OPERATIONAL USE OF SAR DETECTIONS FOR ENHANCING MARITIME ANOMALY DETECTION

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1 INTRODUCTION

Sensors on Earth Observation (EO) satellites can enhance maritime surveillance capabilities, especially when treated as part of a larger sensor network and integrated with land and sea-based sensors. Specifically, Earth Observation Synthetic Aperture Radars (EO SAR) are active sensors that can provide vessel images day and night which can augment the many cooperative, transponder-based sensors with a non-cooperative capability. This means EO sensors have the potential to detect vessels which are not reporting their positional information or confirm ship detections and provide other reported information including vessel identity. Within this framework, the paper presents a methodology to beneficially correlate SAR detections with traffic patterns derived from clustering positional contacts from coastal and satellite AIS. The proposed methodology can be beneficial in areas with sparse data in order to propagate ship detections along confirmed routes and potentially inform EO SAR acquisition by more accurately predicting the future vessel location. The uncorrelated SAR detections will be useful to highlight 'dark targets' in the area under investigation.

2 RELATED WORK

The Automatic Identification System (AIS) is a cooperative network that allows the real-time exchange of vessel movement and location information. Its main purpose is maritime collision avoidance and traffic monitoring, but increasingly maritime surveillance applications have also made use of AIS data. While certain vessels are required to transmit their information through AIS, others are not obliged to do so, have malfunctioning AIS equipment, or purposefully omit required information. In this context, SAR imagery can be an alternative source of information for refining the global maritime traffic picture and for enhancing surveillance, because it does not rely on cooperation from the monitored vessels[1,2]. In fact, by adopting appropriate data fusion strategies, SAR data can be used to cross-reference AIS data and to identify anomalous and non-compliant vessels[13]. In particular, three sources of data are usually considered when fusing satellite imagery data: the reported (AIS) data acquired over a given area of interest; the current maritime traffic picture, typically provided by vessel tracking algorithms in the form of tracks of interpolated AIS data; SAR acquisition parameters.

Considering the uncertainties in SAR detections and in the tracking algorithms, fusing these sources of data is not a uniquely solvable problem. Several techniques have been proposed in the literature[3,4,12] that can be grouped in two main approaches, one based on Boolean logical statements, the other on fuzzy logic. In the logical statement approach, Boolean rules associate AIS and SAR data based on nearest-neighbor searches in space and time. Specifically, for a given point of interest, the geographical area within a given radius is searched for data points with reported time stamps within a given time window and the nearest neighbor is chosen. This approach is particularly suited for smaller datasets with few crossings of track trajectories. In the fuzzy logic approach[5], in addition to determining the selected datum to be associated with a given point of interest, a confidence score is provided to assess the validity of the association. Typically the association confidence is a function of the bearing, speed, geographic distance and temporal gap of the AIS and SAR association candidates. Depending on the type of SAR sensor available, additional data may be available, such as estimated vessel size, speed, and heading. These measured parameters can be used to further disambiguate candidate associations in order to improve the final association.

Finally, contextual information can be used to resolve difficult association cases. In this paper, we use pre-computed vessel patterns-of-life derived from historical AIS data as prior information when no AIS positional reports exist in proximity of SAR detections. The historical patterns are computed with an algorithm called Traffic Route Extraction and Anomaly Detection (TREAD) [7,8,9]. The combined use of specialized association functions and historical patterns can be a powerful tool for detecting maritime traffic anomalies.

3 PROPOSED APPROACH

The paper proposes a heuristic approach to exploit the SAR/AIS associations, with the goal of enabling maritime traffic anomaly detection. Central to the approach is the definition of a confidence function that measures the correlation between AIS data and the SAR detections. The resulting association score can be used to identify possible traffic anomalies, as will be discussed in the result sections.

A SAR detection can be represented as:

$$\mathrm{SAR} = \{t, x, y, \hat{h}, \hat{s}, \hat{L}, \widehat{W}\},$$

where t is the acquisition time of the image and (x, y) are the coordinates (longitude and latitude) of the SAR position. Estimated vessel features may also be available: heading $\hat{h}$ (with 180° ambiguity), speed $\hat{s}$ (if a wake is visible and the ship is not stationary), ship length $\hat{L}$ and width $\widehat{W}$. Note that the estimated kinematic and static features are subject to uncertainty from the measurement process.

