Vessel Profile Indicators using Fuzzy Logic Reasoning and AIS

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***Abstract*— Early vessel profiling and risk assessment is a critical component of advanced maritime tracking systems, required by a number of maritime stakeholders including custom controls, port authorities, coastguards and others. This paper reports on the development of a fuzzy logic reasoning tool for generating maritime vessel profile indicators through the Automatic Identification System (AIS). The report describes the need and the underlying statistical methods applied, which are based on Fuzzy Logic Reasoning, for finding potential profile indicators and classifying vessels to a degree of "risk", thus requiring further examination and monitoring. Under conservative assumptions, some preliminary results about the probabilities and boundaries of potential indicators are presented and discussed.**

Keywords-AIS; Maritime Domain Awareness; Anomaly Detection; Fuzzy Logic System.

I. INTRODUCTION

Maritime Domain Awareness (MDA) is the effective understanding of activities, events and threats in the maritime environment that could impact global safety, security, economic activity or the environment [1]. Recent advancements in Information and Communications Technologies (ICT) have created opportunities for increasing MDA, through better monitoring and understanding of vessel movements. The International Maritime Organisation (IMO) identified this issue as affecting the safety and efficiency of navigation and initiated a work program named e-Navigation to reduce the "confusion of profusion". The IMO defines e-Navigation as: "the harmonised collection, integration, exchange, presentation and analysis of maritime information onboard and ashore by electronic means to enhance berth to berth navigation and related services, for safety and security at sea and protection of the marine environment" [2]. e-Navigation is expected to contribute to safer waterways, reducing accidents and environmental incidents through improved situational and traffic awareness both afloat and ashore [3].

Sea transport surveillance has been ineffective in the past decades due to lack of data, but nowadays tracking technology (i.e., Automatic Identification System, AIS) has transformed the problem into one of data overload [4]. For the last decade AIS has been inseparable part of the modern maritime industry. The original purpose of the system was to reduce collision risks, by providing vessels' crews the necessary traffic information. The AIS transponders are capable of communicating in range of a few kilometres (i.e., less than 50km) and although the AIS system was not designed to be monitored in a centralised method, the maritime industry has been extremely interested in such systems (e.g., MarineTraffic, etc.).

Positional data together with the departure and destination ports transmitted in AIS messages can be used for route prediction and in conjunction with vessel's speed, time of arrival prediction is possible. Performing complex operations over such large datasets can give extra insights besides route prediction. For instance, combining route forecasts for multiple vessels can provide early warnings of possible collisions (by determining whether vessels' routes will meet in space and time) and actual route data can be used to perform various kinds of complex analytics (e.g., root-cause analysis in case of forensic investigation). In addition, improving the route analysis process can offer to various maritime stakeholders (e.g., shipping companies, charterers, insurance companies and port authorities) the opportunity to perform risk analysis and understand better any possible threats of vessels' manoeuvres, or even perform environment impact assessment, providing CO_2 emissions and fuel consumption predictions. Ultimately, AIS historical data can be used to determine actual sea lanes, their capacity and port connections, produce realistic vessel operational profiles that determine the normal behaviour of specific vessel types, detect any anomalies (i.e., irregular behaviour) and much more.

Anomaly is a "strange" deviation from a vessel's normal behaviour, meaning that it is inconsistent with, or straying from what is usual, normal or expected, or because it is not conforming to rules, laws or regulations [5]. Detecting an anomaly can be defined as a method that supports situation assessment by indicating objects and situations that deviate from the expected behaviour and thus may be of interest for further investigation. The understanding of the complex maritime environment and a vessel normal behaviour though, can never be limited to simply adding up and connecting various vessel positions as they travel across the seas. A combination of static information such as reporting information, vessel's flag (i.e., country), ship's owner, vessel's name, IMO and Maritime Mobile Service Identity (MMSI) and destination port with dynamic information such as speed/course changes, proximity with other vessels or structures, etc., is needed to classify possible abnormal ship's behaviour. An anomaly can be classified as either static or dynamic depending on the vessel's characteristics that distinguish the behaviour as anomaly. Static anomalies are related to vessel's identification information mismatches or irregular changes. This information includes vessel's flag, IMO, MMSI, vessel's name and owner company. In addition, irregular changes in destination reported from AIS messages (particularly when the vessel is under-way) is a potential indicator of risk. Combining such information with port inspections or incident reports that prove vessels are not conforming to regulations can also assist in anomaly detection; thus, classifying a vessel as potentially riskier than others and worthy of further investigation and monitoring. Dynamic anomalies are mostly related to vessels' voyages and deviations from these. Speed or course changes, proximity with other vessels, and mismatches between the ship type and the sea lane (or zone) travelling are aspects that could constitute a dynamic anomaly.

