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Integrating AIS and SAR to monitor fisheries: a pilot study in the Adriatic Sea

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Abstract – **The synergic utilization of data from different sources, either ground-based or spaceborne, can lead to effectively monitor fishing activities in close proximity of managed areas, and help tackle the problem of global overfishing. To this end, the integration of spaceborne Synthetic Aperture Radar (SAR) data and cooperative Automatic Identification System (AIS) information has the appealing potential to provide a better picture of what is happening at sea by detecting vessels that are not reporting their positioning data (intentionally or not) and, on the other side, by validating ships detected in satellite imagery. In this context, this paper deals with the investigation of "suspicious" AIS data gap and the integration of SAR-based ship detection by a point-to-point and a point-to-line types of association. Time-filtered and classified AIS transmissions (according to the gear in use) are used to predict SAR positions, with the next step being to search/match corresponding SAR-based targets. A case study is analyzed, in which the method is tested in proximity of managed areas characterized by significant AIS blackouts, using occasional Sentinel-1 images of the central Adriatic Sea and AIS data.**

I. INTRODUCTION

Improving the Maritime Situational Awareness (MSA) and the sustainable use of oceans, seas and marine resources is nowadays of paramount importance [1] and requires monitoring tools which can provide long-term observations of fish stocks and fishing fleets' activity [2] [3].

The latter can now be monitored by several systems that can be broadly classified as cooperative or non-cooperative. Cooperative systems rely on the ships reporting information about themselves (e.g., identification, position, and speed), as it happens with Automatic Identification System (AIS), Long Range Identification and Tracking (LRIT) and Vessel Monitoring System (VMS). While these systems are powerful tools to track the self-reporting vessels, they only give a partial picture of the situation. Most small vessels do not need to carry AIS or LRIT, and small or even all fishing vessels do not carry VMS depending on the region. Moreover, positions reports can drop out for many reasons, such as weak signals, signal interference in crowded areas or intentionally turning off/tampering when entering port or in close proximity of fishery forbidden areas [4].

On the other hand, non-cooperative systems employ radar and optical sensors (coastal, shipborne, airborne, and spaceborne) to detect the ships from the background sea clutter without relying on their cooperation [5] [6] [7]. Compared with optical remote sensing, satellite Synthetic Aperture Radar (SAR) imaging appears more suited for maritime traffic surveillance in operational contexts, as it allows ship detection over wide swaths without being critically affected by weather conditions and day-night cycles [8] [9] [10] [11].

Obviously, the synergic exploitation of the above mentioned different data sources represents a breakthrough approach to strongly improve maritime situational awareness and effectively monitor of fishing activities [12] [13]. Indeed, ship-related information gathered by both cooperative and non-cooperative systems could result in the quantification and additional mapping of the non-reporting ship traffic, giving a more complete picture of vessels' activity, including Illegal, Unreported and Unregulated (IUU) fishing [14].

Considering the above, this study focuses on AIS blackouts in close-proximity of fishery managed areas, and use open-source Sentinel-1 SAR data to seek and additionally map non reporting ships that could be involved in suspect behaviour.

II. MATERIALS AND METHOD

Terrestrial AIS data (poll rate: 5 minutes) are first processed to map transmission gaps, and investigate their overlay with known managed areas, such as the 3 nautical mile zone where the use of towed gears shall be prohibited (as defined by Article 13 of EU Council Regulation 1967/2006).

According to the management measure under investigation and the gear type that is likely to be illegally used, only some AIS report positions are retained (i.e. the ones broadcasted by trawlers) and a distance criteria is applied to match them with ship positions from SAR images. To this end, a classification process is carried out to pre-assign AIS transmissions to specific fishing gears.

