Systems & Advanced Technologies Engineering S.r.l.

EO AND GNSS DATA TO IMPROVE NAVIGATION SAFETY ASSESSMENT

(Idea ETD-ML-2019-032)

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DELIVERY 6.2

EXECUTIVE SUMMARY

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REVISION SHEET

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Rev.	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
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Changes other than typing/grammar proofing, brought with Rev. x, are marked by the following annotation on the right margin and shaded in yellow.

Rev. X

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1 SCOPE

This document is the report on the Executive Summary (Delivery 6.2), summarising the activities performed under the contract (Ref. 2.1.4).

The report has been structured as follows:

- Chapter 2 reports general information about reference documents, bibliography and acronyms
- Chapter 3 summarises the entire work carried out.

2 REFERENCES

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2.2 Acronyms, abbreviations and definitions

2.2.1 Acronyms and abbreviations

Symbol	**Description**
AIS	Automatic identification system
EO	Earth Observation

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3 EXECUTIVE SUMMARY

3.1 Introduction

With the increased frequency of shipping activities, such as tourism and freight's transport, navigation safety has become a major concern, especially when human casualties, environmental issues and economic losses are considered. Even if new technologies have already supplied aids to pilots for the navigation risk reduction, the International Maritime Organization (IMO) reports that the majority of accidents could have been avoided by providing suitable input to the navigation decision-making process [Ref.2.4.1]. The number of consequences due to accidents in open sea or close to the harbour is relevant, including loss of multiple human lives, pollution which leads to death of marine lives and cargo or infrastructures damage.

In an autonomous shipping scenario, vessels will navigate following prescribed routes, adaptively changed based on risks and environmental conditions. GNSS and its augmentation systems will represent the key enabling technology to attain safety of navigation, especially considering systems providing accuracy and integrity information. However, they may not be sufficient to assure safety of navigation, when ships are not using good quality GNSS receivers or switch off positioning systems. Also "non-collaborative" objects (ships/objects in the sea not transmitting AIS), such as natural and artificial debris, may represent possible hazards.

Therefore, EO data can represent complementary or redundant information to improve traffic monitoring. Indeed, EO data can be used to detect sailing vessels with no AIS receiver and to compare the AIS position versus the position detected in optical and SAR images. The combined use of such EO data will increase the available information and could provide support to vessels detection (shape, dimension, and route).

The current project relies on EO and GNSS information fusion that is not novel by itself, as from the inspection of SoA emerged that a number of other (ongoing) projects and services exploit different sources to address improvements in marine safety. However, the NARAS project has three important additional goals that are unique in comparison with the SoA on maritime applications:

- The utilization of the information of the features identified to **improve navigation risk assessment models and to enable near real-time applications, including the modification of the planned or preferred routes** (described by space-time waypoints and tolerances) set for either the shore assisted navigation or, in the future, for the autonomous ship navigation. This will exploit the previous technology developed by SATE and MARIN under a preceding ESA contract (Ref.2.1.5).
- **The suitability of the approach defined to the combination of AIS/VTS data and SAR images with optical images** to improve, when the latter are available, the detection of unreported features in the AIS system and the statistical **evaluation of the accuracy** of current positions data available through the AIS system or **their alignment with EO extracted positions**;
- The assessment of the benefits using MARIN **risk model to quantify the collision risk** with and without EO information.

With this novelty NARAS could enhance services already carried on by the coast guard which monitor possible hazards (i.e., objects/vessels in the sea not transmitting AIS) but in a considerable cost saving, wider coverage and automated way.

3.2 Areas of interest

The areas of interest for the project have been selected based on criteria described in Ref. 2.1.6, that translated into the following selection:

1. The first area of interest is the area **North of the Wadden Islands in the North Sea**, due to the consistent traffic which has led to accidents such as the case of MSC Zoe and OOCL Rauma, occurred respectively in January 2019 and in February 2020, in which ships lost containers in the sea.

