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Ship Safety Management Using Mobile Applications with Cloud and Big Data Environment

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ABSTRACT: In this system, we tend to use huge information with final server storage capability. Our datasets indicate the GeoSpace nature, which can be regenerate into compression mean by suggests that of SVM classifier and trimming operate. The abstraction question possibility is employed for looking out the resultant information from the large information server. The advance in Maritime Situational Awareness, the potential of understanding events, circumstances, and activities inside and impacting the maritime atmosphere, is today of predominant importance for safety and security. the mixing of area borne artificial aperture radiolocation (SAR) information and automatic identification system (AIS) data has the appealing potential to supply a much better image of what's happening embarrassed by police work vessels that aren't reportage their positioning information or, on the opposite facet, by confirmative ships detected in satellite mental imagery. During this approach, we tend to propose a unique design that's able to increase the standard of SAR/AIS fusion by exploiting information of historical vessel positioning data. Experimental results square measure conferred, testing the rule within the specific space of capital of Delaware Strait exploitation real SAR and AIS information. For all the entire system deals with manipulation of GeoSpace Dataset with two powerful classification algorithms to predict the future analysis of the marine vessels, the algorithms are C4.5 and Support Vector Machine (SVM).

KEYWORDS: component; marine traffic; AIS; MobileAIS; SmartAIS; SmartShips; cloud; bigdata; analytics; mobile application; VSAT; GPS; NMEA; cognitive.

I. INTRODUCTION

The collection of maritime positioning data from self reporting systems such as the automatic identification system (AIS), although subject to reliability and manipulation issues, is providing a wealth of data for Maritime Situational Awareness (MSA). In particular, the AIS is mandatory for a portion of traffic, which is identified by ships of 300 gross tons and above in international voyages and 500 tons and above for cargoes not in international waters and passenger vessels. In addition, all EU fishing vessels of overall length exceeding 15 m have been required to be equipped with AIS since May 2014. The information content of self-reporting data, apart from the state vector and other kinematic information, may also include voyage-related (e.g., destination, estimated time of arrival, etc.) and static (e.g., size, ship type, etc.) information about the ship.

Synthetic aperture radar (SAR) is a radar technique that, in the remote sensing context, takes high-resolution images of the Earth's surface from an aerial or space platform. It is operationally used in, among others, maritime surveillance applications, where it can detect non-cooperative vessels, during day and night, and through clouds. Space borne SAR sensors have a global coverage, although at any one moment, they can only monitor an area that ranges from a few tens to a few hundreds of kilometers wide. Additional shortcomings of spaceborne SAR are their long tasking and update times and the fact that most SAR satellites fly in the same dawn–dusk orbit, which limits the observation opportunities.

AIS and spaceborne SAR clearly have their own advantages and weaknesses, and a level of integration and fusion can overcome the limitations of each one. AIS data have previously been used as non automatic ground-truth verification for ships detected in SAR imagery, but the fusion between observation based and self-reporting data has much more to offer in terms of surveillance. It is well known that one of the main issues with cooperative systems is the possibility



(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 5, May 2016

for malicious users to behave non-cooperatively during illegal operations by switching off their devices or spoofing their own identity. Moreover, illegal activities could be accomplished by using small ships that are not obliged to mount an AIS transponder on board. These non-reporting ships can be detected from SAR images, as described. On the other hand, ships not detected by SAR might be broadcasting AIS messages.

Current state-of-the-art data fusion algorithms mainly rely on 1) the AIS position projection step, aiming at deriving the ship position at the SAR image acquisition time, and 2) the matching step, aiming at associating the positions extracted from a SAR image and the projected AIS reports. Existing prediction methods based on dead reckoning use the zero-order, first-order, and second-order derivative polynomial models to model ship anchoring, straight-line motion with uniform speed, and uniform acceleration speed, respectively. In more complex models based on the Gray Systems Theory have been proposed. Actual methods for matching use nearest neighbor (NN), point pattern matching and fuzzy logic techniques based either on positioning information or ships' multiple features (heading, speed, and size).

II. PURPOSE OF WORKING

The purpose of this letter is to present architecture for SAR ship detections and self-reporting data fusion using a knowledge-based (KB) AIS position projection step, as preliminarily explored. In particular, the proposed algorithm exploits the maritime traffic patterns extracted from historical self-reporting AIS data, as described, to project AIS positions to the SAR image acquisition time. The matching step, instead, is based on the well-known global NN (GNN) criterion applied both on positioning information and ships' multiple features. We apply the proposed strategy to a real scenario in the specific area of Dover Strait by using historical traffic data extracted, and we show that our architecture outperforms the most prevailing linear-propagation-based technique both in terms of AIS projection accuracy and of correct SAR/AIS associations.