A. AIS Data and Processing

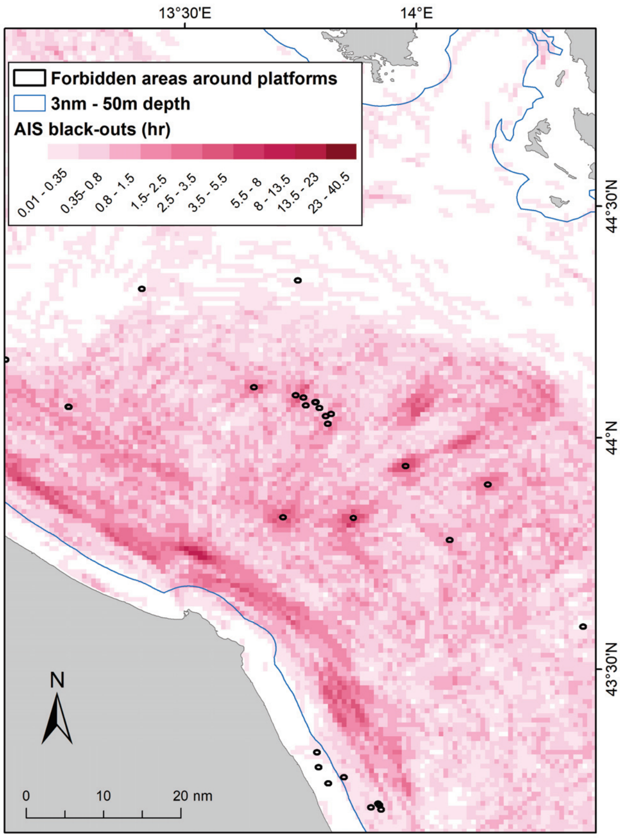

Fig. 1. Aggregated AIS black-outs (1kmx1km grid).

The Maritime Mobile Service Identity (MMSI) is used to create a tracking layer and values of duration and speed are computed for each segment from the difference between consecutive pings. Tracks with a duration exceeding a predefined threshold of 30 minutes are kept and considered as black-out tracks and gaps in AIS data coverage. Annual black-outs are aggregated intersecting the over mentioned tracks with a 1-km grid, spatial joining each cell with overlapping track portions, and summing relative duration values (hours, Fig. 1)

For each vessel individual trips are first identified, from the time vessels leave ports until they return, and then characterized by a machine learning approach with a boosting algorithm (Fig. 2) that identifies the type of fishing when it occurs, according to pre-defined gear classes: bottom otter trawl (OTB), beam trawl (TBB), pelagic trawl (PTM), purse seine (PS), longline (LL), and other (including cargo and cruise vessels). The Fourier transformation is applied on position and course data and the performance improved by subdividing the spectrum twice into 20 and 100 power sub-bands from which additional features (median, maximum and area) can be extracted. The classification approach extends what already developed for towed gears in Galdelli et al., (2019) [15] with the aim to identify additional gear classes such longlines and purse seines.

Trip by trip, the classification algorithm is executed to label single trips according to the gear class showing the highest accuracy index.

B. SAR Data and Processing

The Constant False Alarm Rate (CFAR) approach developed by Mancini et al., (2013) [16] for ship detection and CosmoSkyMed data, is adapted to Sentinel-1 images. The approach is based on the use of integral images and allows to directly manage the presence of masked pixels/invalid data while reducing the computational time. It significantly boosts he performance up to 50x even in case of very high resolution images and large kernels.

The output of the data-processor is a list of georeferenced centroids of the detected ship pixels (Fig. 3), with an estimation of the vessel size. This length estimation is used to filter out targets that are likely too long to be a fishing vessel.

C. AIS-SAR Matching and Data Integration

To integrate AIS and SAR data, a point-to-point type of association is used to assess if a vessel detected by SAR is correlated with an AIS position within a given time-frame, while a point-to-line type of association is attempted in case of AIS black-outs. We identify the following main cases:

- Case #1: The SAR-based estimated vessel location is within a buffer area centered on AIS data. The buffer distance is calculated considering the distance travelled in the time frame of N AIS pings at v speed.
- Case #2: A SAR target is detected but with no AIS report available. This could be caused by a transmission problem or a voluntary switching off. An attempt is done to associate the SAR target to the nearest black track, by connecting the SAR detection with the latest before the switching off and the first available ping after the power on (the connection could consider a series of N missed pings).
- Case #3: A SAR target is missed even if AIS data is available. It is due to the failure of the vessel detection algorithm.

The value of N is also function of the typical speed / class of the vessel (e.g. 2.5-3.5 kn for trawlers during the fishing activity). Values of N too large could generate wrong results.