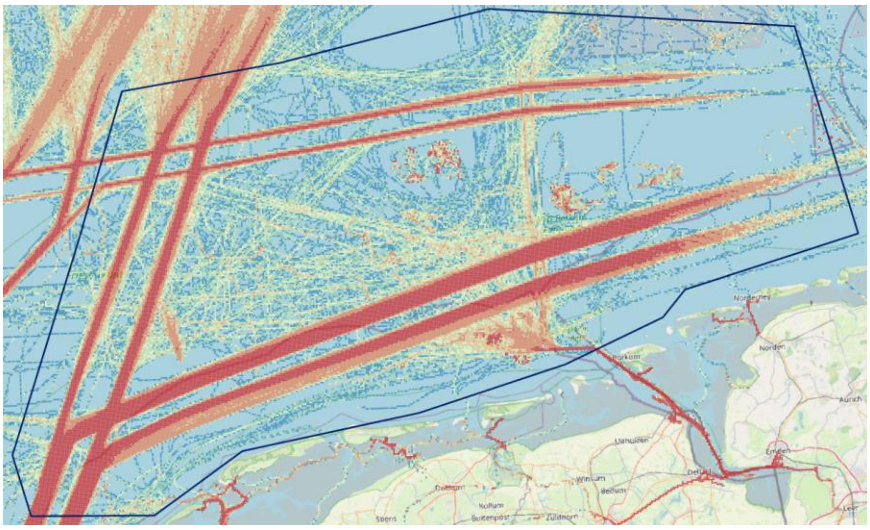

Figure 1 - Area of interest north of the Wadden Islands in the North Sea

2. The second selected area is the **North of the Dutch Westcoast** (also referred to as the **Rotterdam area** in the rest of the document). The factors that make this area of importance are:
    i. The traffic density in the sea (especially in the summer period)
    ii. The number of objects that could be found in the sea, such as:
        - Offshore infrastructures: at least one platform just north of Rotterdam (next to Scheveningen) and a wind turbine or OHVS (offshore high voltage station) in a windfarm.
        - Ships in an anchorage area, with a low update rate of the AIS position.
        - Small vessels along the coast (e.g. recreational vessels).
        - Drifting vessel.
    iii. The accessibility to GNSS and EO data.
3. The third area selected is the **North Adriatic Sea** (also referred to as the **Venice area** in the rest of the document) because of its relevance in terms of traffic density and for the accessibility to GNSS and EO data, considering the already available GNSS dataset collected from the previous SATE-ESA project (Ref.2.1.5). Also, in that area the presence of the MOSE infrastructure to be closed in case of high tides to protect the Venice lagoon, and the CNR (Consiglio Nazionale delle Ricerche) offshore meteo-oceanographic platform represent elements that influence navigation in that area. In addition, this area is well covered by EO data, which can be freely provided by e-Geos for research purposes. Moreover, the physical and morphological structure of the Venice lagoon makes it of particular interest.

3.3 EO data selection

Among the available EO data sources, particular attention is made to the achievable revisit time, spatial resolution and data acquisition modes that represent critical aspects for the development of maritime safety improvement services.

As regard future data sources, besides already planned developments such as for ICEYE, Capella X-SAR, Landsat-8 and WorldView series, several new constellations consisting of radar microsatellites are paving the way for unexplored monitoring applications thanks to their improved capabilities in terms of both resolutions and revisit time.

Among the number of available data sources only a tight number of them have been selected for the project according to the criteria defined as follows (Table 1):

CO1: accessibility and availability of satellite data	
CO2: resolution	**CO2a**: for SAR at least 6 m
	CO2b: for optical less than 6 m
CO3: AOI revisit time (time elapsed between two subsequent acquisitions in the same Area of Interest) ≤ 6 days	
CO4: footprint	**CO4a**: for SAR in the range of [100;150] x [100;150] km
	CO4b: for optical in the range of [30;50] x [30;50] km

Table 1 - Criteria for the selection of the data sources for the current project

The following SAR missions have been selected for the development of the activities of NARAS project:

1. Cosmo-SkyMed
2. ICEYE
3. TerraSAR-X

NARAS EO products were collected from commercial providers in the frame of the ESA Earth Online Programme. Additionally, data from Cosmo-SkyMed mission over the Italian territory have been provided by the Italian Space Agency in the frame of the MAP ITALY project.

The most commonly used techniques for object detection in maritime areas leverage the fact that in EO images, objects appear generally brighter than their surroundings. **Adaptive threshold algorithms** are the most suitable techniques for target detection in radar imagery. The **object detection tool developed for the NARAS project** implements the **algorithm workflow** described hereafter by the following six main steps:

1. *Data Ingestion and Pre-processing*. Before starting the ship detection processing, the SAR image is pre-processed masking land parts and black borders, to analyse only significant pixels.
2. *Adaptive thresholding*. The thresholding algorithm compares the intensity of each pixel to the average value of the surrounding area to determine if they belong to a ship.
3. *Clustering*. Considering the spatial resolution of the selected EO dataset and the common ship size, the clustering step connects neighbouring pixels belonging to the same ship.
4. *Property Calculation*. Once the objects are detected, the location, size, and orientation are calculated for each of them.
5. *Confidence Level Evaluation*. For each detection, a confidence level ranging in [0,1] is estimated.
6. *Output Formatting*. At the end of this procedure, the results obtained from the algorithm are provided as a user-readable HTML report, and a KML-formatted file.

3.4 Collection and processing of GNSS (AIS) data for the extraction of routes databases

From the available AIS data, the trajectories of the vessels are clustered in different routes on the basis of their intersection with pre-determined lines and areas of anchorage, as shown in Figure 2.