In this paper, we propose a decision support system that evaluates modifications of vessel identities and mismatches between reported destinations and actual port calls to determine possible risks (i.e., static anomalies). As this is a complex problem that requires the evaluation of multiple criteria while relying on inexact or partial knowledge obtained from the analysis of the AIS messages, we introduce a fuzzy-logic based mechanism that maritime stakeholders can use to detect risk indicators and classify vessels.

The rest of this paper is structured as follows; Section II provides the state-of-the-art analysis for anomaly detection. Then, Section III presents the proposed Fuzzy Logic (FL) Reasoner and Section IV provides the analysis of the correlation of the FL inputs with the produced output. Finally, Section V concludes our work and discusses possible future extensions.

II. RELATED WORK

Static anomaly detection is mostly treated as a decision-making process driven by risk identification/assessment in the related literature. Two classes of solutions are dominant in this perspective; the ones relying on probabilistic risk assessment and the ones using fuzzy logic as a relaxation approach to the definite boundaries of probabilistic approaches. Probabilistic risk assessment has been introduced as a solution for the assessment of risk in the maritime domain in [6]. In [7], the authors applied a Bayesian simulation for the occurrence of situations with accident potential and a Bayesian multivariate regression analysis of the relationship between factors describing these situations and expert judgments of accident risk, to perform a full-scale assessment of risk and uncertainty. A fuzzy approach that evaluates the maritime risk assessment when applied to safety at sea and more particularly, the pollution prevention on the open sea is introduced in [8]. The proposed decision-making system exploits a set of open datasets combined with human expert experience to perform information analysis and define the risk factor. Besides this solution, other approaches [9][10] also rely on Fuzzy-Bayesian networks to model maritime security risks.

Dynamic anomaly detection is highly related to efficiently handling vast amount of mostly positional data. Previous works have been focused on extracting knowledge regarding motion patterns from AIS data in support of MDA including numerous methods of supervised and unsupervised clustering data mining techniques. In their work [11], Pallotta et al. propose the TREAD methodology as a method of automatically learning a statistical model for maritime traffic from AIS data in an unsupervised way as a framework for anomaly detection and route prediction. A statistical analysis upon AIS data to extract motion patterns, predict vessel movements and detect possible anomalies in their itineraries is introduced in [12]. In relation to AIS and sea ports research, AIS data are used in [13] to model maritime terminals operations, specifically focusing on the Port of Messina. In [14], the authors introduce a two-step methodology for anomaly detection that attempts to deal with the scalability issues caused by the vast amount of raw AIS data by distributing the learning process. Firstly, a density-based clustering algorithm that uses spatial and voyage information is used to distinguish "normal" vessel positions from the "abnormal". Then, the labelled dataset is fed as training data into a distributed supervised learning algorithm running on Hadoop.

Spatial join queries, which combine trajectory datasets and a spatial objects dataset based on spatio-temporal predicates, have high computational requirements, which often lead to long query latencies. In [15], Ray et al. propose a parallel in-memory trajectory-based Spatiotemporal Topological join (PISTON), a parallel main memory query execution infrastructure designed specifically to address the difficulties of spatio-temporal joins. Generally, the methods which are used in the context of anomaly detection are based on statistical/probabilistic models [16]–[19], such as the Gaussian Mixture Model (GMM) and the adaptive Kernel Density Estimator (KDE) [12][20], Bayesian networks [21]–[24], but also neural networks [25]–[27] and hybrid approaches [28].