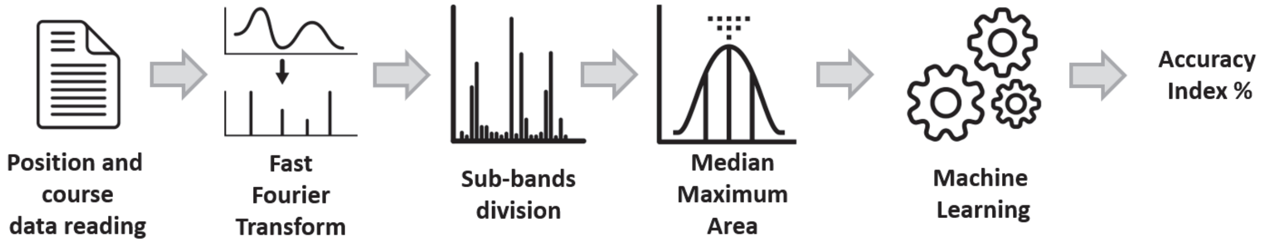

Fig. 2. Classification Vessel Algorithm.

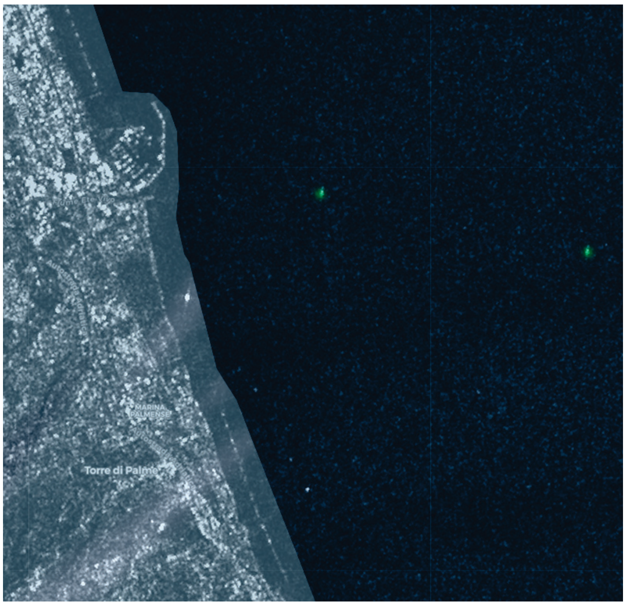

Fig. 3. Example of Sentinel-1 image (Central Adriatic coast, July 2020) and ship detection by CFAR. Land mask is overlaid with stretched SAR amplitude data, while green pixels represent detected ships.

While Case #1 validates the performance of the SAR-based detection algorithm, Case #2 discriminates collaborative and non-collaborative ships, playing a key-role to detect potential suspect behaviours in a given area.

Of course from a single satellite image is not possible to state that a given fishing vessel is really performing suspect activities. Nevertheless, the positions detected by SAR can be correlated with AIS black-outs to reveal previously unmonitored dark vessels.

III. RESULTS

As case study it was chosen an area in the central Adriatic Sea (south coast of the Marche Region), because of the presence of many offshore installations and associated 500 m safety zones within which, under the Italian law, it is forbidden to anchor, fish or navigate. Fig. 5 is related to the above mentioned area and shows the overlay of a portion of a Sentinel-1 image (2017-03-20 at 16:56:52 UTC) and the corresponding AIS transmissions that were selected according to the time window straddling the SAR acquisition time (+/- 10 minutes). Once classified, all AIS report positions were retained (regardless of the type of gear in use) and consisted in 91 pings transmitted by 20 different vessels (unique MMSI). For 8 of these vessels the switch-off rate exceeds 40% during the single trip. These selected vessels were mainly classified as trawlers (8 OTB, 5 PTM and 3 TBB), while only 3 vessels were labelled as "other" (cruise/cargo).

Applying the CFAR algorithm, 22 objects were automatically detected, consisting of 19 ships and 3 fixed offshore platform targets. They all fell within Case #1 since it was possible to correlate them with AIS pings or platform positions downloaded from the EMODnet - Human Activities portal[1] (Fig. 6).

The 19 ships identified in the Sentinel-1 image are between 16 and 27 meters in length, while one vessel was too small to be detected (Case #3). This small ship was self-reporting during the time window straddling the SAR acquisition time (orange ping located in port in Fig. 5) and was classified as cargo/cruise by the Classification Vessel Algorithm. Its monthly plotted AIS tracks confirmed that it acted as a platform supply vessel (Fig. 4).

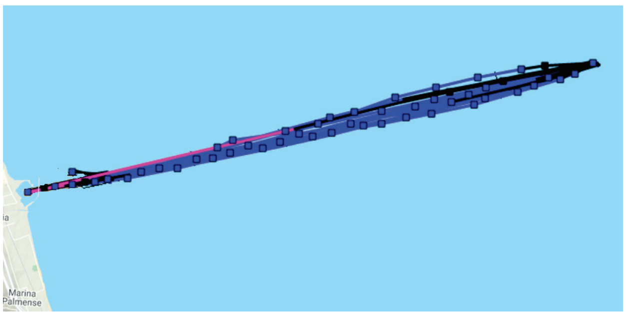

Fig. 4. Case #3 with the small platform supply vessel broadcasting AIS signals (blue points) during March 2017.