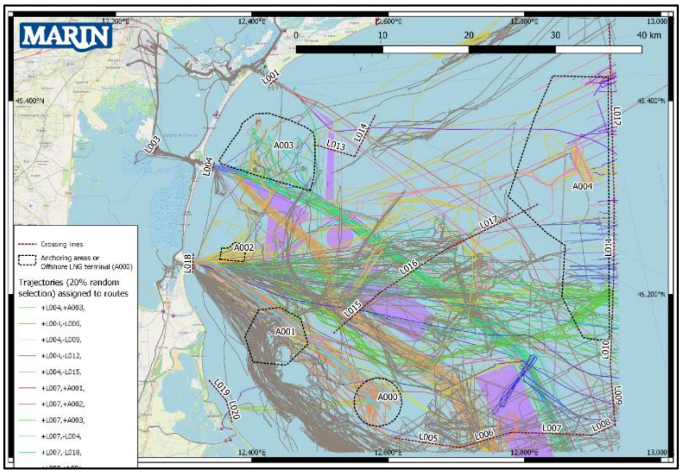

Figure 2 - Journey trajectories of merchant vessels that are assigned to routes (coloured) or not (grey)

For each cluster, a *representative trajectory* is identified, described by a set of waypoints, characterised by tolerance bounds in both time and space, which are determined by the historical AIS data. In addition, the cluster composition is analysed in order to define the applicability of the representative trajectory (for example, which environmental conditions characterise the cluster, which ship types and lengths, which traffic flow direction). From the set of *representative trajectories*, a set of *preferred route* will be extracted according to the following criteria:

A. Compliance with the maritime navigation rules;

B. Reliability of the clustering result (evaluating each cluster).

The results are provided in terms of reference trajectory and its waypoints as shown in Figure 3 where the main reference trajectory is represented by the continuous black line. The coloured tracks are a subset of the trajectories belonging to that cluster, which are plotted to visualise the cluster variability and the waypoint clouds. The waypoints are indicated by markers on the reference trajectory indicating the time at which the ship should reach that waypoint (in the format HH:MM:SS). The waypoint tolerance in the space domain is represented by the black dashed line around each waypoint. The colour of each point of the tracks is associated to the time values, so purple corresponds to early times and yellow to later times. This allows to have an overview of the time variability into each waypoint as well to easily understand whether a trajectory is entering or exiting the port.

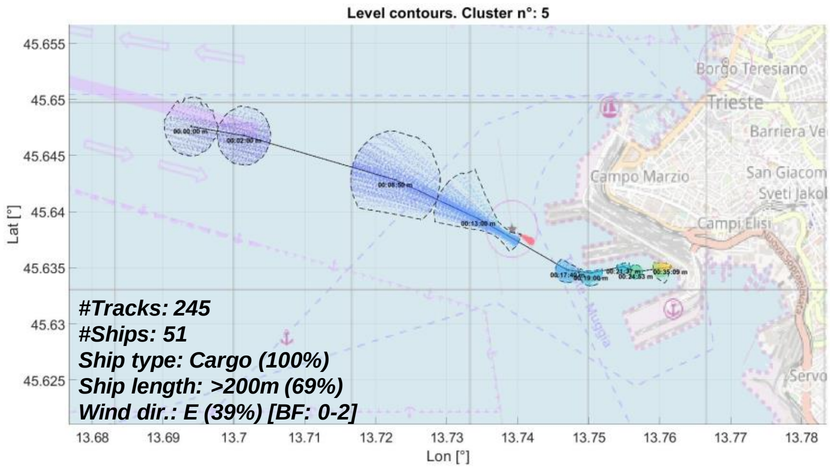

Figure 3 - Waypoint visualisation example. Points are coloured based on the time at which the ships are in that geographical position. Black dashed lines contour the waypoint area.

3.5 Data fusion (EO and GNSS) and generation of the derived information

The workflow for the data fusion of EO and GNSS data consists in the following:

- Given an EO acquisition, discriminate the collaborative from the non-collaborative object.
- Estimate the trajectory of the non-collaborative objects.
- In case of a risk of collision between collaborative and non-collaborative objects, suggest a modification to the preferred route of the collaborative object to avoid the collision.

As shown in Figure 4, the EO object is identified as a certain AIS object if their sizes are compatible and their distance is below a fixed maximum value. If an AIS object does not have an EO object compatible with its size within the maximum distance considered, it counts as a missed detection. If an EO object does not satisfy the above criteria for the association with an AIS object, it is classified as a non-collaborative object.

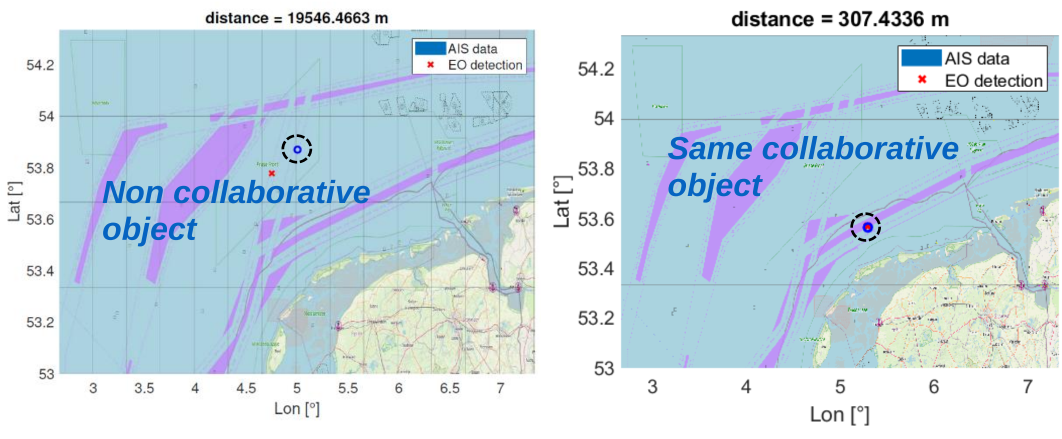

Figure 4 - Example of classification of collaborative and non-collaborative objects.

