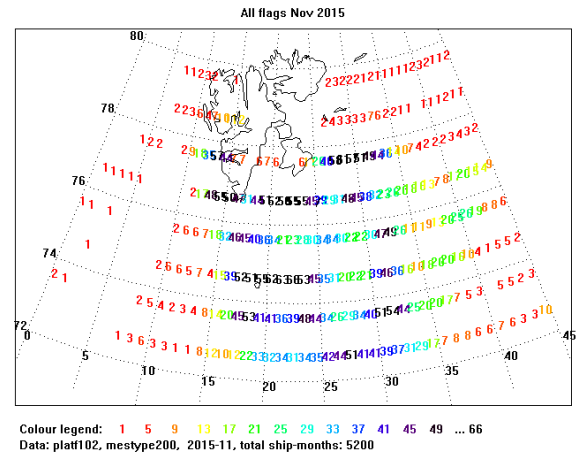

Figure 1 Ship density in Nov 2015, 72-80°N, 0-45°E.

The sum of the ship counts of all the grid cells, referred to as the total ship-months, is used as an aggregated figure for the ship activity in the area. In November 2015 the value was 5 200 ship-months. The highest value in 2015 was 6 149 ship-months in August, the lowest was 1 374 in January, plots are shown in [2].
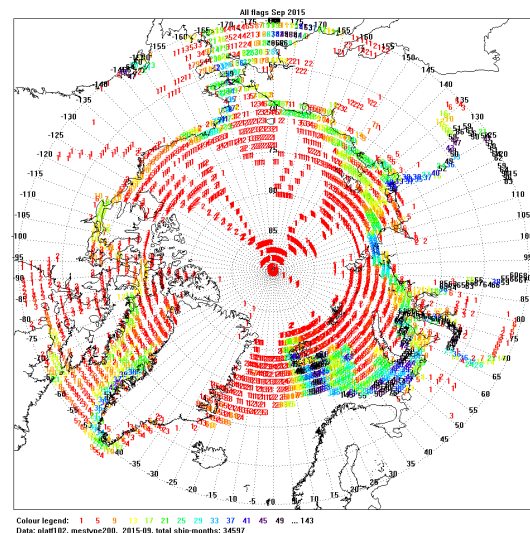

Figure 2 Shipping intensity in Sep 2015 in polar waters.

Figure 2 shows the shipping intensity in the area given by the polar-waters definition in the Polar Code [4]. The highest number of ship-months in 2015 occur in September; 34 597 ship-months. The annual variation in the number of ship-months (red) as well as the number of ships (blue) is shown in Figure 3; 1 719 ships contributed to the activity in September.
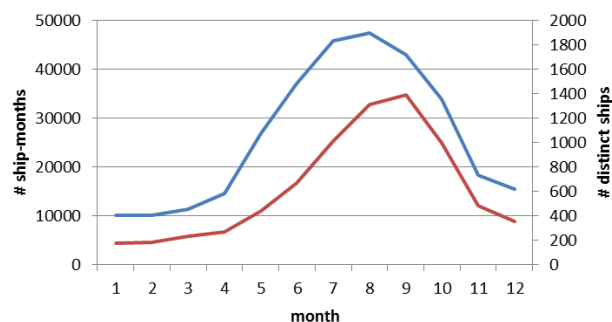
**Figure 3** Variation of shipping in polar waters 2015.

The number of ships per flag state in September is shown in Figure 4. Russia has the highest number of AIS-reporting ships, 805; the USA is second with 258 ships; Norway third, 120; Greenland fourth, 70; and Canada fifth, 65. It can be noted that 84MMSI's cannot be associated with a flag state. It is 55 flags states observed.
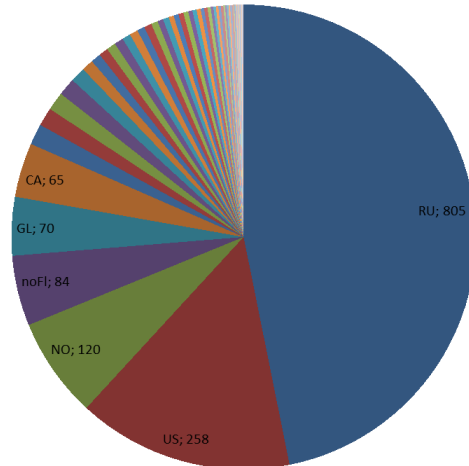
Figure 4 Number of ships per flag state in Sep 2015.