Here, we describe an architecture aimed at fusing SAR ship detections and self-reporting system data by exploiting knowledge of traffic patterns regulating the area under analysis. The proposed approach, as depicted in Fig. 1, relies on ship detections obtained from SAR imagery through an ad hoc vessel detection system (VDS), self-reporting system data stored in a database (DB), and traffic patterns extracted by a knowledge discovery process.

SHIP DETECTION

The Joint Research Centre's in-house VDS (called SUMO) have been used for the detection of the ships in the SAR images. SUMO can analyze images from most of the current SAR satellites. There are three steps in the processing. First, the land areas in the image are masked out. Then, a constant false alarm rate detector is applied to the sea areas, after modeling the sea background using the K-distribution. A false alarm rate of 10-7 has been empirically chosen, along the lines of typical values suggested. Finally, vessel discrimination is used to reduce the number of false alarms and to cluster the detected pixels into ships. For the ith detected ship, SUMO outputs a vector Dvds, $i = {xi, yi, li, wi, hi}$ containing its geographical location (longitude and latitude) and estimates of its length, width, and heading, respectively.

TRAFFIC KNOWLEDGE

The recent buildup of terrestrial networks and satellite constellations of AIS receivers provides a rich source of cooperative vessel movement information. Self-reporting data can be processed to infer different levels of contextual information, ranging from the identification of ports and offshore platforms to spatial and temporal distributions of traffic routes. In Pallotta et al. presented a methodology to extract the historical traffic patterns from AIS data by using an unsupervised and incremental learning approach. The same knowledge discovery approach is used to produce hierarchical graph-based representations of maritime shipping lanes. The output of the traffic knowledge process in Fig. 1 exploits the outcomes of the algorithm, i.e., a set of N routes, $\{Ri\}N i=1$.

SAR/AIS DATA FUSION

The core of the architecture in Fig. 1 is the data fusion between ships detected from SAR imagery and selfreporting observations. In the remainder of this letter, without loss of generality, we refer only to AIS observations, i.e., xAIS, that are gathered and stored in a DB structure, as well as the set of ship detections Dvds and the set of SAR images metadata I. In the following, we discuss in detail the proposed Algorithm 1.



(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 5, May 2016

Algorithm 1 KB Fusion

Require: $\mathbf{I}_l, \mathbf{D}_{vds}, \mathbf{x}_{AIS}, \{R_i\}_{i=1}^N, \Delta_w, \delta, k, \epsilon, d_{th}$ 1: $R \leftarrow []$ 2: $\mathbf{V} \leftarrow DataExtraction(\mathbf{x}_{AIS}, \mathbf{I}_l, \Delta_w)$ 3: for j = 1 to length (V) do 4: $[\mathbf{P}_j(1), \Delta_t] \leftarrow FindClosestPoint(\mathbf{V}_j, T_{SAR})$ 5: $N_C \leftarrow [|\Delta_t|/\delta]$ 6: $\hat{R} \leftarrow RouteClassification(\mathbf{V}_i, \{R_i\}_{i=1}^N, k, \epsilon)$ 7: for n = 1 to N_C do 8: if is empty (\hat{R}) then $\mathbf{P}_{j}(n+1) \leftarrow LinearPropagation(\mathbf{P}_{j}(n))$ 9: 10: else $\mathbf{P}_{i}(n+1) \leftarrow KBPropagation(\mathbf{P}_{i}(n), \widetilde{COG})$ 11: 12. end if 13: end for 14: $\mathbf{P}_i(T_{SAR}) \leftarrow \mathbf{P}_i(N_C)$ 15: $\mathbf{P}_{j,c}(T_{SAR}) \leftarrow DopplerShiftCorr(\mathbf{P}_{j}(T_{SAR}), \mathbf{I}_{l})$ 16: end for 17: $\mathbf{A} \leftarrow GnnAssociation(\mathbf{P}_{c}(T_{SAB}), \mathbf{D}_{vds}, d_{th})$

III. EXISTING SYSTEM

Difficult to maintain the periodic updations from moving vessels, because of the mobility of the ship. Data Duplication causes the failure in Big Data Server. Data Repetition takes more and more time to process the information retrieval. For all the above notions this system produces only slow results, which automatically leads into low Performance. While implementing this same system into practical means we have to spend huge cost.

Disadvantages:

o Low Performance o Privacy is missing o Time taken process o Cost Expensive Methodology



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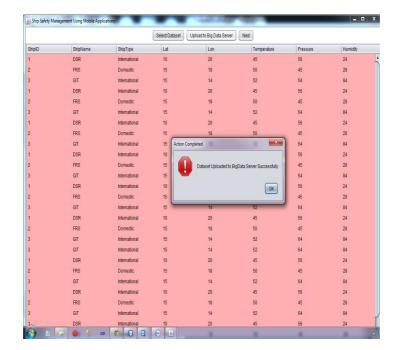
Vol. 4, Issue 5, May 2016