The value of the maximum distance between the AIS and EO objects should be established empirically, as it depends on the precision of the EO that depends both on technological limits as well as on environmental effects. With the available data, the average distance between the EO and AIS object was estimated to be about 200 m and the 90th percentile at about 400 m (see Ref 2.1.10). Using a threshold value of 500 m, which could be used to associate most of the objects detected in the AOIs, the amount of correct detections and missed detections are reported in Table 2.

AoI	Correct detections	Missed detections
Rotterdam Sep 2019	32	1
Venice 2017-2019	19	4
Wadden Island	19	7
TOTAL	70	12
Fraction	85.4%	14.6%

Table 2 - Synthesis of corrected and missed detections of AIS objects from EO.

To track the non-collaborative objects it is necessary to identify the same object in two different frames. To do so, each non-collaborative object identified in a given EO acquisition is associated with the closest non-collaborative object with a compatible size and direction in a subsequent EO acquisition. Once recognised a same object in two subsequent acquisitions, the information from the two subsequent object positions is used to predict the position of the non-collaborative object in the next hour or so, assuming it continues in a uniform rectilinear motion at velocity given by the mean velocity deduced from the last two EO data acquisitions. With any new EO acquisition, the object identification takes into consideration the compatibility of sizes and distances explained above as well as the history of the motion. The knowledge of the preferred routes would be used to prioritize the tracking and trajectory forecasting of non-collaborative objects nearby preferred routes, as those would be more relevant and to a higher risk of collision with other ships.

Assuming that the collaborative objects follow the preferred (or recommended) routes, it is possible to forecast if at any time a collaborative object is at risk of collision with a non-collaborative object. The risk of collision is determined as follows:

1. Given a non-collaborative object, its trajectory is extrapolated to the next hour.
2. If its trajectory intersects a waypoint of a preferred route, the time to the beginning of the intersection (i.e. when the non-collaborative object enters the waypoint) and the time to the end of the intersection (i.e. when the non-collaborative object leaves the waypoint) are computed.
3. If there is a collaborative object on a route towards the waypoint of the intersection, the time at which it should enter the waypoint according to the schedule of the preferred route is computed.
4. If there is a time when both the collaborative and non-collaborative objects would be in the waypoint, a modification of the route is suggested to the collaborative object.
5. In case the collaborative object is scheduled to enter the waypoint before the non-collaborative object, a suitable increase of velocity would allow it to leave the waypoint before the non-collaborative object enters. Otherwise, a suitable decrease of velocity would allow the non-collaborative object to leave the waypoint before the collaborative object enters.

For a concrete example of the method, it has been considered the case of a fictitious non-collaborative object intersecting a preferred route outside Rotterdam. In Figure 5, a non-collaborative object, represented by a red cross, is expected to cross the waypoint ahead of the collaborative object 1. The trajectory of the non-collaborative object is such that it would enter the waypoint before the collaborative object 1 can leave. Therefore, the scheduled times for the collaborative object 1 are modified to anticipate its arrival in the waypoint of the intersection and to the waypoint passed it. The second collaborative object instead is sufficiently far behind in the preferred route that the non-collaborative object is expected to leave the waypoint well before the collaborative object 2 enters it, so no modification of its route are suggested at this stage.

A validation of this method would be possible only with a greater number of EO at high frequency of the same area, as it is already the case for the tracking of non-collaborative objects.