3. ANOMALY DETECTION AND DATA FUSION

Anomaly detection is performed by Smart Agents (Chapter 3.1), and by an in-house developed target tracking algorithm; the Multi Hypothesis Tracker(MHT) using data fusion for automatic identification of ships detected in radar satellite images (Chapter 3.2).Several Smart Agents implemented to facilitate the anomaly detection are shown in Figure 5.
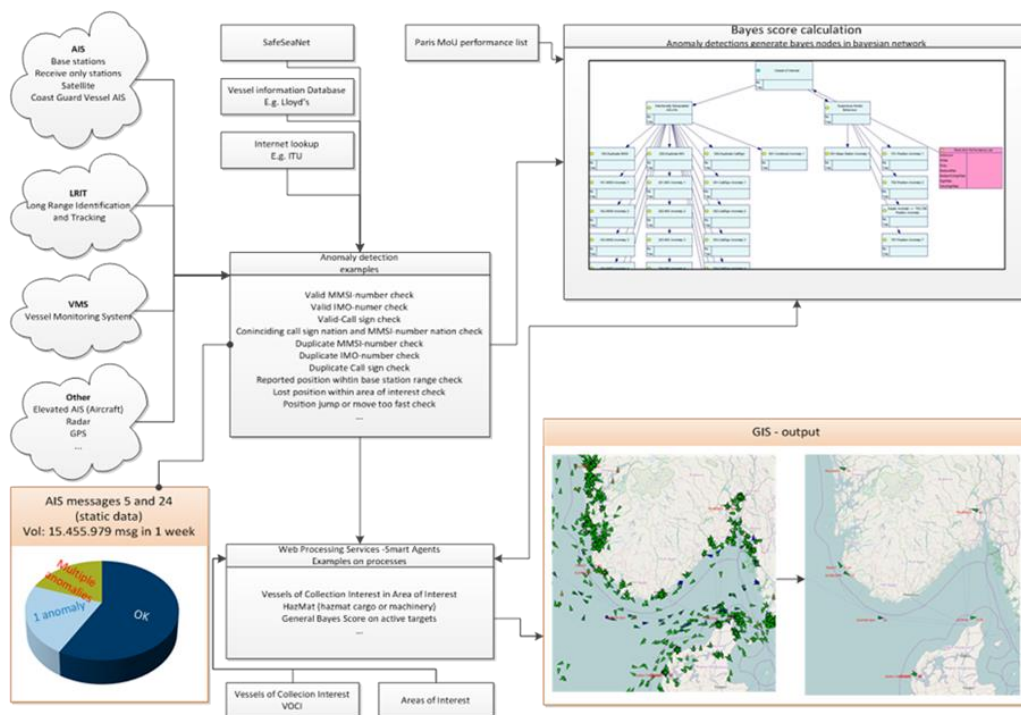
Figure 5 Smart Agents flow chart.

3.1. Vessel of interest in the maritime picture

Each Smart Agent is an algorithm containing anomaly detection logic - searching for classes of ships that should get special attention by the operators. This is done by e.g. checking data accuracy and data quality from several mandatory reporting systems and other information sources, such as the Safe Sea Net Norway, a vessel information lookup database and other trusted internet sources of information like International Telecommunication Union (ITU) Maritime mobile Access and Retrieval System (MARS) database.

The use of a service-oriented architecture (SOA) was a high priority and was achieved by implementing Web Processing Services (WPS)[8]. Through the use of a WPS-client the end-user is able to flexibly configure a network of several different Smart Agents (setting up a mathematical Bayesian network on the server-side) and start the data/computer intensive analysis on demand. Each node in the network is used to detect one type of anomaly (e.g. the validity of the reported data, mandatory reporting system turned off, and vessel is on a Grey/Black flag list). Historical data and the experience of the operator are used to set the probability threshold of anomaly detection for each node. The operators receive a more informative maritime picture where vessels of interest (VOI) are highlighted.
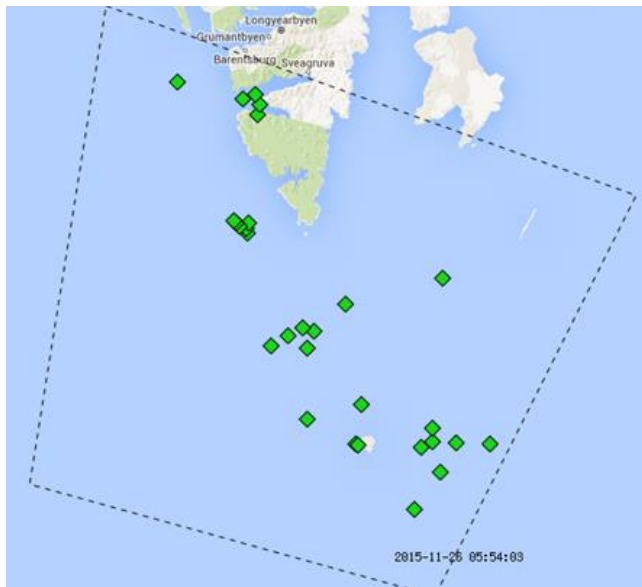
Figure 6 Ship detections from satellite-borne SAR**.**

---

[8] Open standard - OGC (Open Geospatial Consortium).
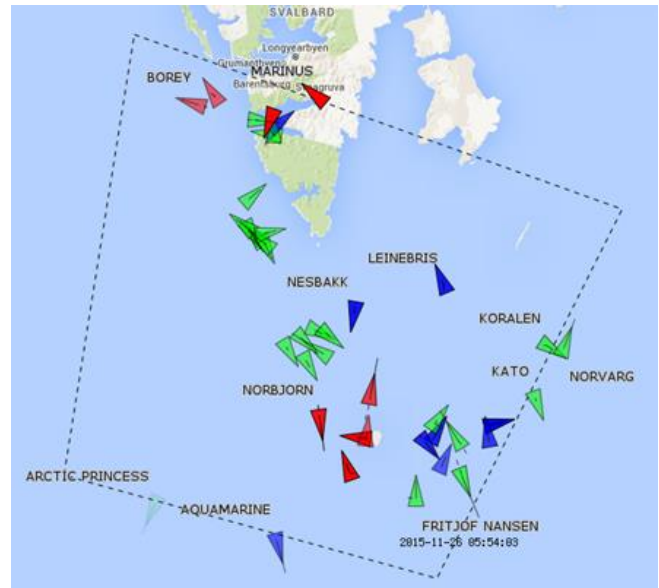
Figure 7 Data from mandatory vessel reports.