Lengths ranging from 16 to 27 meters are compliant with the available resolution of satellite imagery even if in

[1]https://www.emodnet-humanactivities.eu

harsh environmental condition the detection could be negatively affected.

A close up view of the post-matching phase is shown in Fig. 7, where it is depicted that one vessel is close to the 500m safety zone surrounding the offshore platforms (on the top-left, and hereafter named as vessel 1), while a second vessel navigates at a distance of 1.4 kilometers from one of the managed areas (on the top-right, and hereafter named as vessel 2). Even if the AIS data gaps for these 2 vessels exceed 50% of their trip duration, they do not switch-off near the platforms allowing the point-to-point type of association foreseen by Case #1.

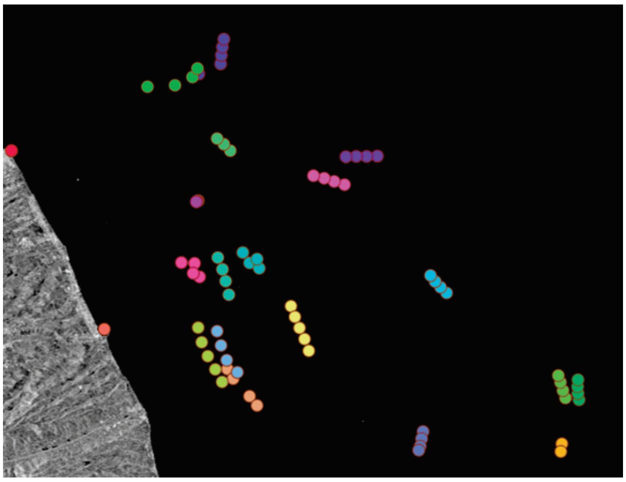

Fig. 5. Sentinel-1 image and selected AIS transmissions under analysis. Pings are categorized by MMSI.

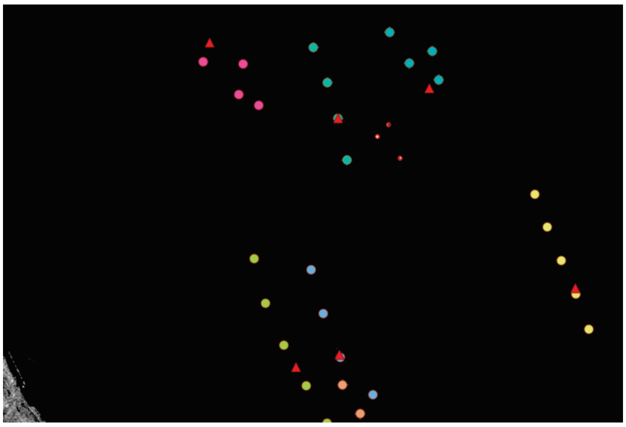

Fig. 6. AIS-SAR matching Case #1 and close up view with SAR targets classified as gas platforms (red circles) and vessels (red triangles). AIS pings are categorized by MMSI.

Lastly, since no significant black-outs were present in the area chosen as case study, Case #2 was simulated, omitting few AIS pings transmitted by vessel 1 in close proximity to the platform .

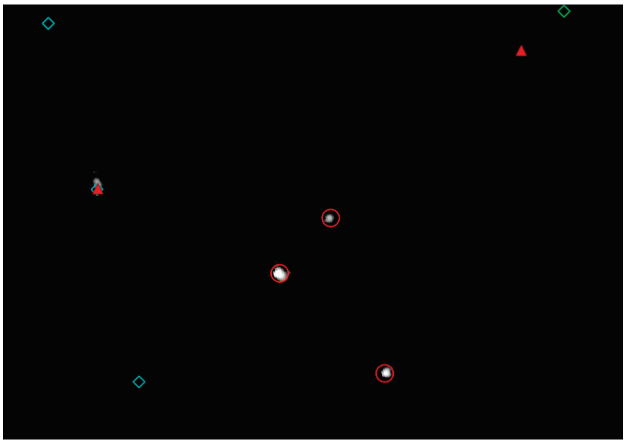

Fig. 7. Zoom detail of Fig. 6. Three gas platforms and two vessels are identified and marked with red circles and triangles respectively. The light blue and green circles are the AIS pings related to the 2 different ships (vessel 1 and vessel 2, respectively).