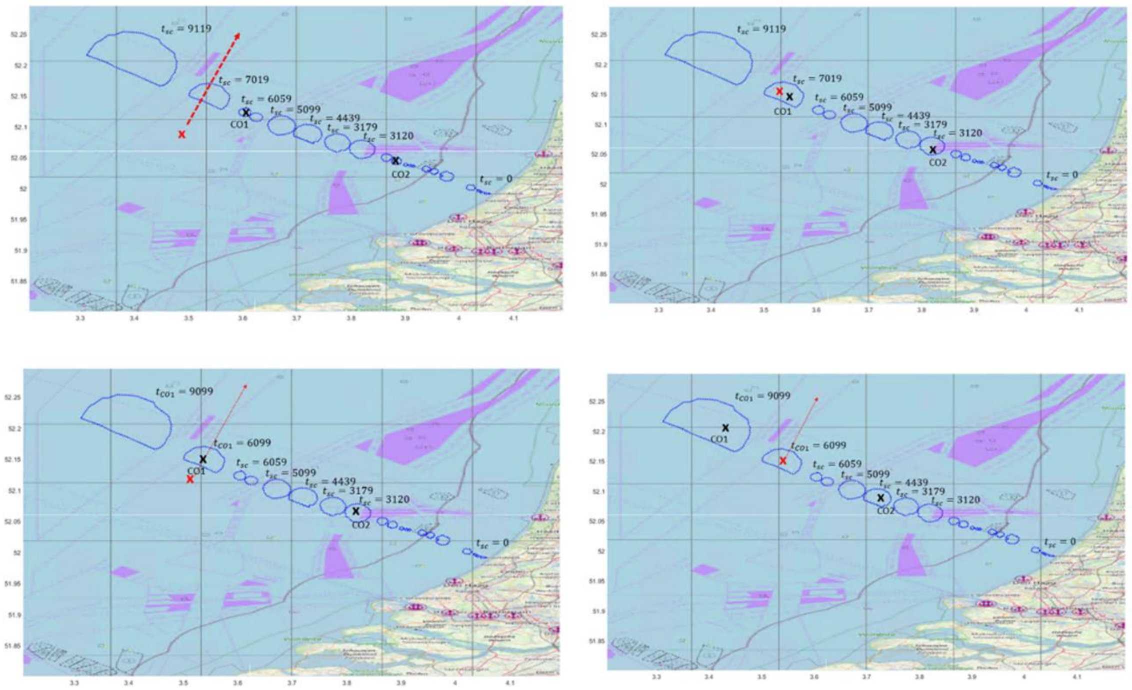

Figure 5 - Case study of route adaptation. t_{sc} are the scheduled times of the preferred route. The non-collaborative object would enter the waypoint before the collaborative object 1 can leave it (top panels). The method would suggest to increase the velocity of the collaborative object 1 to pass through the waypoint before the non-collaborative object enters.

3.6 Estimation of benefits in terms of reduced risk of navigation when EO data are exploited

The effect of EO-detected objects on risk of navigation was modelled and visualized with the MarinRisk model. This model, which is also referred to as the nautical risk index, is described among other models in the chapter Maritime Navigation Risk Assessment in Ref.2.1.6. It is very suitable for calculating historical risk, and for monitoring changes in risk levels over time, as well as in real time, for example to assist vessel traffic services (VTS). As it will be shown here to some extent, it is also suitable for calculating risk of collisions with objects that are detected via EO.

To illustrate the enhanced navigation risk, two AIS data sets were used:

- The original AIS dataset for the area above the Wadden Islands, from January 5 to January 9, 2019, containing AIS messages from ships with 60 seconds intervals,
- The same dataset, extended by AIS messages with 60 seconds intervals for the objects that were detected by EO and for which it was determined that these were not already present in the AIS data as ships.

Given the possibly temporal character of the location of many of the detected objects, the detected objects were modelled as moving objects, but only having a one-time observed location that was added and repeated in the AIS data from 3 hours before the moment of detection until 3 hours after the moment of detection. This time spell was chosen arbitrarily, short enough to reflect the temporal observations, but long enough to have a good number of ships passing the objects.

Figure 6 show the calculated collision rates without and with EO-objects for only three ships, and in particular for ship 20005, the northern ship sailing westward, and interacting with the other two ships.

The dotted lines in the figures connect the simultaneous positions of the ships where the collision rates start increasing due to the encounter, where the encounter is over (CPA has been reached), or where the objects are passed by ship 20005 (the CPA to the object has been reached).

The graph in Figure 7 shows the timeline of the collision rates for ship 20005, and also shows the dotted lines in time.

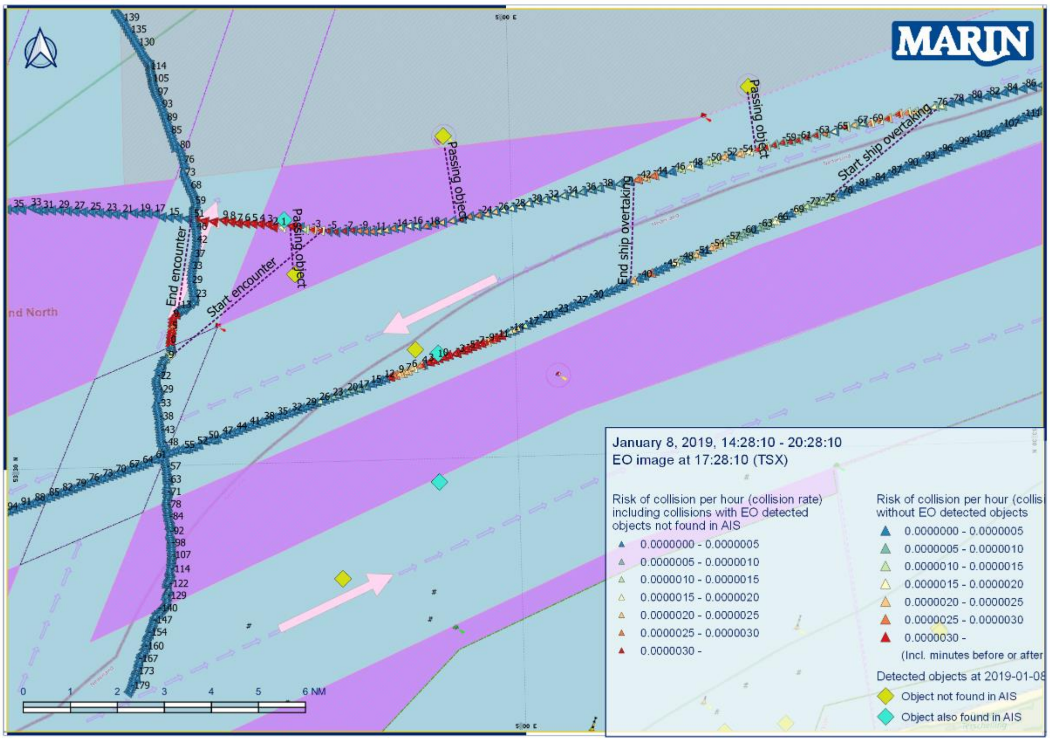

Figure 6 - Calculated collision rates with the MarinRisk model for ship 20005 (northern ship sailing westward), with and without EO-detected objects, from January 8 at 14:28:10 to 17:28:10