3.2. Automatic identification of ships in radar satellite images.

A computerized system for identifying ships detected in satellite imagery has been developed by FFI. Satellite-borne Synthetic Aperture Radar (SAR) delivers images with a resolution sufficient to detect ships at sea; Figure 6 shows the image boundary and the detections made in a SAR image taken 26 Nov 2015.

Figure 7 shows data from mandatory automatic vessel reports and anti-collision systems (AIS, Long Range Identification and Tracking (LRIT) and Vessel Monitoring System (VMS)). These data are associated to the SAR ship detections by the MHT.

The MHT algorithm uses results from a range of earlier ship detections and position information when associating ship detections to vessel. For each hypothesis the probability is calculated. The MHT tracks are shown in Figure 8, and the identified SAR ship detections are shown in Figure 9.

In coastal areas, all data sources may be available, but for Arctic waters (far from the coast), Norwegian polar orbit AIS satellites, VMS and satellite SAR images are the main data sources.

Vehicle IDs are received from AIS (as MMSI numbers), VMS (as call signs) and LRIT (as IMO numbers). SAR ship detections that are not identified may be false detections (i.e. clutter in the image) or VOIs. The ship identification system contributes to a more effective use of resources, since the attention and surveillance resources may now be used for the vessels that are not identified in the SAR image.
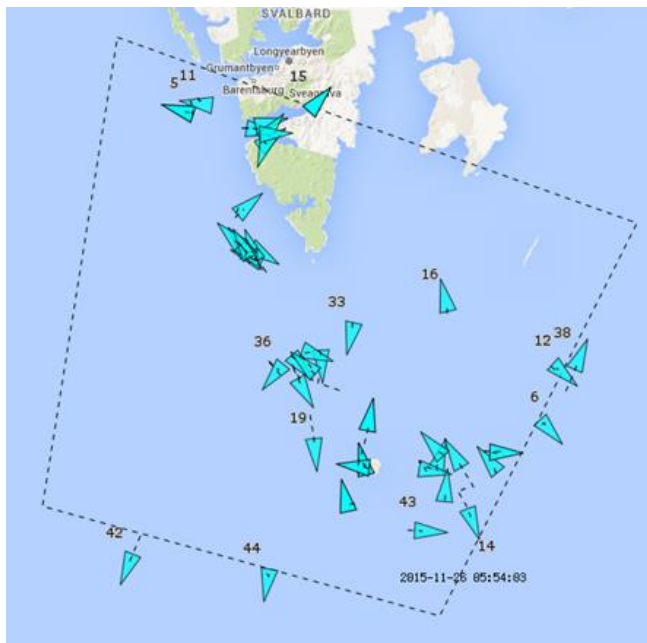
Figure 8 Association of ship detections to MHT tracks.

Figure 9 Identification of detected ships.

4. SUMMARY AND CONCLUSION

This paper has shown that up to 1700 ships were observed with SAT-AIS in the polar-waters polygon in the Polar Code [4]. Earlier work has shown that almost 2300 ships

were observed north of 67°N, a majority of them in Norwegian waters [3].

Detection of anomalous behaviour in a maritime context forms a natural part of the surveillance in the High North. Its main purpose is to distinguish abnormal activity from the normal background. It enables efficient use of surveillance assets, necessary for timely response to incidents threatening safety or security. FFI is presently working on further development and refinement of the MHT and Smart Agents to support operation of decision makers.

More sophisticated algorithms to support decision support will be explored further in future work. Machine learning, or pattern classification, provides a suitable theoretical framework and a wide range of general algorithms that may be applied to detect anomalies in the maritime domain. An on-going survey of methods of anomaly detection published in open literature will be an important input for evaluating current and future activities within this area. Adding new types of sensors as input to the MHT algorithm will result in a more complete maritime picture, thereby enhancing the situational awareness in the high north.

Ship density figures can serve as background information about the normal situation, basis for sailing plans, as well as the likelihood of observing a ship in given position for anomaly detection.

REFERENCES

[1] International Telecommunication Union, "Technical Characteristics for a Universal Shipborne Automatic Identification System using Time Division Multiple Access in the VHF Maritime Mobile Bad", ITU-R M.1371-4.