AIS reports are used as ground truth. Each AIS report contains rich information regarding both static and kinematic features of the ship, as follows:

$$\mathrm{AIS} = \{t, x, y, h, \mathrm{COG}, \mathrm{SOG}, \mathrm{MMSI}, \mathrm{ShipType}, L, W, D\},$$

where t is the timestamp of the message, (x, y) are the coordinates (longitude and latitude) of the AIS positional report, h is the vessel heading, COG is the Course over Ground, SOG is the Speed over Ground. The MMSI is a vessel's Maritime Mobile Service Identity, that is a nine digit identification number, uniquely identifying the ship. Additional static information about the vessel may be available, such as ship type (e.g., cargo, fishing vessel, etc.) and ship size (i.e., length L, width W and draught D).

In the first step, given a SAR detection as described above, only AIS positional reports with time stamps that fall within a user-chosen temporal window around the SAR time stamp are considered for further analysis. Each candidate AIS report that falls within this time window is then ranked by an association function that depends on its physical and temporal distance to the SAR detection, as described below.

It is noteworthy to recall that the information provided by the vessel AIS track (position, SOG and COG) together with sensor geometry configuration, can be used to correct the position of AIS contacts and compensate for SAR position errors for vessels having a high range velocity component[2].

Let $\{\mathrm{AIS}_1, \mathrm{AIS}_2, \cdots, \mathrm{AIS}_n\}$ be the set of n AIS reports that fall into the chosen time window and range. The function $d_{\mathrm{assoc},i}$ proposed for the association of each AIS_i candidate report is defined as follows:

$$d_{\mathrm{assoc},i} = \frac{d_{\mathrm{SAR}-i}}{R} \cdot \frac{|t_i - t_{\mathrm{SAR}}|}{\max_i |t_i - t_{\mathrm{SAR}}|} \cdot \frac{1}{\left|\cos\left(\mathrm{circ\_dist}(\hat{h}_{\mathrm{SAR}}, h_i)\right)\right| + \epsilon}$$

where:

- $d_{\mathrm{SAR}-i}$ is the displacement between the SAR detection and the i^{th} nearest AIS report, normalized by the radius R used in the range search. $d_{\mathrm{SAR}-i}$ is ultimately computed as the Euclidean distance between the SAR and AIS positions, since most observed distances are relatively small, with a reduced curvature effect;
- $|t_i - t_{\mathrm{SAR}}|$ is the absolute time lag between the SAR detection and the i^{th} nearest AIS report, divided by the maximum observed time lag $\max_i |t_i - t_{\mathrm{SAR}}|$ among the candidate AIS reports; in this way, when only one compatible AIS report is in the range of the SAR detection, the effect of this term on the overall value is null;
- $\left|\cos\left(\mathrm{circ\_dist}(\hat{h}_{\mathrm{SAR}}, h_i)\right)\right|$ is a coefficient whose value can range between 0 and 1 that is a measure of the angle displacement between the estimated heading of the SAR detection $\hat{h}_{SAR}$ and the heading h_i of the i^{th} nearest AIS report. It is the scalar projection of the SAR estimated heading on the AIS heading direction. Taking into consideration the 180° ambiguity of the SAR estimation, the worst-case happens when the two headings differ by 90°; consequently the term at issue assumes its minimum value, 0, and the value of the association function tends to diverge. An additive, fixed and small term $\epsilon \ll 1$ can possibly be added in order to improve the numerical stability of the computation.

Note that $d_{\mathrm{assoc}} = 1$ corresponds to the worst-case scenario for association when there is only a single AIS candidate that falls at the maximum distance R from the SAR observation, and for which the heading is absolutely coherent with the SAR observation, *i.e.* $\cos\left(\mathrm{circ\_dist}(\hat{h}_{\mathrm{SAR}}, h_{\mathrm{AIS}})\right) = 1$ (ignoring the regularizing factor ϵ).

The flow chart of the proposed procedure is reported in Figure 1.