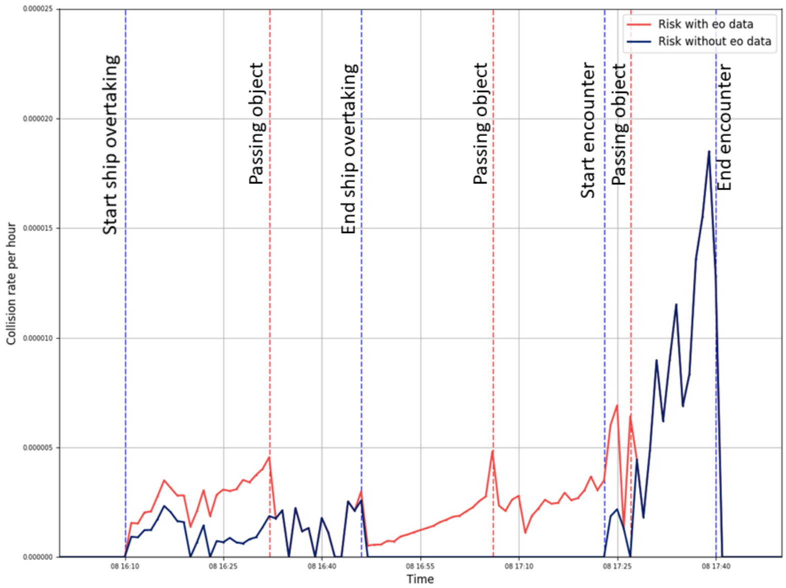

Figure 7 - Timeline of the collision rates for ship 20005

The maps and the graph show that the differences between the calculated risk for the two datasets is indeed only with regard to the added objects (obviously). But more importantly, the graph shows that the extend of the extra collision rate due to non-AIS objects for one particular trajectory is significant in comparison to the already present objects (ships) in the AIS. However, it can be assumed that most of these non-AIS objects are clearly visible and marked on the maps. Also, the original AIS data that is used, does not contain all AIS messages sent from objects.

Without knowing the exact locations of the objects, many ships already adjust their routes around the location of the objects. It was shown in the previous section that a risk exposure (in this case a rate of collision) can be calculated. Using wind and current predictions, the risk can be interpolated after detection by satellite. In that way, areas where the presence of the object will be more likely, can be avoided.

Adaptive recommended routes form a good way to instantly provide ships with updated information and predictions about the location and risk of detected objects. Estimates and predictions of the location where and when the ship will pass the object can be provided, and can also be used to make recommendations about speed or course adjustments, or even a change of routes.

However, the amount of detected objects and predictions that is taken into account, needs to be limited. Only those that may cause harm, should be considered. The uncertainty about the current position of the object, but also about what the object actually is, and what risk it poses, should be small enough for ships to actually take this extra information into account, since unnecessary detours are costly for ships. Therefore, to address this issue it would be necessary to establish a suitable threshold of the risk index to cause an alert, either by application of the model to a statistically representative historical dataset, or through simulations of traffic with non-collaborative objects.

3.7 Conclusions and derived requirements for future missions

The project demonstrated the capabilities of the algorithms for:

- object detection,
- object classification in collaborative or non-collaborative objects,
- preferred routes extraction.

The results also suggest that it is feasible to:

- track the non-collaborative objects,
- estimate the risk of collision,
- adapt the route to mitigate the risk,

although more data are necessary to validate these methods.

The results obtained in WP6 discussed in the previous chapter suggest that it is possible to extend the list of NARAS' use cases to include:

- **early warning**: the risk index can be computed well in advance of a possible encounter with a non-collaborative object, giving enough time to take countermeasures.
- **route optimization**: the risk index can be used to find the optimal trajectory that limits the risk of navigation while minimizing the deviation from the preferred route in terms of both time and space. Rev. 1
- **iceberg monitoring**: besides non-collaborative vessels and lost cargo at sea, it would be possible to monitor the presence and trajectories of icebergs and consider them to assess the navigation risks in relevant areas.
- **check AIS data**: the quality of AIS data can be spoiled by both human error (wrong information inserted in the system) as well as technical problems (spoofing, multipath…). NARAS could be used to identify and correct the erroneous data.