[2] Carlos Santamaria, Harm Greidanus, Mélanie Fournier, Torkild Eriksen, Michele Vespe, Marlene Alvarez, Virginia Fernandez Arguedas, Conor Delaney, Pietro Argentieri, "Sentinel-1 Contribution to Monitoring Maritime Activity in the Arctic". Proc. ESA Living Planet Symposium 2016, 9-13 May 2016, Prague, Czech Republic.

[3] Eriksen, T. and Olsen, Ø.. "Vessel tracking using Automatic Identification System data in the Arctic", In Proc. Joint WMU-IMO-Arctic Council International Conference on Safe and Sustainable Shipping in a Changing Arctic Environment (ShipArc 2015), 25-27 Aug 2015, Malmö, Sweden, under revision.

[4] IMO, International Code For Ships Operating in Polar Waters (Polar Code), MEPC 68/21/Add.1, Annex 10.

ANOMALY DETECTION AND KNOWLEDGE DISCOVERY USING VESSEL TRACKING DATA

A. Alessandrini, M. Alvarez, H. Greidanus, V. Gammieri, V. Fernandez Arguedas, F. Mazzarella, C. Santamaria, M. Stasolla, D. Tarchi and M. Vespe

European Commission, Joint Research Centre

ABSTRACT

The information available to understand what is happening at sea is nowadays enabling many monitoring applications. Nevertheless, the size of the areas to be controlled and the amount of tracking data collected by a multitude of sensors and systems in real-time make the effective detection of illegal activities a challenging goal since often left to human operators. This work will introduce recent JRC research activities relevant to automatic anomaly detection and knowledge discovery in the maritime domain. Data mining, data analytics and predictive analysis examples are introduced using real data. In addition, this paper presents approaches to detect reporting messages anomalies and unexpected behaviours at sea.

Index Terms— Maritime Surveillance, Knowledge Discovery, Anomaly Detection

1. INTRODUCTION

The overwhelming amount of information made available by the recent build-up of real time tracking systems can be used to extract knowledge and perform predictive analysis and automatic anomaly detection. The paper offers a list of research areas explored by the JRC Blue Hub team to improve Maritime Situational Awareness (MSA). Such activities range from Knowledge Discovery (mapping activities at sea including fishing and shipping, coverage analysis), predictive analysis (knowledge based Estimated Time of Arrival - ETA, long term route prediction), and data analytics. In addition, this paper presents approaches to detect reporting messages anomalies (AIS On/Off, spoofing and malfunctioning) and unexpected behaviours at sea (low-likelihood event detection).

2. KNOWLEDGE DISCOVERY

The term Knowledge Discovery in this paper refers to the "overall process of discovering useful knowledge from data" [1]. In the maritime domain, Knowledge Discovery can be applied to map activities at sea, predict future vessel

positions or to build the basis for model based anomaly detection.

2.1. Mapping Human Activities at Sea

The value of maritime Big Data has been recently demonstrated for better understanding maritime activities at sea. Historical vessel tracking data from systems such as Automatic Identification System (AIS)[9] or Long Range Identification and Tracking (LRIT)[10] can help in building context of maritime uses, especially in remote areas where the information is difficult to access or unavailable [2]-[5].

2.1.1. Mapping Maritime Routes
The knowledge of maritime routes is particularly needed in areas where the traffic is highly regulated. Specific methods to extract maritime patterns have been developed and refined (*e.g.*[2], [3]). The underpinning model is based on waypoints detections ("entry", "exit", "port" areas). Such waypoints are then collectively connected by vessel tracks that shape the "normal" patterns at sea by clustering common trajectories as shown in Figure 1.
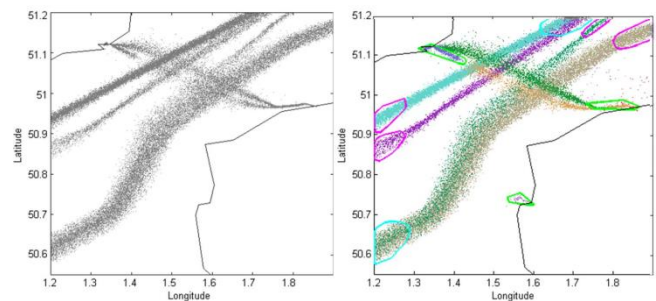
Figure 1 Dover Strait traffic: (left) two-weeks of AIS data and (right) the resulting maritime traffic routes connecting previously detected waypoints (green: ports, magenta: exit and cyan: entry areas).

---

[9]IMO (1998) Resolution MSC.74(69), Recommendation on Performance Standards for Universal Automatic Identification System (AIS), Annex 3; adopted on 12 May 1998.
[10]IMO MSC.210(81), Performance Standards and Functional Requirements for the Long Range Identification and Tracking of Ships. Resolution adopted on 19 May 2006.
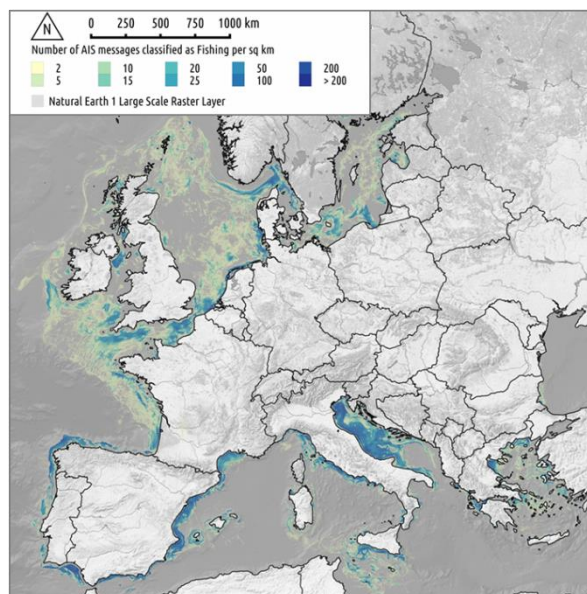
Figure 2 Fishing intensity by EU trawlers with length greater than 15 m using one-year AIS data archive.