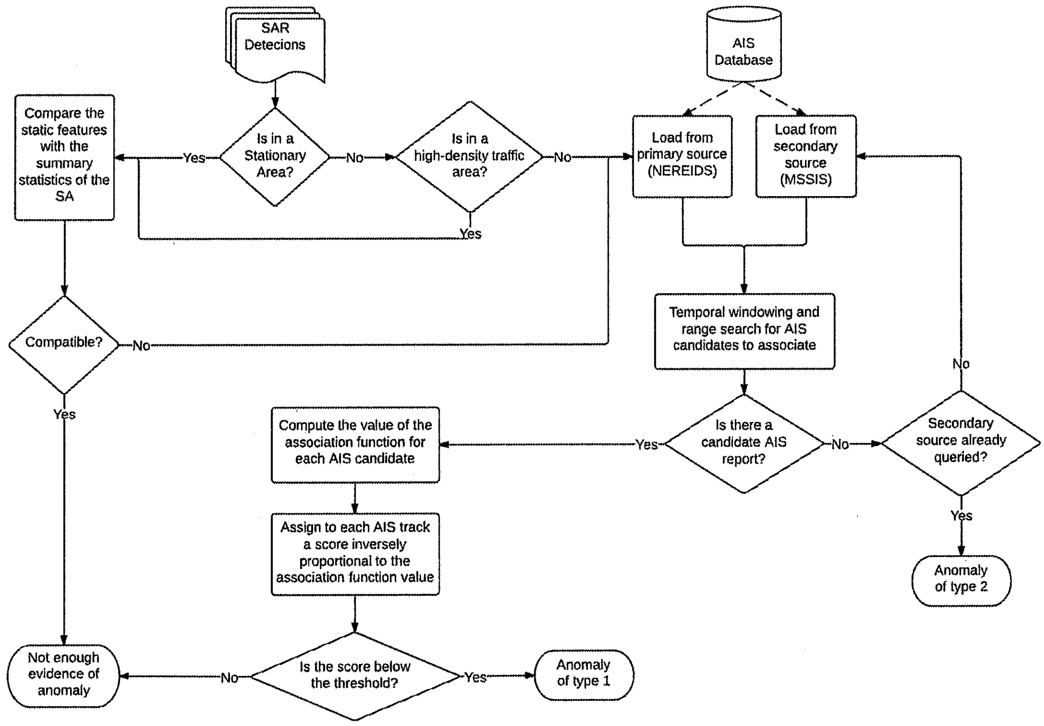

Figure 1 Functional flow-chart of the proposed association process

The candidate AIS reports, which do not necessarily originate from the same vessel, are arranged into AIS tracks according to the MMSI identifier. The score assigned to each AIS track is inversely proportional to d_{assoc} which is the lowest among the values $d_{\mathrm{assoc},i}$ assigned to the candidate AIS reports belonging to the same track. The higher the value d_{assoc}, the lower the score, and, hence, the lower the confidence in the association. Thus, low-scoring associations are flagged as potential anomalies.

Anomalies of type 1 are those SAR detections not reliably associated with any available AIS tracks, being d_{assoc} above a given threshold $d_{\mathrm{assoc}}^{\mathrm{MAX}}$. In this case, the ship is classified as potential anomaly, and the resulting output is stored in a list of 'uncorrelated' ships. Anomalies of type 2 are those SAR detections for which no corresponding AIS detection can be made. This can be due to lack os sensor coverage, or gross errors in the SAR imagery acquisition process. In this case historical patterns can be helpful in refining the final decision. In the next section, we present results on real-world data by way of case studies.

4 REAL-WORLD EXPERIMENTAL RESULTS

A dataset of fifty SAR detections in the Alesund (Norway) area, obtained from the NEREIDS project[10], was used to illustrate the proposed approach. The corresponding terrestrial AIS data was provided by the NATO Science and Technology Organization Centre for Maritime Research and Experimentation (STO-CMRE), which also collects historical AIS data from the MSSIS sensor network[11]. The considered datasets are illustrated in Figure 2.

