Research Note

Application of Machine Learning and Artificial Intelligence for Automatic Identification System (AIS) Database

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Background

Artificial Intelligence : The word Artificial Intelligence comprises of two words “Artificial” and “Intelligence”. Artificial refers to something which is made by human or non-natural thing and Intelligence means ability to understand or think. There is a misconception that Artificial Intelligence is a system, but it is not a system. AI is implemented in the system. There can be so many definition of AI, one definition can be ***“It is the study of how to train the computers so that computers can do things which at present human can do better.”***

Machine Learning : Machine Learning is the learning in which machine can learn on its own, without being explicitly programmed. Here we can generate a program by integrating input and output of that program. Machine learning is a method of data analysis that automates analytical model building. It is a branch of artificial intelligence based on the idea that systems can learn from data, identify patterns and make decisions with minimal human intervention [1]. One of the simple definition of the Machine Learning is ***“Machine Learning is said to learn from experience E w.r.t some class of task T and a performance measure P if learners performance at the task in the class as measured by P improves with experiences.”***

Need for ML and AI in Maritime Industry:

Artificial intelligence (AI) can collect and analyze data for the container shipping industry to chalk out plans more accurately. AI is pursued as the digital game changer in a variety of industries, which can render effective support to containerized supply chains with in-time transits and equipment availability.

AI’s use in the marine industry is not just limited to big business. It can help play a huge role in disaster assistance, rescue and relief too. The ability of AI to study massive amounts of raw data, infer patterns, and come up with various data models can be used to analyze the data collected by AIS and work on it.

Automatic Identification System (AIS) is a tool for monitoring and identifying maritime traffic which uses transponders to send messages through Very High Frequency (VHF) marine bandwidth [2,4]. AIS is transmitted on two worldwide reserved channels in marine VHF allocation - 87B and 88B [5]. AIS was primarily designed to operate in one of the following modes:

- In a ship-to-ship mode for collision avoidance.
- As a means for coastal states to obtain information about a ship and its cargo.
- As a traffic management tool when integrated with a Vessel Traffic System (VTS) [6].

The transponder in AIS is linked with a Global Navigation Satellite System (GNSS) which computes its location as well as external sensors (electronic compass for instance) in order to fill in several data fields within the messages [2]. Originally, AIS was used terrestrially, meaning the signal was sent from the boat to land, and had a range of roughly 40 nautical miles (74 km). As ships began sailing further and further away from land, with the advent of Satellite AIS (S-AIS), they began sending the signal to low orbit satellites, which then relayed information back to land [3] .The S- AIS makes it possible to keep a track of a vessel even beyond the radio horizon. One kind of message (number 27) is shorter than all other messages and is especially dedicated to satellite reception [2].

The AIS data that are exchanged are divided into three different types:

- Static data (e.g., vessel name and the dimensions of the vessel).
- Dynamic data (e.g., vessel position, course over ground and heading).
- Voyage-related data (e.g., current draught, description of cargo, and destination) [7].

Need for an Automatic Identification System (AIS):

Crossroads of international issues, the maritime domain is facing growing human activities. The ocean has a central place in multiple domains such as goods transportation and energy transportation where 90% of the global traffic is done by sea. The traffic generated by maritime activities (including fishing, sailing and cruising) is important and is still increasing [2]. Hence, it is necessary to have a system that monitors the vessel movement in order to control the maritime traffic. Also, a large part of Maritime Domain Awareness (MDA), deals with activities related to movement of vessels and therefore detection, classification, identification and monitoring of vessels is a key component of MDA [3].

<u>Applications of AIS</u>

The concept of AIS is derived from the work of a Swedish inventor named Håkan Lans, who developed in the mid-1980s, an ingenious technique for spontaneous, masterless communication, which permits a large number of transmitters to send data bursts over a single narrowband radio channel by synchronizing their data transmissions to a very precise timing standard [6].