2.1.2. Mapping Fishing Activities

By analysing the speed profile of trawlers, it is possible to distinguish fishing activities from movements from/to the fishing grounds (further information on the speed profile validated approach can be found in [6] and [7]). This led to a first map of trawlers fishing intensity was produced at EU scale [8]. Such map (Figure 2), highly correlated to the local bathymetry and biased by the AIS spatial coverage performance, provides contextual information that is useful not only to fisheries management and fisheries science, but also for MSA.

2.2. Knowledge Based Prediction

The knowledge of maritime routes can be used to improve the accuracy of predictive analysis as shown in Figure 3.
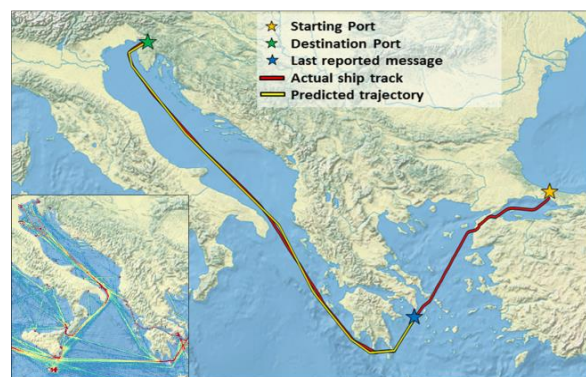
Figure 3 Prediction of a vessel track using only knowledge of previously observed tracks in the area (inset).

The performance of vessel position prediction offered by the knowledge of routes increases with the complexity of the routeing systems ([9], [10] and [11]). The accurate prediction of positions for periods longer than a few hours can be used to enhance situational awareness, to improve data fusion (see *e.g.* [9] and [10]) and to better estimate times of arrival in ports [11]. A progressive refinement of times of arrival in ports is essential in order to better plan port operations and efficiently allocate resources and facilities.

2.3. Event Based Knowledge Discovery

Event-based methodologies for Knowledge Discovery enable the analysis of maritime traffic data to detect maritime events and aggregate them in a georeferenced grid as in Figure 4. The method offers the possibility to quickly perform structured queries with respect to traditional approaches [13]. Such events include but are not limited to: "enter/exit a cell", "track birth/death", "motion start/stop", "proximity between ships", and "fishing/steaming".
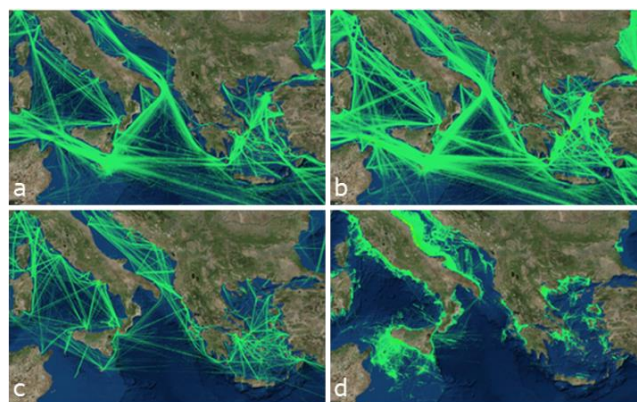
Figure 4 Density maps per type of vessel over part of the Mediterranean Sea using one-month AIS data: a) tanker, b) cargo, c) passenger vessels and d) fishing activities.

3. ANOMALY DETECTION

The knowledge that is extracted using statistical or model-based analysis can also be used to detect anomalous behaviours. Moreover, such knowledge can help in further interpreting suspicious movements by providing context information to data analytics.

3.1. Low-Likelihood Behaviour

The knowledge of maritime routes helps not only the understanding of maritime traffic. It also represents key information to detect unusual patterns or behaviours, as shown in Figure 5. Although not necessarily anomalies,

such low-likelihood activities represent a first filtered set of behaviours to be further investigated [12].
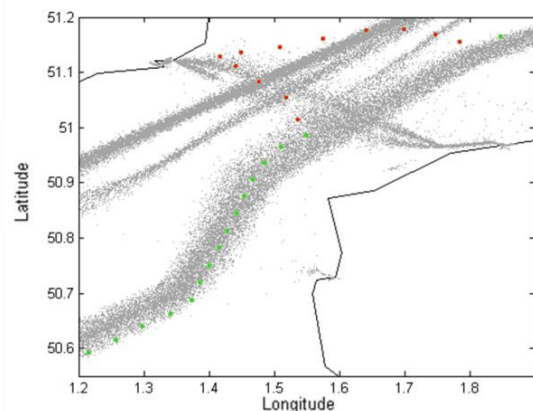
Figure 5 Local anomaly example extracted from the Dover Strait. The vessel deviates from the known route (red dots), approaching a port without stopping and finally returning to its declared route.

