Aggregated risk assessment from multi-source data fusion

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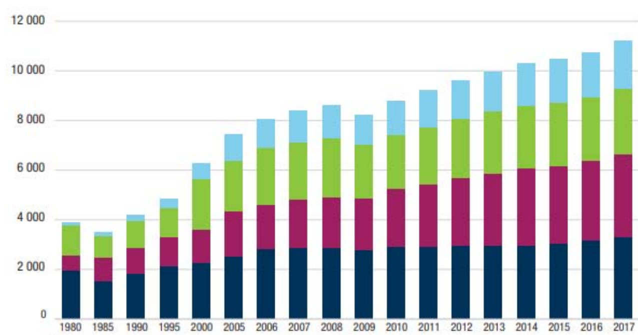
ABSTRACT

The increasing maritime trade and the considerable availability of huge amounts of maritime data, gathered by multiple sensors and sources, provides new approaches to allow efficient monitoring of the maritime traffic for different application domains such as security and intelligence, environmental protection, marine resource management, market analysis and emergency response. Gathering and analyzing these large volumes of maritime data is challenging because of frequent changes in regulations, security conditions, ship features, crew, operators and registration. In this paper, a new approach is proposed for the early identification of maritime threats and assessing the risk of each vessel, by analyzing and fusing dynamic data (e.g. anomalous behavior, visited ports and geographical areas), collected from multi-sensor satellite images and AIS messages, with static information (e.g. the vessel type, the presence of the vessel's IMO/Company Name/Manager Name in black- or sanction lists). The process is assigning customizable weights on each identified risk type in order to adapt the results to the application in hand. The evaluation of the aggregated risk assessment allows for an optimization of allocated resources by allowing attention to be focused on the vessels reporting a high risk profile.

Keywords: Data fusion, risk assessment, remote sensing, AIS, vessel detection, anomaly detection

1. INTRODUCTION

According to the latest UNCTAD and Eurostat reports, the global seaborne trade is expanding quickly and progressively, currently confirming the fastest growth in the last five years and the total volumes reaching 10.7 billion tons (Figure 1). The vast majority of global trade travels through the open ocean, which is a relatively lawless zone with very limited possibility (in terms of costs and efficiency) to be systematically monitored with traditional assets. Over 184,000 ships exceeding 100 gross tons navigate the seas between more than 10,000 ports worldwide, carrying more than 1 million seafarers and 20 million shipping containers - not counting vessels for fishing, research, recreation, military and other purposes.



	1980	1985	1990	1995	2000	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Containers	102	152	234	371	598	1 001	1 092	1 215	1 272	1 134	1 291	1 411	1 458	1 532	1 622	1 660	1 734	1 834
Other dry cargo	1 123	819	1 031	1 125	1 928	1 975	2 197	2 232	2 269	2 060	2 087	2 188	2 304	2 392	2 408	2 471	2 459	2 526
Main bulks	608	900	988	1 105	1 295	1 711	1 713	1 840	1 946	2 022	2 259	2 392	2 594	2 761	2 988	2 961	3 041	3 196
Oil and gas	1 871	1 459	1 755	2 050	2 163	2 422	2 698	2 747	2 742	2 642	2 772	2 794	2 841	2 829	2 825	2 932	3 055	3 146

Figure 1. International seaborne trade volumes per cargo type, reported in millions of tons, over the last years.

At the same time, new sensors and information sources have been introduced for improving the Maritime Picture and the Maritime Situational Awareness (MSA) activities. In the space domain, the introduction of new constellations of satellites, with different size and performances, allows systematic monitoring of any area of interest around the world, thus allowing for the detection and monitoring of vessels and their behavior, in all sea and weather conditions, during the day and night:

- There are new constellations of satellites that are able to gather AIS messages and quickly forward the information to the ground stations using satellite-to-satellite communication, thereby reducing the latency in the messages delivery to less than 1 minute.