IV. PROPOSED SYSTEM

In proposed approach we maintain two servers in virtual place called Intra Server and Inter Server. Whenever the signal between ship and control room is available the inter communication process is in progressing and update all the periodic information into the remote server. Whenever the signal between ship and control room is low, then the ship communication protocol pass the message alert to the control room regarding the position and speed of the ship, then performing the intra communication. No Data lost occurs. Cost efficient and best performance processing. *Advantages:*

- o User friendly methodology
- o Privacy preserving scheme
- o Cost effective methodology
- o Failure Free Data Maintenance

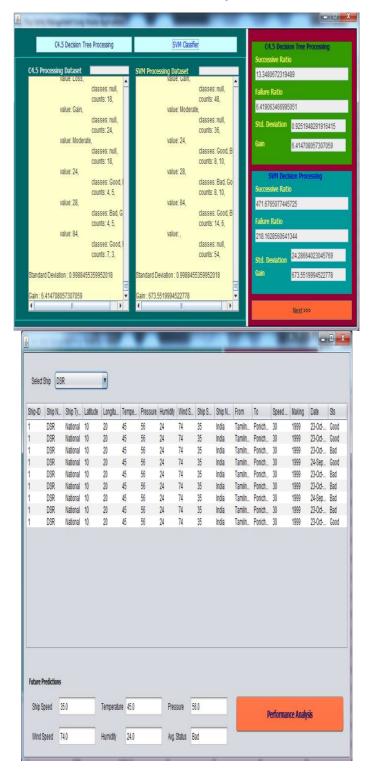
V. EXPERIMENTAL RESULTS





(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 5, May 2016

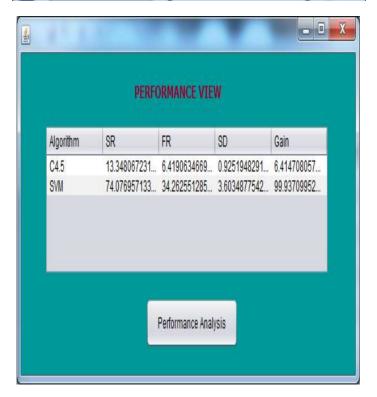




(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 5, May 2016

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	GIT	National	15	14	52	64	84	65	45	India	Thanja	Pudukk	40	2011	23-0d	Bad
	GIT	National	15	14	52	64	84	65	45	India	Thanja	Pudukk	40	2011	23-0d	Good
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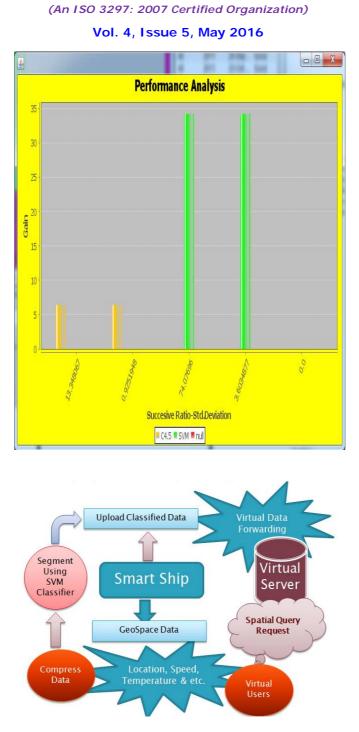


Fig.1. System Design

VI.CONCLUSION

This system has shown the relevance of maritime traffic knowledge on the SAR ship detection and self-reporting data fusion. We have demonstrated through real data and an objective comparison with the most popular linear-propagationbased strategy that it is possible to increase the quality of correlation by exploiting knowledge of historical traffic patterns to project self-reported AIS observations to the SAR image acquisition time. In addition, the performance gain increases with the complexity of the routing system regulating the traffic in the area of interest.



(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 5, May 2016

References

[1] Density map info sheet, exactearth, unpublishing.

[2] Review of Maritime Transport 2013, United Nations Conference on Trade and Development. ISBN 978-92-1-112872-7.

[3] Lloyd's Register Fairplay (1900-2010) World Fleet Statistics, Redhill: Lloyd's Register Fairplay Ltd, unpublishing.

[4] Safety and Shipping 1912-2012: From Titanic to Costa Concordia, Allianz Global Corporate & Specialty, 2012, unpublished.

[5] A. García-Domínguez "Smart ships-mobile applications, cloud and bigdata on marine traffic for increased safety and optimized costs operations", In

Proceedings of the 2014 2nd International Conference on Artificial Intelligence, Modelling and Simulation (AIMS'14). IEEE Computer Society

[6] G International Hydrographic Bureau (February 2008). IHO Standards for Hydrographic Surveys (5th Edition).

[7] Robert A. Nelson, The Global Positioning System, November 1999.

[8] http://www.esa.int/Our_Activities/Navigation/The_future_Galileo/What_is_Galileo, accessed October 2014.

[9] SOLAS'1974, December 2000 amendments.

[10] Radar Technology, Guy Kouemou (Ed.), InTech, 2010, ISBN 978-953-307-029-2.