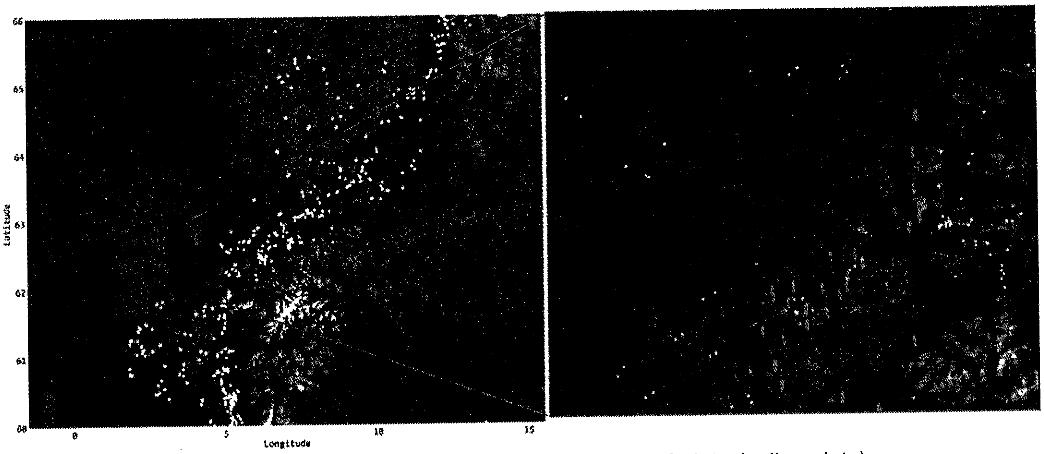

Figure 2 Overview of the used SAR dataset (red dots) and the AIS data (yellow dots).

4.1 Case I – Single association, but low association score

A first association case is vessel A shown in Figure 3. Within a radius $R = 1$ km from the SAR observation there is only one reported AIS position whose timestamp is compatible with the time of the SAR detection, *i.e.,* it occurs within an interval of 10 minutes centred on the acquisition time of the SAR observation. The corresponding compatible AIS track, shown in green in Figure 3, has a value for the association function $d_{\text{assoc}} = 0.938$, that is very close to, but still below, the threshold $d_{\text{assoc}}^{\text{MAX}} = 1$, allowing the association.

The value of the association function results are inflated because the only compatible AIS position is at the limit of the search range, although the estimated heading from the SAR observation is almost aligned to the direction reported by AIS.

A plausible reason for that is the position error along the SAR azimuth direction. In fact, SAR processing algorithms usually assume ship to be stationary. If the ship is moving, the target position in the image is shifted in azimuth from its actual position (*i.e.,* the position of the ship wake).

This phenomenon is observed for those targets having a high range velocity component. If the position error is not adequately compensated, association errors between SAR and AIS contacts may occur. A possible way[2] to address the azimuth shift error is to consider only the AIS contact acquired at the closest time to the SAR from the vessel AIS tracks within the area of interest and the AIS contact position is compensated for the estimated azimuth shift using the SOG and COG of the AIS report.

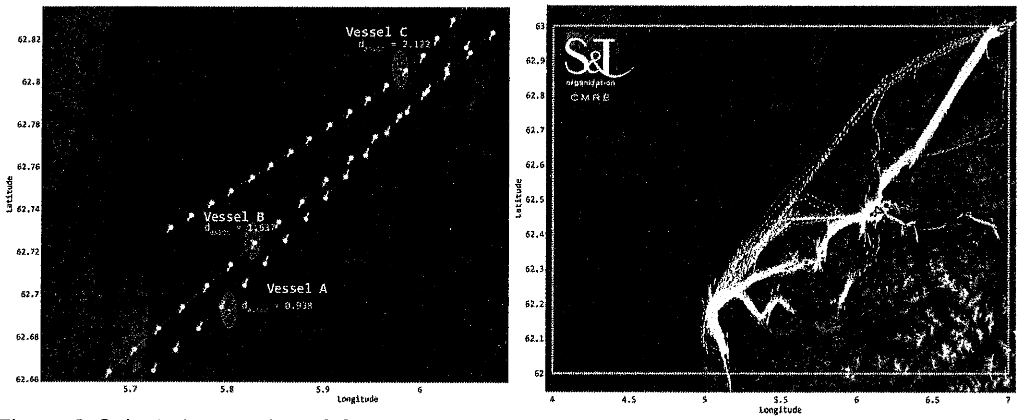

Figure 3 Selected examples of SAR associations in open sea (left) and recurrent routes of the vessels transiting in the area of interest, derived via TREAD algorithm (right)