- In the context of Earth Observation (EO), new or extended satellite constellations provide both free and open data (e.g. the Sentinel satellites managed and operated in the context of the European space program Copernicus) and commercial on-demand data (e.g. COSMO-SkyMed and COSMO-SkyMed Second Generation, SAOCOM, ICEYE, BlackSky, Planet). These new space assets, equipped with SAR and/or optical sensors, together with the new processing technologies, are ready to: (i) be federated for granting systematic monitoring of global areas, (ii) better contextualize the detected anomalous events (e.g. the triggering of fast tasking of VHR optical acquisitions as a result of the anomaly detection process from systematic SAR monitoring), (iii) reduce the reaction time and analysts'/operator's allocated effort.

The vessel identification information coming from "cooperative systems" (such as AIS, VMS or LRIT) is also used for the identification and tracking of vessels detected in the satellite images and to highlight the presence of potentially dark vessels.

The MSA activities can be aimed at many different applications such as security and intelligence, environmental protection, marine resource management, market analysis and emergency response. Government agencies track vessels, their movements and related entities, searching for anomalous behavior, whether for strictly trade-related reasons or for law and regulatory enforcement, anti-smuggling or defense initiatives.

One approach for identifying which vessels to track, is to make a risk assessment and assign a risk value to each vessel around the world. In the maritime environment there are a number of different risk factors that can be considered and used to compute an aggregated risk value. It is possible to customize the aggregation of the different factors depending on the aim of the analysis (e.g. giving more relevance to the security or to the environmental aspects). If the aggregated risk value supersedes a certain threshold, the vessel is of interest for further ad-hoc analysis and/or monitoring.

The risk factors can be divided into two groups: **dynamic** and **static** risk factors. Possible dynamic risk factors to be assessed and evaluated with different weights can be related to:

- anomalous behavior, e.g. engagement in meeting at sea, switching off the AIS transponder or loitering,
- current and historical routes,
- list of visited ports,
- crossed national waters, Exclusive Economic Zones (EEZ) or critical geographical areas.

Using the vessels' IMO code, there are various static risk factors that can be calculated, based on for example:

- vessel and/or owner is present on a black list (e.g. Paris MoU, IUU vessel list or UN Security Council Blacklists),
- vessel has been involved in previous detentions.

2. RISK ASSESSMENT APPROACH

The increased availability of data from heterogeneous sources (satellite and in situ) and the related big data technologies are creating information superiority for various maritime applications. In particular the availability of new satellite constellations enables new approaches for enriching the maritime picture; the efficient federation of the different space assets permits to extend the continuous monitoring above all over remote areas of interest where it is difficult (or too expensive) to maintain a persistent monitoring by traditional assets only.

In the presented work, the European space program Copernicus is used to enable sustainable continuous monitoring of global sea thanks to the free and open satellite images acquired by multiple sensors (*Sentinel-1* and *Sentinel-2*), while exactEarth's new Real-Time Satellite AIS Constellation, *exactView™ RT*, is used to acquire and access the global AIS messages (Figure 2). In case there is a need for ad-hoc and on-demand acquisitions over the monitored areas (e.g. in case of detected anomalies), the commercial EO satellites (e.g. COSMO-SkyMed) can be tasked for providing better knowledge of the detected event, with the possibility to acquire VHR images with pixel resolution < 1m.

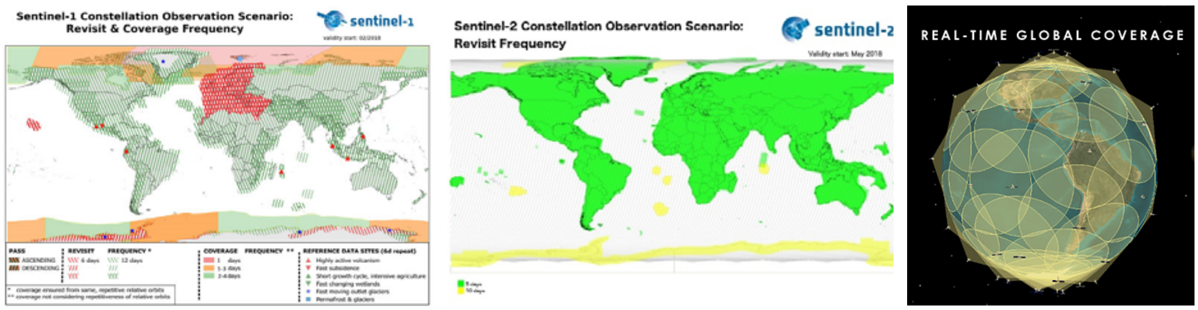


Figure 2. Examples of current coverage of Earth Observation satellites (Sentinel-1 on the left, Sentinel-2 in the middle - source ESA) and Satellite AIS (on the right, source exactEarth)