A number of prototype systems have been developed for experimental and operational reasons. For example, SeeCoast [29] is installed at Kount Harbor Operations Center in Portsmouth, Virginia. The system uses the Hawkeye system to fuse video data with radar signals and AIS messages to produce fused vessel tracks in or close by the port and reliably detect anomalies on such tracks. SCANMARIS [30] is a feedback-based system tested at "Centre Régional Opérationnel de Surveillance et Sauvetage Corsen" on Ouessant traffic management. It uses a rule-based learning engine to process data fused from maritime traffic imagery, alert operators based on the rules defining anomalies and adapt its operation through the operators' feedback. LEPER [31], which was tested successfully at the Joint Interagency Task Force South (JIATF South), is a system that performs primitive geohashing using a military grid reference system upon which it decomposes ship's trajectories into sequences of discrete squares and uses Hidden Markov Model to calculate transition probabilities between grid locations. The predicted location is compared with the vessel's position (determined by the speed and heading of the vessel) and if the distance between these two positions is above a predefined threshold, an anomaly is raised. Other notable prototypes that currently exist are SECMAR [32], FastC2AP [33] and MALEF [34].

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In our work, we introduce a Fuzzy Logic Reasoner in which the thresholds of the Fuzzy Logic Rules are based on statistical analysis and not on experts' view.

III. Fuzzy Logic Reasoner for Anomaly Detection

Fuzzy logic was first introduced in [35] by Lotfi Zadeh and relies on the theory of fuzzy sets. Contrary to the classical set theory, such sets contain element with degree of membership. This approach exploits the notion of degree in the verification of a condition, enabling conditions to be in intermediate states between the states of conventional evaluations, thus allowing variables to be "partially" true, or "not definitely yes" etc. Such notions can be formulated mathematically and processed by machines, giving thus a more human-like interaction between the programmer and the computers [36]. Fuzzy logic has been selected for static anomaly detection as it is considered to be an ideal tool when dealing with imprecise or contradictive data, which can be modelled adequately with fuzzy sets, and combined with human logic [37].

A Fuzzy Inference System (FIS) is the fundamental implementation of fuzzy logic schemes comprising three key elements, namely the fuzzifier, the inference engine and the defuzzifier. The first element is responsible for transforming crisp values (e.g., real, integer, natural number, etc.) to fuzzy degrees of membership to states (i.e., values between the [0,1] interval). Then, the inference engine exploits a set of if-then rules compiled by experts to link the inputs with the outputs and afterwards it collects and aggregates all the outputs of every rule into one fuzzy set. Multiple aggregation schemes have been proposed and applied relying on the maximum value, summing up the outputs or performing a probabilistic analysis on the produced fuzzy set. The sum aggregation is the most common one and also the one applied in our Fuzzy Reasoner. Finally, the defuzzifier aggregates the outcomes of all the fuzzy rules defuzzifies them to a single crisp value which is the output of the Fuzzy Reasoner.

Thus, in order to define the FIS, the set of inputs and the output of the rule set should be defined. In the context of static anomaly detection, the inputs are the vessels' static characteristics and the output is the fuzzy anomaly detection indicator. Table I sums up the rule set that drives the Fuzzy Inference System. Each rule is a union of conditions that when met the corresponding output is triggered (based also on the fuzzy degree). Thus, each set of input values may match to multiple rules with a certain degree. The defuzzifier will take this fact into account when transforming the fuzzy values into a crisp output.