3.2. Data Analytics

Recent news[11] reported about an anomalous vessel track in the Mediterranean Sea. By analysing AIS data, LRIT archive data (Figure 6) and remote sensing images (Figure 7), through the Blue Hub it was demonstrated that the behaviour could have been a consequence of a route planning mistake.
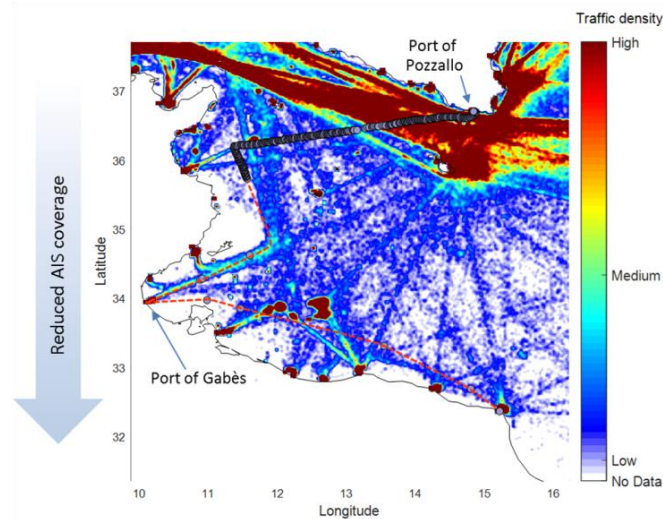
Figure 6 AIS data (grey circles) of the ship. The track (red dashed line) is estimated by interpolating the available data and using the density of shipping in the area (derived from historical LRIT data).
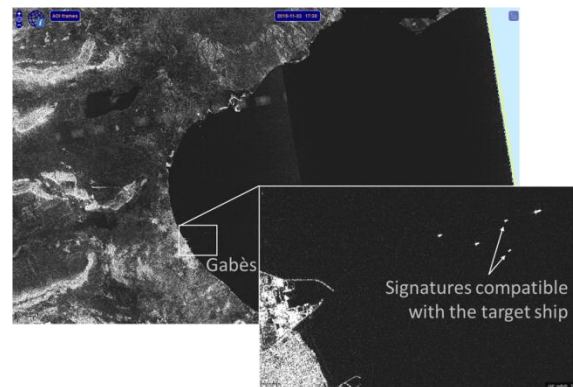
Figure 7 Sentinel-1 images showing signatures compatible with the size of the target of interest.

In particular, the vessel probably did not switch off its AIS: the North African area is characterised by low terrestrial AIS coverage and this is why there is a lack of information. AIS messages from the ship were in fact captured by satellites and a compatible signature is visible from remote sensing images. The vessel then sailed avoiding shallow waters (as the LRIT density of previous tracks shows) to cross the Sicily Channel, directed towards the Tyrrhenian Sea. Finally, the vessel slowed down and made a sharp turn towards the Port of Pozzallo. In that specific moment, by as seen in the voyage related data, the declared destination changed from "Pozzouoli" (in the Tyrrhenian Sea) to "Pozzallo", highlighting a possible mistake in the planned route. This example shows how, after an anomaly is detected, the data must more deeply analyised before a true threat can be confirmed.

3.3. Spoofing Detection

The AIS standard allows the recording of the timestamp of the received messages at the base station.
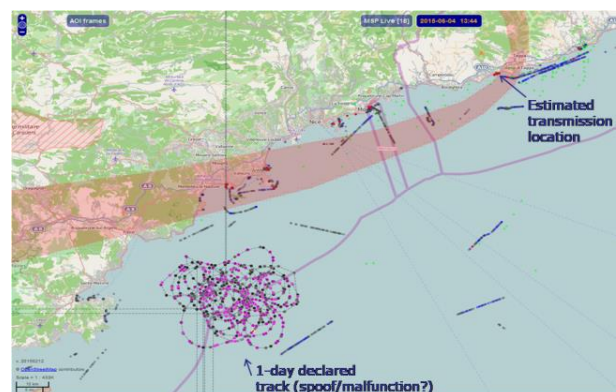

Figure 8 Spoofing case of a vessel located in port (top right) and broadcasting messages more than 100 km away from its actual position.

A network of base stations can provide Time Difference of Arrival information that enables multi-lateration of the AIS emissions. This can be used to successfully detect spoofing or malfunction of AIS that would result in security and safety issues (Figure 8). The methodology (demonstrated in [14]) has recently led to the implementation of a real-time AIS verification tool.