The use of optical data in conjunction with SAR data poses various challenges, from the algorithmic point of view to the availability of suitable dataset to use. As discussed in Ref. 2.1.7-8, the incompatible timing of the SAR and optical satellites' orbit translates into the impossibility of having simultaneous acquisitions of the same scene in both SAR and optical. However, this does not imply the impossibility to use both to train a neural network (NN): one could pre-train the NN on optical data and then use the same NN to train on the SAR data, a strategy known as transfer learning. Various datasets have already been made publicly available such as the SENT1-2 (Ref.2.3.23), Spacenet 6 (Ref. 2.3.22), and the QXS-SAROPT (Ref. 2.3.21) datasets. In the context of semantic segmentation of building footprints in images, Ref. 2.3.22 showed that pre-training the NN on optical images and using transfer learning on SAR images produces a 55% increase in performance for training on the SAR dataset alone. While ship detection and classification are more challenging than segmentation of building footprints, encouraging results showing a ~1.3% increase in performance using both SAR and optical data (Ref. 2.3.21) suggest that it is worth further investigation.

An interesting complementary possibility would be to use thermal (i.e. infrared) sensors in addition to SAR instruments. While the thermal cameras are limited by the weather conditions as for the optical cameras, they would be effective even during night time. While the current resolution of these instruments (about 100 m) might not be sufficient for NARAS' scopes, future missions will be capable of resolution to 3.5 – 4 m (Ref.2.4.11-12) similar to SAR resolution. Even though the acquisition approach is very different between SAR and thermal cameras, it could be considered to install them on the same platform. Rev. 1

In a future scenario the software shall work in the near real-time. The selection criteria identified for the future missions have been proposed in WP3

- **CN1**: accessibility and availability to the satellite information

  The main criteria for the selection of data sources are the possibility to access information collected by the selected satellite within the available budget and the availability of EO images in the defined AOI.

- **CN2**: data latency in the order of few minutes

  It is defined as the total time elapsed between the satellite observation and time at which they are available to the user [Ref.2.4.5]. For the envisaged NARAS application, the near real-time mode is deemed feasible if the provider is able to deliver the data within few minutes from the acquisition, considering that the objective is to provide the object detection output within 20-30 min from data availability. In this way, the overall information latency (data latency and processing time) will be in the order of 30 min.

- **CN3**: resolution

  In a future scenario, higher resolutions are expected and could be exploited to detect smaller objects with respect to what is possible to detect at the moment. An example of future resolutions may be:

  - **CN3a**: for SAR, less than 3 m
  - **CN3b**: for optical, less than 1 m

- **CN4**: AOI revisit time ≤ 1 hour

  AOI revisit time was defined as the time elapsed between two subsequent acquisitions in the same Area Of Interest. Considering an area of interest (for example the black rectangle in Figure 8), a vessel speed in open sea of 16-27 knots (i.e. 30-50 km/h) and a swath width of the EO images of 30-50 km (width of blue rectangles 1 and 2 in Figure 8) the purpose is to trace the trajectory of a vessel with at least 3 points every 100 km. To reach the goal, the acquisition of more images in the same area of interest is necessary: referring to the figure below as general case, the vessel takes not more than one hour to reach the position B starting from the position A, that means that the time elapsed between the acquisition of EO image 1 and EO image 2 shall be not more than one hour.

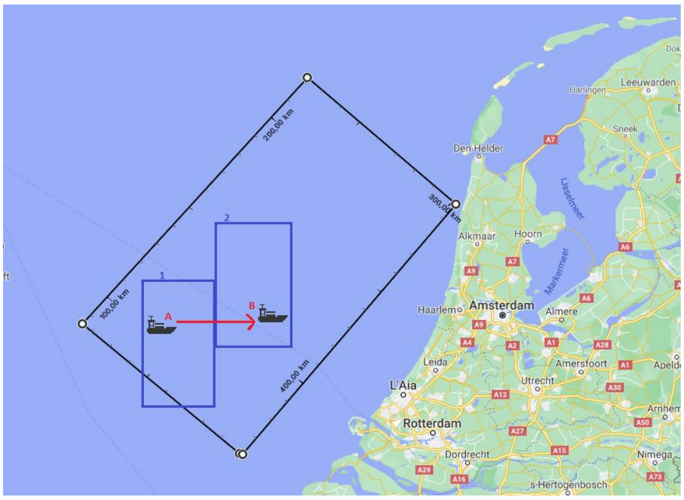

Figure 8 - Example of two successive EO image acquisition for vessel detection.

- **CN5**: revisit time (RT) ≤ 1 hour

  By definition, the revisit time is the time elapsed between two subsequent observations of the same ground point. For the future operational NRT mode the detection of non-collaborative objects in the sea will be performed on the basis of EO images and then checked and updated each time a new EO image will be available, hence considering what discussed above (**CN4**) a revisit time of less than one hour will be necessary in a near real-time perspective, for both SAR and optical EO.

  It is reasonable expecting that such low revisit times will be reached in the future considering two main strategies: the first one is the use of *constellations* of satellites, indeed augmenting the number of satellites in orbit lowers the waiting time between observations of a same scene. The second strategy is based on the definition of *agility* of a satellite, i.e. the ability of a satellite to modify its attitude in order to observe scenes outside its ground trace [Ref.2.4.6].

- **CN6**: footprint

  As discussed in **CO4**, the same criteria can be applied also considering a near real-time scenario.