The continuous monitoring of the seas by collecting images, acquired by space-borne SAR and optical sensors, and by real-time global AIS, is one of the most complete approaches for the systematic monitoring of the sea allowing the automatic detection of the vessels and the main maritime features (e.g. vessels, offshore platforms, wind farms) and the extraction of maritime patterns of life (see Figure *3*. Example of systematic monitoring over the Mediterranean sea by fusing Sentinel-1 and AIS data for detecting vessels and extracting maritime patterns of life.Figure 3).

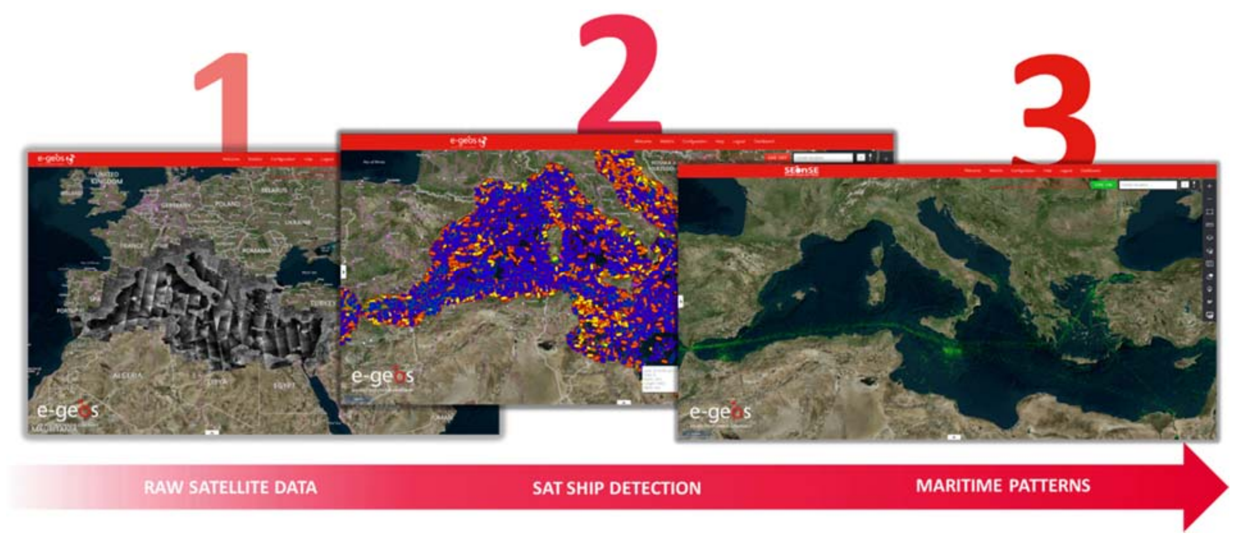


Figure 3. Example of systematic monitoring over the Mediterranean sea by fusing Sentinel-1 and AIS data for detecting vessels and extracting maritime patterns of life.

The collected datasets are subject to an anomaly detection process (see Figure 4) and, in case of positive matching of the defined anomalous behaviour rules and thresholds, the automatic workflow supports the decision making process by:

- automatically generating a satellite acquisition plan over the areas of the detected anomaly taking into account the closest (in time and space) satellite passage, required image resolution (e.g. considering the dimensions of involved vessels) and weather conditions (for optical satellites);
- forwarding an automatic notification to the team of experts/operators for focusing their attention on the detected event;
- triggering a mission planning activity for requiring the tracking of the detected event by the Authorities' assets (e.g. boats, airplanes, UAV).