The proposed Fuzzy Reasoner (FR) produces a vessel anomaly indicator which captures the behavior of the vessel according to its static characteristics. The FR takes into consideration three inputs, namely "flag changes frequency", "name changes frequency" and "destination changed/port arrival deviation". "Flag changes frequency" captures how many times a vessel has changed its flag over a specific time period. Although this is not a de facto metric of abnormal behavior, frequent changes may be linked with fraudulent registrations or other illegal activities [38]. Furthermore, in order to minimize the probability of false negative cases (i.e., falsely assuming a vessel to be performing abnormaly), we take into account only flags that according to Paris MoU organization perform poorly [39]. "Name changes frequency", similarly to the previous input is the input that captures how many times a vessel has transmitted a different vessel name through its AIS transponder in a specific time period and it is another indicator that a vessel may be trying to spoof its messages and hide its identity (e.g. O Ka San vessel that falsely transmitted its name to be Sarisa) [38]. Destination changed/Port Arrivals deviation: This input captures the mismatches between the number of destination ports a vessel reports through its AIS transponder compared to actual port arrivals. The latter have been produced through spatial analysis of the vessels' reported positions and the ports locations. The metric for this input is calculated based on. (1). Finally, the output of the Fuzzy Inference engine is an indicator for vessel anomaly that the related stakeholders should further investigate its compliance to international safety, security and environmental standards.

$$\text{Deviation} = 1 - \#\text{Dest\_changed} / \#\text{Port\_Arrivals} \quad (1)$$

As depicted in Table I, we have selected two Membership Functions for the first two inputs labeled as Low and High and three Membership functions (i.e., Low, Normal and High) for the third input. This decision was due to the nature of the inputs. More specifically, "flag change frequency" and "name change frequency" are bounded in the [0, +∞) range with zero being the less risky situation (i.e., normal) while the "destination changed/port arrival deviation" is bounded in the [-∞, 1) range with zero being the normal situation, in which case the reported number of destinations is equal to the actual port arrivals.

TABLE I. FUZZY LOGIC RULES

Rule No.	**Inputs**			**Output**
	Flag changes frequency	***Name change frequency***	***Destination changed/Port Arrivals deviation***	***Vessel anomaly indicator***
1	Low	Low	Low	Medium
2	Low	Low	Normal	Low
3	Low	Low	High	Medium
4	Low	High	Low	Medium
5	Low	High	Normal	Low
6	Low	High	High	Medium
7	High	Low	Low	High
8	High	Low	Normal	Medium
9	High	Low	High	High
10	High	High	Low	High
11	High	High	Normal	High
12	High	High	High	High

Although the Fuzzy Logic ruleset is compiled by experts, determining the shapes and the boundaries of the membership functions for each input is a difficult process that should be carefully designed. In our approach, shapes and boundaries are determined based on statistical analysis of observed flag changes, name changes and destination changed/port arrivals mismatches. The data used in this study is an AIS dataset provided by MarineTraffic, covering the entire globe and collected during 2017.

Multiple shapes for the membership functions can be used relying on the nature of each input (i.e., the data distribution) with the triangular, trapezoidal and Gaussian being the most commonly used. In our system, triangular membership functions have been used for the flag change frequency and the name change frequency, because at certain values we are certain about the state that they are capturing. On the other hand, for the destination changed/port arrivals input gaussian membership function has been used for exploiting the continuous and non-negative nature of this membership function at the definition domain. Finally, Gaussian membership function has also been applied on the output for its smoothness in the decision-making process.

In order to determine the boundaries of the Membership Functions of each input, we have calculated the probability distribution of each input. Figure 1, Figure 2 and Figure 3 show the Cumulative Distribution Function (CDF) for the vessel flag changes, name changes and destination reported/arrival deviation respectively. As shown in Figure 1, most of the vessels (i.e., 91%) have made one or two flag changes in 2017, thus the boundary between the low and the high membership function of this input is set to two.

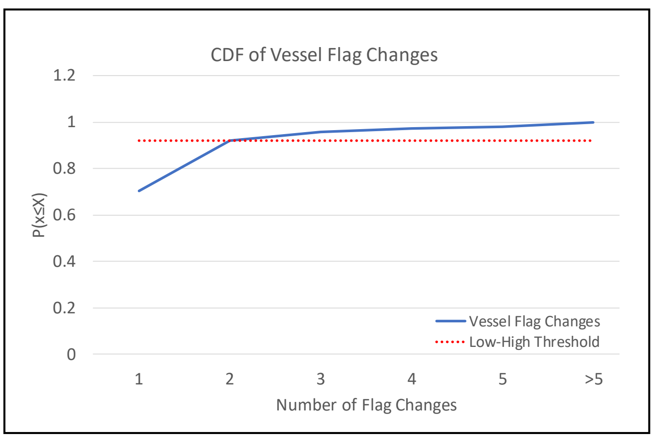

Figure 1. Cumulative Distribution Function of number of vessel flag changes

Figure 2 highlights the CDF for the Vessel name changes. The curve in this case is smoother compared to the Flag Changes and most of the vessels (i.e., 89%) have four or less name changes in a full year. Thus, the boundary between Low and High is set to four for this input.