  - **C6a**: for SAR, in the range of [100;150] x [100;150] km
  - **C6b**: for optical, in the range of [30;50] x [30;50] km

Based on the experience gathered during the WP5, a possible refinement of CN2, CN4 and CN5 could be proposed, as the requirements for future missions depend on the service that it is intended to provide. For example a real-time navigation assistance in busy areas requires higher observation rate and lower latency than open sea areas.

Supposing that the busiest area that NARAS would serve covers an area A, containing on average N vessels (collaborative and non-collaborative) travelling at speed v in all directions, the average distance between the vessels is about $\sqrt{A/N}$ and therefore the time scale between collisions/close encounters can be estimated to be

$$T \sim \frac{\sqrt{A/N}}{v} .$$

In case a ship loses cargo (e.g. containers) at sea or a non-collaborative vessel loses power and drifts driven by current, waves and wind forces, the average time that another unalerted ship would take to eventually collide with such drifting bodies can also be taken to be approximately in the order of T.

By indicating with T_{RT} the average EO satellites revisit time and with T_{lat} the latency of NARAS processing time, the three time quantities must satisfy the following requirement to allow proper and timely manoeuvres by the threatened ships:

$$T_{RT} + T_{lat} < T ,$$

otherwise the service would be less informative to the user in that area than, say, direct communication between collaborative ships. In fact, if the above constraint would not be satisfied, statistically a ship would have had a close encounter with the non-collaborative object before the EO information is acquired and processed by NARAS, and said ship could communicate the relevant information (coordinates, estimated size, etc.) to other ships in the surroundings.

This argument applies also to autonomous shipping considering that autonomous ships should be equipped with obstacle avoidance systems and objects identification and classification capabilities, independent from the external AIS information.

The values of T as a function of the average vessel velocity is plotted in Figure 9. The arrows in the figure point at the curves corresponding to the respective areas considered, whereas the shaded areas indicate the typical velocity range of fishing and merchant vessels. The value of maximum density taken in the plot corresponds to 100 hours per square km. The vessel density can be even higher in areas closer to harbours and channels.

As it is possible to see, the curves quickly reach values of T below the hour and are mostly distributed in the 20-40 minutes range for the values of reference vessel densities and velocities taken into consideration. A better estimate on the requirements could be obtained considering the velocity distribution in an area of given density. However, even for velocities of 3 kn, the time T takes easily values under the hour at high densities.

In conclusion the requirements for future missions depend on the service that NARAS is intended to provide, both in terms of geographic area and scale (large or local), taking into account that a real-time navigation assistance in busy areas requires higher observation rate and lower latency than open sea areas.

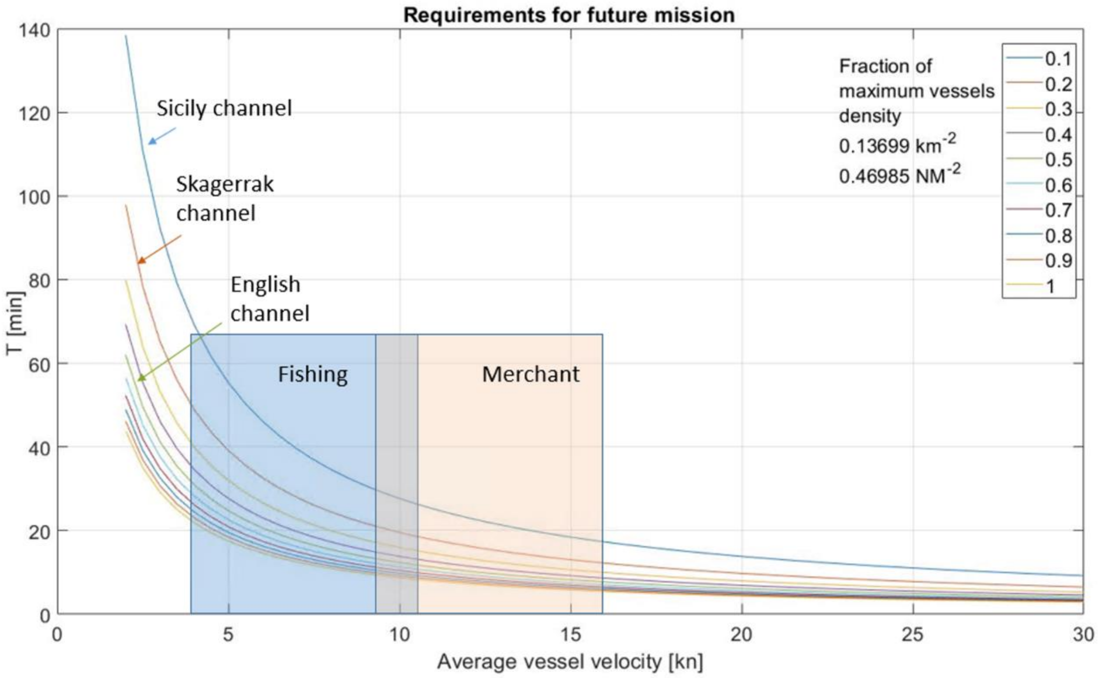

Figure 9 - Sensitivity curve of the time T as a function of the average velocity for different values of vessel densities.