4.2 Case II – Using contextual information to resolve possible anomalies (B and C)

Sometimes the correlation of SAR detections with AIS reports is a more controversial task. This is the case of the two SAR detections, whose corresponding AIS reports, shown in Figure 3 as vessel B and C, are compatible in position and time. Nonetheless, the function values $d_{\text{assoc}} = 2.122$ and $d_{\text{assoc}} = 1.637$ are both above the confidence threshold $d_{\text{assoc}}^{\text{MAX}} = 1$. This is due mostly to the discrepancy between SAR and AIS reported heading. Specifically, considering that reported AIS and SAR headings, in both cases, differ by approximately 90 degrees and taking into account the 180 degrees ambiguity for the estimation of the heading from the SAR image, these two examples represent worst-case scenarios. However, when crosschecking the historical contextual information, in the form of traffic routes extracted by the TREAD algorithm, a different conclusion can be drawn.

The above-mentioned ships are both oil/chemical tankers, more than 120m long, so it seems very unlikely that the processing algorithm of the SAR image could have missed them; moreover, the positions fall within the area of influence of a well-known route transited by tankers, as highlighted in the red square in the right plot in Figure 3. In addition to that, it seems even less likely that another ship, as big as the other two, is crossing the same route (due to its heading) and even less likely that a ship different from a cargo or tanker is travelling in such an area and has been detected by the SAR image processing algorithm.

Thus, by integrating AIS and SAR information together with the contextual traffic knowledge in the area it seems very unlikely that these are anomalies. Instead they are simply SAR detections for which the heading estimates are inaccurate.

4.3 Case III – Resolving multiple possible associations within the search radius

The proposed approach enables the correlation of SAR and AIS detections also in highly dense traffic areas, as in the case of inshore areas. In fact, the methodology for ranking a possible correlation between reported SAR and AIS positions performs well also if more than one AIS position is candidate to be correlated with the SAR detection, provided that the heading values reported by AIS and SAR are not completely out of phase.

In these cases, as shown in Figure 4, the association function plays a key role since, in absence of further information, the association of the SAR detection is made with the nearest AIS position, *i.e.*

with the AIS report showing the lowest value for the association function d_{assoc}. Moreover, the speed of the vessels is lower when close to the coast line, compared to open sea scenario, and, hence, the possible error in azimuth can be considered negligible.