3.4. AIS On/Off Detection

AIS off-switching is recently becoming of interest to maritime operational authorities since such events could be linked to attempts to conceal illegal activities. Through the analysis of historical received signal strength it is possible to characterise the reception capabilities of AIS base stations and provide valuable knowledge to flag AIS drop-outs as intentional especially in areas where the signal strength is expected to be high [15].
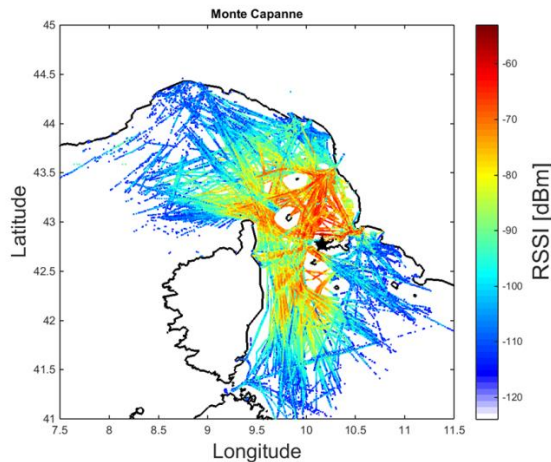
Figure 9 Map of Received Signal Strength Indicator (RSSI) from the Elba Island base station (star). The pattern is shaped by Line Of Sight propagation loss and the receiving antenna pattern. Shadow areas can also be seen in correspondence to islands.

4. CONCLUSIONS

This paper introduced a number of applications to improve the understanding of what is happening at sea beyond maritime surveillance. Knowledge Discovery, data analytics and situation prediction applied to historical vessel tracking data are promising tools to implement the next generation of anomaly detection services.

REFERENCES

[1]   Fayyad, Usama, Gregory Piatetsky-Shapiro, Padhraic Smyth, "From data mining to knowledge discovery in databases." AI magazine 17, no. 3 (1996): 37.

[2]   Pallotta, G., Vespe, M., Bryan, K.,"Vessel pattern knowledge discovery from AIS data: A framework for anomaly detection and route prediction". *Entropy*, 15(6), 2218-2245, 2013.

[3]   Fernandez Arguedas V., Pallotta G., Vespe M., "Automatic Generation of Geographical Networks for Maritime Traffic Surveillance", Proc. 17th Int. Conf. on Information Fusion, 2014.

[4]   Vespe M., Greidanus H., Alvarez M., "The declining impact of piracy on maritime transport in the Indian Ocean: Statistical analysis of 5-year vessel tracking data", *Marine Policy* 59: 9-15.

[5]   Vespe, M., Greidanus, H., Santamaria, C., Barbas, T., "Knowledge Discovery of Human Activities at Sea in the Arctic using Remote Sensing and Vessel Tracking Systems", In Proc. ShipArc 2015, in press.

[6]   Mazzarella, F., Vespe, M., Damalas, D., Osio, G., 'Discovering Vessel Activities at Sea using AIS Data: Mapping of Fishing Footprints', Proc. 17th Int. Conf. on Information Fusion, 2014.

[7]   Vespe, M., Gibin, M., Alessandrini, A., Natale, F., Mazzarella, F., Osio, G. C., "Mapping EU fishing activities using ship tracking data", *Journal of Maps*, DOI: 10.1080/17445647.2016.1195299, 2016.

[8]   Natale, F., Gibin, M., Alessandrini, A., Vespe, M., Paulrud, A., "Mapping fishing effort through AIS data", *PloS one,* 10(6), 2015.

[9]   Mazzarella, F., Vespe, M., Santamaria, C. (2015). SAR ship detection and self-reporting data fusion based on traffic knowledge. *IEEE Geoscience and Remote Sensing Letters*, 12(8), 1685-1689.

[10] Mazzarella, F., Fernandez Arguedas, V., Vespe, M., "Knowledge-based vessel position prediction using historical AIS data", IEEE Sensor Data Fusion: Trends, Solutions, Applications (SDF), 2015.

[11] Alessandrini, A., Mazzarella, F., Vespe, M., "Data-driven Estimated Time of Arrival using Historical Vessel Tracking Data" submitted for consideration to the International Conference on Data Mining (ICDM 2016).

[12] Fernandez Arguedas, V., Mazzarella, F., Vespe, M., "Spatio-temporal data mining for maritime situational awareness", OCEANS 2015.

[13] Alvarez, M., Fernandez, V., Gammieri, V., Mazzarella, F., Vespe, M., Aulicino, G., Vollero, A., "AIS Event-Based Knowledge Discovery for Maritime Situational Awareness", Proc. 19th Int. Conf. on Information Fusion, 2016.

[14] Papi, F., Tarchi, D., Vespe, M., Oliveri, F., Borghese, F., Aulicino, G., Vollero, A. (2014). Radiolocation and tracking of automatic identification system signals for maritime situational awareness. *IET Radar, Sonar & Navigation*, 9(5), 568-580.

[15] Mazzarella, F., Vespe, M., Tarchi, D., Aulicino, G., Vollero A.,"AIS Reception Characterisation for AIS on/off Anomaly Detection", Proc. 19th Int. Conf. on Information Fusion, 2016.