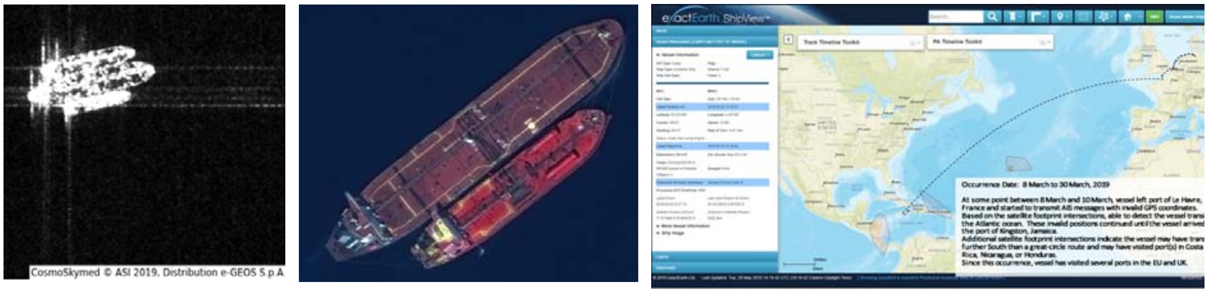


Figure 4. Examples of anomaly detection: meetings at sea as detected by SAR satellite (on the left) and optical satellite (in the middle), AIS position spoofing as detected by satellites (on the right).

The data fusion between satellite detected vessels and AIS messages allows to classify all the vessels of interest as **cooperative** (detected by satellite imagery and identified by the correlation with AIS, offering the possibility to analyse also historical tracks and gaps of AIS transmissions) or **dark** (detected only by satellite imagery).

The correlation between vessels detected by EO data analysis and AIS data is based on a global optimal algorithm that minimizes the error in the linking between AIS signals and detected vessels, taking into account all the AIS data and detected vessels in the satellite scene and in the relevant temporal range (across the acquisition time).

The data fusion algorithm consists of the following steps:

1. Retrieve AIS ship positions and velocities in a specified area and at times of the satellite image acquisition.
2. Transform AIS ship positions and velocities in image coordinates in order to compare them with positions and velocities derived from satellite images.
3. Interpolate AIS positions and velocities at the time of the satellite image acquisition by using cubic spline interpolation.
4. Global matching of positions, velocities and dimensions between AIS and satellite-based vessel detections. The matching is based on the Maximum Matching Bipartite Algorithm (based on network flow optimization).
5. Assign an assessment on the matching error e_h to each match h ($h=1, \ldots, N$) with the formula:

$$\epsilon_h = \frac{w_{\delta p}\delta p + w_{\delta v}\delta v + w_{\delta s}\delta s}{w_{\delta p} + w_{\delta v} + w_{\delta s}}$$

   where δp, δv and δs are the percentage differences (percentage relative errors; e.g. $\delta p = \frac{|\bar{p}_{AIS} - \bar{p}_{EO}|}{|\bar{p}_{EO}|}$) respectively for the positions, velocities and sizes between AIS and EO derived vessel parameters; $w_{\delta p}$, $w_{\delta v}$ and $w_{\delta s}$ are weights used respectively for δp, δv and δs.

6. Assign an empirical reliability index r_h to each match h (h=1, …, N) ranging from 0 (low confidence) to 1 (high confidence):

$$r_h = e^{-k\epsilon}$$

where k is opportunely calibrated in order to have a reasonable dynamic of the confidence behavior.

The correlation algorithm has been extensively tested on different cases and its behaviour is completely in agreement with the aim of the objective function of the global optimal algorithm.

The **dynamic** component of the risk is based on an assessment of the provided information in terms of:

- analysis of suspicious behaviour of each vessel, based on the set of defined rules, such as rendezvous at sea (Figure 4), changing of identity during the voyage (e.g. name, IMO) or gaps of AIS transmission,
- comparing the provided information in the AIS message (e.g. position, dimension) w.r.t parameters estimated from satellite images,
- identifying position spoofing, comparing the transmitted position w.r.t. the receiving satellite's position, Figure 4,
- analysis of the historical route of each vessel, e.g. presence in ports or national waters of countries with a high risk factor (using e.g. JWC Oceanic Zones, JWC Territorial Zones and Sanctioned Countries as sources).