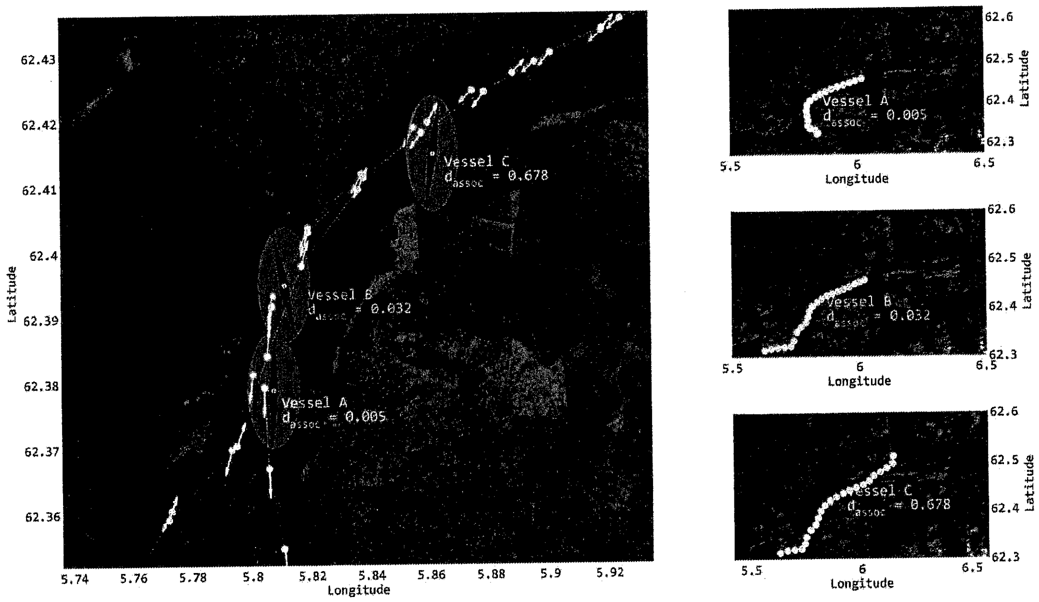

Figure 4 Selected examples of SAR associations close to the coastal area: vessel A is a tug boat, B is a general cargo and C is a chemical tanker.

5 CONCLUSIONS AND FINAL REMARKS

A heuristic methodology was presented to provide an insight into the operational use of SAR detections for maritime traffic anomaly detection in the maritime domain. The proposed approach can work in areas where only sparse data are available, such as in the open sea, and in areas where dense data are available. For the case of sparse data, incorporating historical traffic pattern data as contextual information can help resolve possible anomalies. For the case of dense data, an over-abundance of possible associations can be addressed effectively by the proposed association process.

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7 REFERENCES

1. Use and Analyse of satellite SAR images, http://www.cedre.fr/en/publication/conference/guide-sat.pdf, accessed on June 10th 2014.
2. R. Grasso, S. Mirra, A. Baldacci, J. Horstmann, M. Coffin, M. Jarvis, Performance Assessment of a Mathematical Morphology Ship Detection Algorithm for SAR Images through Comparison with AIS Data, ISDA, 602-607, (2009).

3. M. Guerriero, P. Willett, S. Coraluppi and C. Carthel, Radar/AIS data fusion and SAR tasking for Maritime Surveillance, Proc. 11th Intern. Conf. on Inform. Fusion (FUSION), 1-5 (June2008).
4. F. Mazzarella, A. Alessandrini, H. Greidanus, M. Alvarez, P. Argentieri, D. Nappo, L. Ziemba, Data Fusion for Wide-Area Maritime Surveillance, Proc. COST MOVE, Brest, (2013).
5. G. Margarit and A. Tabasco, Ship Classification in Single-Pol SAR Images Based on Fuzzy Logic, Geoscience and Remote Sensing, IEEE Trans. on , Vol. 49, 3129-3138, (2011).
6. G. Hajduch, P. Leilde and V. Kerbaol. Ship detection on ENVISAT ASAR data: results, limitations and Perspectives, Proc. SEASAR (2006).
7. G. Pallotta, M. Vespe, and K. Bryan, Vessel pattern knowledge discovery from AIS data: A framework for anomaly detection and route prediction, Entropy, vol. 6, pp. 2218-2245, (2013).
8. G. Pallotta, M. Vespe, and K. Bryan, Traffic knowledge discovery from AIS data, Proc. 16th Intern. Conf. on Inform. Fusion (FUSION), Istanbul, Turkey, (July2013).
9. G. Pallotta, S. Horn, P. Braca and K. Bryan, Context-Enhanced Vessel Prediction Based On Ornstein-Uhlenbeck Processes Using Historical AIS Traffic Patterns: Real-World Experimental Results, Proc. 17th Intern. Conf. on Inform. Fusion. (FUSION), Salamanca, Spain, (July2014).
10. NEREIDS project website, http://www.nereids-fp7.eu/, accessed on May 26th 2014.
11. MSSIS website, https://mssis.volpe.dot.gov/Main/home/, accessed on June 11th 2014.
12. G. Pallotta, I. Visentini, K. Bryan, S. Horn, The NEREIDS project for enhancing Maritime Surveillance using Satellite-based observations, CMRE Tech. Report, CMRE-SWP-004 (2014).
13. M. Riveiro and G. Falkman, Detecting anomalous behaviour in sea traffic: A study of analytical strategies and their implications for surveillance systems, International Journal of Information Technology & Decision Making, pp. 1–44, (2014).