CONCLUSIONS AND RECOMMENDATIONS

Operational Authorities

Today's ship reporting data – for the most part AIS – are used on a routine basis by maritime operational authorities to find situations that need attention. A common view of anomalies was identified among the authorities including loitering, rendezvous, location, unusual speed or change of direction. The transformation of available maritime data into information and the reduction of false alarms are essential among the main needs of the authorities. This is particularly true in view of the wide extent of Exclusive-Economic-Zone and Search-And-Rescue areas to be monitored.

Operational authorities also stated the importance of further investigating suspicious events as they often are not linked to illegal activities. This can be done by considering all available data and by factoring expert knowledge in the process.

A regulatory gap on the meaning of "monitoring" in the maritime domain is currently faced by operational authorities. In particular, dealing with alerts originating from areas or behaviours that are not explicitly included in the mandate of an authority presents issues.

Operational authorities welcome the idea to further characterise sea areas in terms of type of use by mapping activities in order to provide context and *a-priori* information for situational awareness.

Additional emerging needs include the capacity to detect AIS spoofing or malfunctioning and AIS On-Off switching: both events might be indication of illegal activities and pose threats to security and safety. Also vessel profiling to improve risk index with respect to safety, security and Illegal Unreported or Unregulated fishing were listed among the most pressing needs for more effective operations at sea.

Private Sector

During the research and development (private sector) session, technical aspects related to knowledge discovery and anomaly detection were introduced. As an example, it is possible to recognise fishing vessels up to the level of fishing gear (*e.g.* trawling, purse seine or longline) based on their trajectory, provided that enough data points are available (see page 22 for additional information).

The role of AIS was acknowledged as "revolutionary", since it opens the doors to MSA applications that in the past would have been unimaginable. A similar role is seen for the future VHF Data Exchange System (VDES), which right now presents a window of opportunity to define new functionalities, such as e.g. enabling a ship to become a sort of in-situ suite of sensors (page 24 and page 40).

The value of historical data when analysing real time streams was recognised as a future direction that has already started to be explored spawning many Knowledge Discovery projects (page 28). Innovative uses of AIS data include the extraction of sea surface currents in real-time (page 31), remotely and accurately. This is an essential element for Search-And-Rescue operations.

Finally, this session offered the opportunity to demonstrate how research can generate commercial and operational systems as well as innovative ideas to counter spoofing attempts (page 36).

Research Centres and Academia

The session was opened by stating the need for a literature review in the field of anomaly detection and Knowledge Discovery. This is a relatively young subject where there has been a rapid increase of publications and it is the right time to start a survey on what is available, also to identify the most promising areas.

The presentations highlighted new data streams and platforms (*e.g.* page 40), methods and also different ways to look at the subject such as the definition of sensing requirements based on the specific behaviours at sea to be detected (page 52).

Ways to model complex events such as encounters at sea were presented, together with approaches to filter them using visual interaction with the data (pages 44 and 83). In addition, similar techniques can be applied to many different domains including aviation, or to the tracking of people on a football pitch.

Data-driven approaches were discussed to detect and characterise port areas taking into account the new trend of limiting human intervention in appropriately setting the parameters of the implemented solution (page 48).

During the session the process of designing use cases to ensure the security and control of fishing activities was introduced (page 57). In addition, the estimation of destination, time of arrival and the detection of inconsistencies are promising research areas (pages 62 and 91).

Remote Sensing and radar also play a key role in anomaly detection since delivering independent information that complements self-reporting systems (pages 66 and 87). The fusion of such data is also fundamental to obtain a more reliable maritime picture (page 78) and therefore more effective anomaly detection.

It is now recognised that the errors in the AIS information cannot be ignored. There is an increase also of intentional AIS manipulation, both kinematics and voyage related data. This can be tackled by message analysis (page 74) or by means of radiolocation techniques (page 91). The need to better quantify AIS performance and reliability was underscored (page 52).

A preliminary work also demonstrated how vessel reporting data can be processed to point to suspicious behaviours of migrants smuggling vessels and what type of features can be used to identify potential "ghost ships" in the Mediterranean Sea (page 69).

Finally, recent results over the Arctic region show how contextual information on human activities at sea can be quantitatively extracted also in remote and seasonally variable regions using vessel tracking data (page 87).

Concluding Remarks

Operational authorities stressed the need to involve the users as early as possible in the design, implementation and quality assessment of anomaly detection and knowledge discovery tools. This is driven not only by the need to align the development objectives to tackle real issues, but also by a strong technology push. Indeed, often users have not enough insight of what becomes feasible in such a fast evolving research and innovation field: a continuous dialogue between authorities, industry and research would be extremely beneficial to the three communities.

How to obtain EU publications

Our publications are available from EU Bookshop (http://bookshop.europa.eu),
where you can place an order with the sales agent of your choice.

The Publications Office has a worldwide network of sales agents.
You can obtain their contact details by sending a fax to (352) 29 29-42758.

JRC Mission

As the science and knowledge service of the European Commission, the Joint Research Centre's mission is to support EU policies with independent evidence throughout the whole policy cycle.

EU Science Hub
ec.europa.eu/jrc

@EU_ScienceHub

EU Science Hub - Joint Research Centre

Joint Research Centre

EU Science Hub

Publications Office