Threats at sea are pervasive, from geopolitical crises and global money laundering to cargo theft, piracy and crew kidnappings. These risks pose a huge challenge to marine insurers, finance institutions, banks, governments and any business with global supply chains. A complete profiling of the ship security risks can be obtained only extending the dynamic risk assessment with the integration of maritime and risk event databases to provide a single maritime risk mitigation solution. Typical information sources for assessing this **static** risk component are:

(i) past casualties, piracy and pollution events,
(ii) vessels/companies in blacklists (e.g. Office of Foreign Assets Control - OFAC, sanctioned countries layer, Paris MoU),
(iii) number (and frequency) of changes of the ship name, flag or owner. In the proposed work, the global vessel database from the IHS Markit *Maritime Intelligence Risk Suite* is used for assessing the static component of the risk, Figure 5 gives some examples of what information can be extracted and fused in the final estimation of the risk.

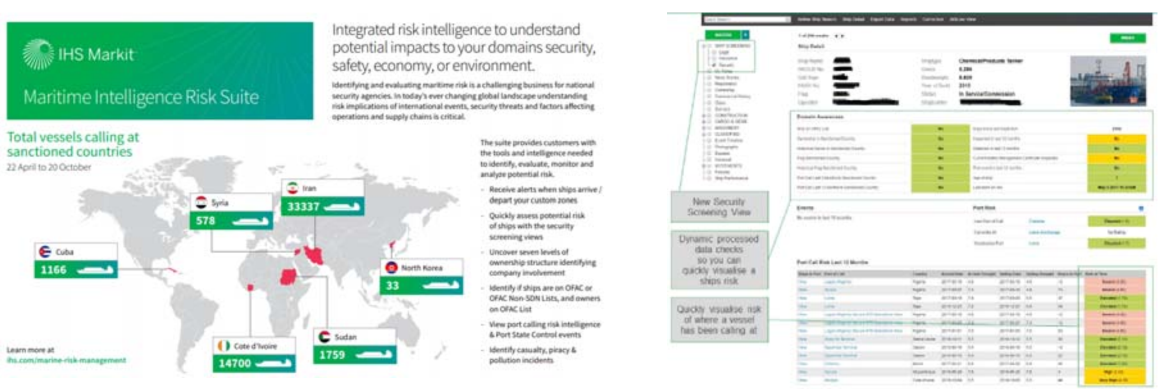


Figure 5. Information for assessing this static risk component

The dynamic and static risk factors are then combined, using a specialized weight assigned to each risk component, customized according to the application at hand:

$$r = \frac{\sum_{i=1}^{n} w_i \Gamma_i}{\sum_{i=1}^{n} w_i}$$

where r is the combined risk factor for a vessel, w_i is the weight assigned to a certain risk i and Γ_i is the binary value if that risk is present or not for the vessel at hand.

The fusion of the dynamic and static risk components, managing the weight of each single parameter for specializing the analysis to a specific domain (e.g. security and intelligence, marine resource management, environmental protection), makes it possible to quickly adapt the algorithm to the different users' interest and use cases (e.g. oil smuggling, illegal fishing or pollution). The methodology of combining the dynamic and static risk factors is promising and the results are under validation process. Figure 6 contains an example of the calculation of each vessel's risk and illustrates how the analysis of maritime traffic and the identification of potential maritime threats is improved by reducing the number of vessels to track and focusing the attention on those reporting a medium and high risk profile.