Figure 8 shows a graphical representation of a simulation where pings are not available in a short period due to blackout. The blue makers are the pings before and after the blackout period, while the green solid line represents the segment that connects the two above mentioned pings. Red circles are centered on the gas platforms p1, p2 and p3 with a radius of 500m. The cyan markers are the contact points between the circles and the minimal route that vessel 1 could follow to enter in the forbidden area. Dashed green lines represent these (potential) routes.

Figure 9 could help investigate the behaviour of vessel 1 during the blackout period. Each row of the table corresponds to the ratio between the potential travelled distance during the blackout period at different speeds over the minimum distance to reach and exit the forbidden area (cyan marker shown in Figure 8) of a given platform considering as starting point the ping before the blackout and the end point as the first ping after the blackout. This ratio could be used to evaluate if a ship performed some kind of activity (e.g. fishing).

IV. DISCUSSION AND CONCLUSIONS

In this paper we presented preliminary results to use both AIS and SAR data to monitor fisheries: a pilot study in the Adriatic Sea was also presented with a focus on the detection of potential illegal activities in critical area (e.g. gas platforms). Even if the quality of AIS-SAR data matching strongly depends on the density of the ships in the area of interest and on the time lag between AIS and SAR data collection, preliminary results suggest that the proposed approach could help monitor fishing activity and rate the effectiveness of fishery-regulated areas, which is critical in the context of the global over-fishing problem.

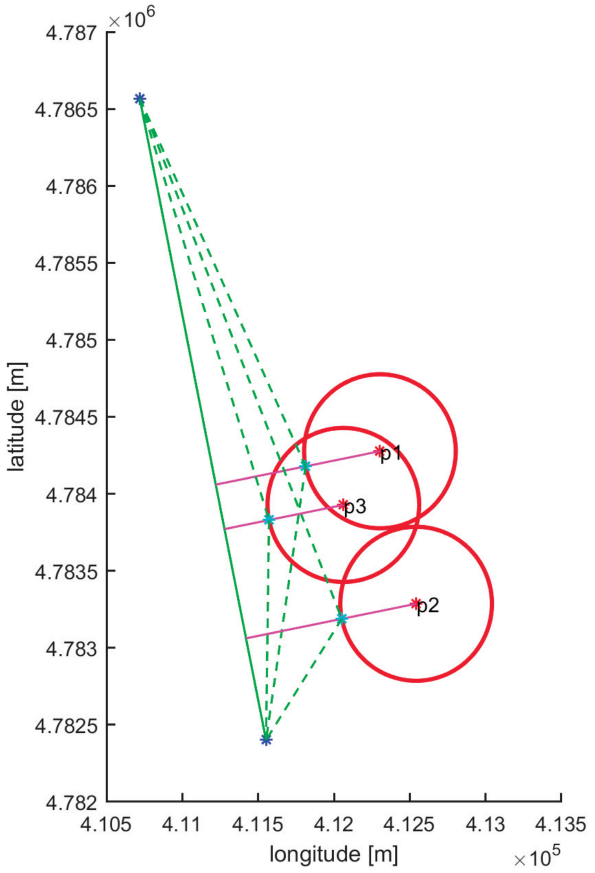

Fig. 8. Graphical representation of a simulated scenario where the green blackout line connects 2 consequent AIS pings broadcasted by vessel 1 (EPSG:32633).

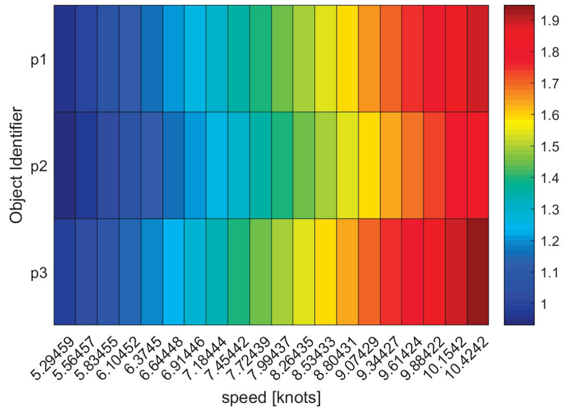

Fig. 9. Graphical representation of the estimated distance travelled by vessel 1 towards the offshore platforms p1, p2 and p3.

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