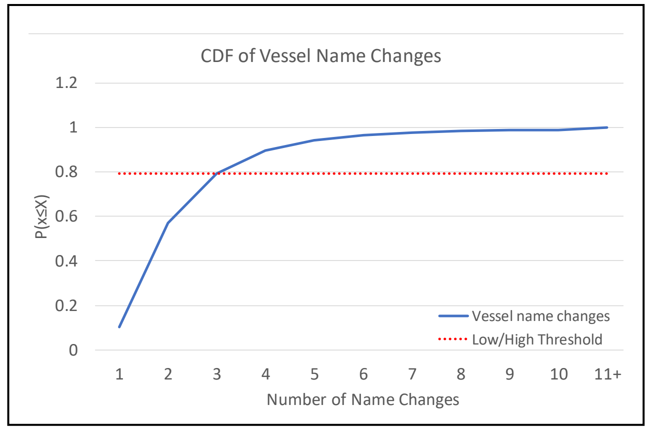

Figure 2. Cumulative Distribution Function of number of vessel name changes

Finally, Figure 3 highlights the CDF for the destination reported/port arrival deviation. This input is calculated based on (1) and normal behavior for a vessel would result in deviation equal, or near to zero. There are two cases of anomalies included in (1). If the deviation is near 1 then the destinations reported are much less than the actual arrivals which implies that the vessel's crew is not reporting vessel's itineraries. On the other hand, if the deviation is negative for a vessel, then this means that it changes its destination more frequently than its actual voyages, which is an abnormal and possibly risky situation. Thus, in this case we have three membership functions, Low, Normal and High capturing these three possible situations. The boundaries are such that Low and High deviation correspond to 7.5% of the vessels each and Normal corresponds to 85%.

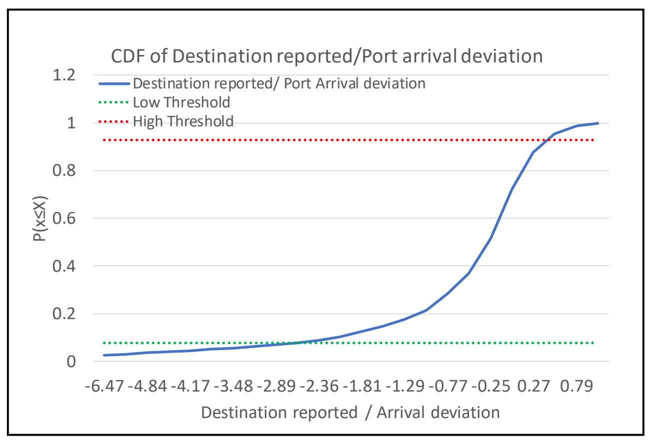

Figure 3. Cumulative Distribution Function of destination reported/port arrival deviation

IV. Discussion and Conclusions

Detection and classification of vessels to profiles of vessels requiring further monitoring is a requirement of many maritime authorities. In this work, we suggest a tool which makes use of Fuzzy Logic Reasoning and exploits open maritime tracking data, such as that collected through the AIS to build such indicators.

We notice that frequent flag and vessel name changes are strong indicators of vessels operating outside normal behavioral patterns. Specifically based on the distribution and while taking into account the uncertainty of the data, we detect that most of the vessels (i.e., 89%) have four or less name changes in a full year, while the majority of vessels (i.e., 91%) have made one or two flag changes. Our broader goal is that of building an expert system of automatic anomaly detection for both positional and static data transmitted by vessels, which would increase the effectiveness of the system and high-level situational understanding. In our future work, we will perform thorough experimental evaluations of our fuzzy inference algorithms in combination with positional anomaly detection.

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