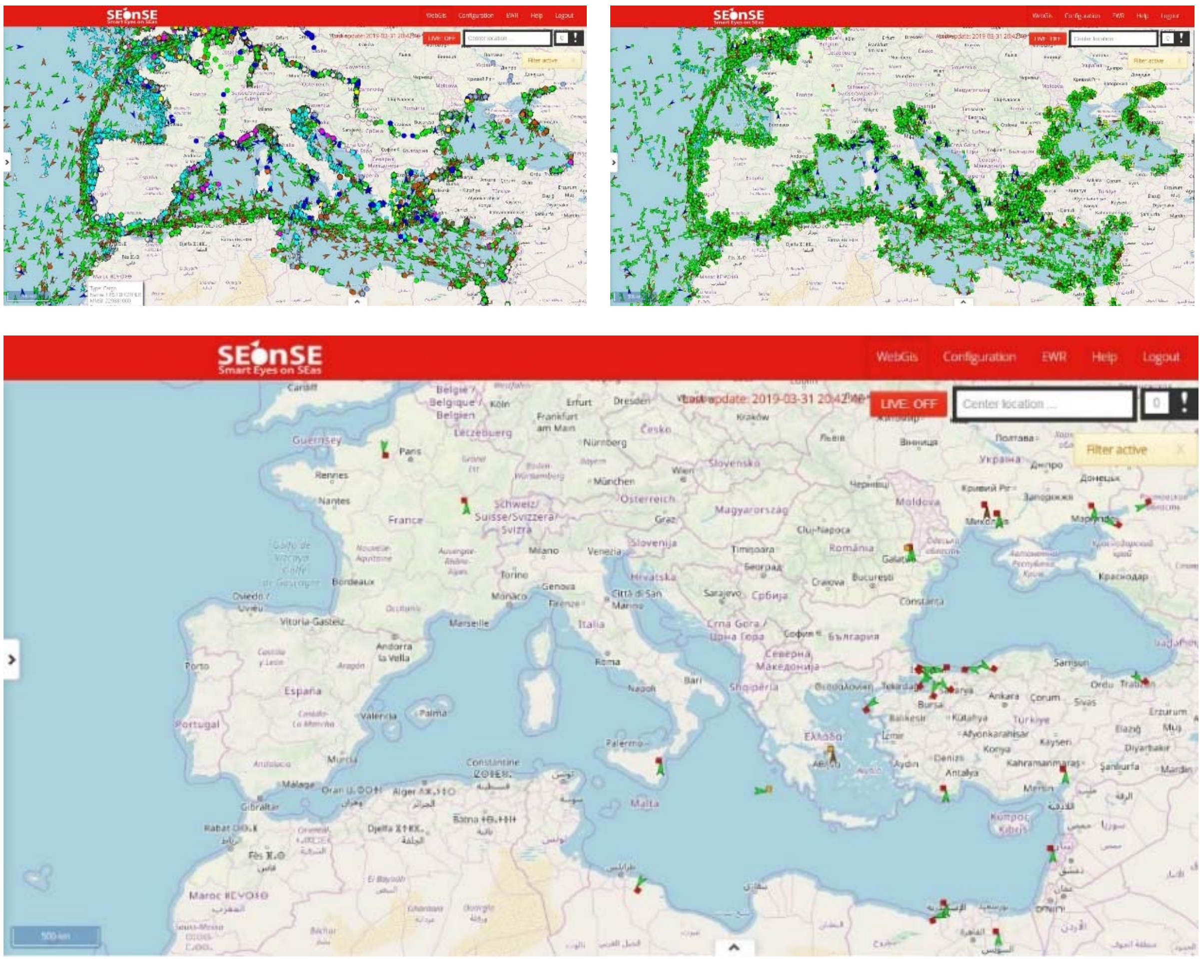


Figure 6. Example of maritime traffic monitoring by analyzing the latest position by AIS in one day (on the top-left), the corresponding risk assessment (on the top-right) and focus only on vessels reporting medium-high risk profile (bottom).

3. CONCLUSIONS

The proposed risk assessment methodology is based on the fusion of information coming from multiple and heterogeneous sources (including multi-sensor space assets), and consider the characterization of both static and dynamic factors of the risk, allowing the definition of various risk profiles by the customization and application of different weights for each risk factor according to the user needs. The evaluation of the aggregated risk assessment allows for an optimization of resources allocated on MSA activities by reducing the number of vessels of interest, focusing the attention of the analysts and operators no longer on the entire maritime traffic but only on the vessels reporting a high risk value. The described approach has been finalized and integrated in SEonSE [9] to be validated in the context of OCEAN2020 [18].

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