AIS was developed in the 1990s by the IMO technical committee as a high intensity, short-range identification and tracking network. After 9/11 incident in United States, vessels were deemed to have important roles in terrorism case so it was crucial to develop a network that would help vessel monitoring [5]. Therefore, in 2002, IMO SOLAS Agreement included a mandate that required vessels over 300GT on international voyages to fit AIS transponder [8]. The original purpose of AIS was solely collision avoidance but many other applications have since developed and continue to be developed. AIS is currently used for:

1. **Collision Avoidance:** AIS was developed by the IMO technical committees as a technology to avoid collisions among large vessels at sea that are not within range of shore-based systems [3]. The AIS standards include a variety of automatic calculations based on these position reports such as Closest Point of Approach (CPA) and collision alarms. As AIS is not used by all vessels, AIS is usually used in conjunction with radar.

2. **Fishing Fleet Monitoring and Control:** AIS is widely used by national authorities to track and monitor the activities of their national fishing fleets. AIS enables authorities to reliably and cost effectively monitor fishing vessel activities along their coastline, typically out to a range of 100 km (60 mi), depending on location and quality of coast based receivers/base stations with supplementary data from satellite based networks [3].

3. **Maritime Security:** AIS enables authorities to identify specific vessels and their activity within or near a nation's Exclusive Economic Zone. AIS improves maritime domain awareness and allows for heightened security and control. Additionally, AIS can be applied to freshwater river systems and lakes.

4. **Aids to Navigation:** AIS transmitters can also be affixed to a floating or fixed aid to navigation (ATON), such as a buoy, beacon, or light. The AIS broadcast provides the position and purpose of an aid, such as a port or starboard lateral buoy, even before it is close enough to be visible from a ship or to provide a radar return. This can help mariners confirm their ship's position or to prepare to make a turn that is based on passing a particular aid. ATONs enable authorities to remotely monitor the status of a buoy, as well as transmit live data from sensors (such as weather and sea state) located on the buoy back to vessels fitted with AIS transceivers or local authorities [3].

5. **Search and Rescue and Accident Investigation:** For coordinating on-scene resources of a marine search and rescue (SAR) operation, it is imperative to have data on the position and navigation status of other ships in the vicinity. In such cases, AIS can provide additional information and enhance awareness of available resources, even if the AIS range is limited to VHF radio range.

6. **Ocean Current Estimation:** Various models have been proposed that estimate the ocean surface current based on the Ship Drift using the location parameters from AIS Data.These models are discussed below.

7. **Infrastructure Protection:** AIS information can be used by owners of marine seabed infrastructure, such as cables or pipelines, to monitor the activities of vessels close to their assets in close to real time. This information can then be used to trigger alerts to inform the owner and potentially avoid an incident where damage to the asset might occur.

8. **Fleet and Cargo Tracking:** Internet disseminated AIS can be used by fleet or ship managers to keep track of the global location of their ships. Cargo dispatchers, or the owners of goods in transit can track the progress of cargo and anticipate arrival times in port.

9. **Ocean Ambient Noise Mapping:** Ambient noise in ocean is a complex combination of numerous types of natural and anthropogenic noise. Various noise models have been developed for modelling the UW channel and for determining the nature sound propagates in such noisy environments using data collected by AIS. The ambient noise spatial mapping, could be used for earmarking and establishing areas for conduct of tuning/ calibration of underwater sensors, submarine sonar trials and various other UW applications [9].

10. **Oil Spill Monitoring:** Various models have been proposed which estimates the risk levels of individual crude oil tankers using AIS data. The main objective of these models is to facilitate the comparison of ships and to support a risk based decision on which ships to focus attention on.

11. **Maritime Spatial Planning:** Marine Spatial Planning (MSP) is a process that brings together multiple users of the ocean – including energy, industry, government, conservation and recreation – to make informed and coordinated decisions about how to use marine resources sustainably. AIS data processing and analysis can produce adequate information for MSP like maritime traffic density, shipping lanes and navigation flows, hierarchical network of maritime routes, alleged fishing zones, spatio-temporal interactions between activities (potential conflicting uses or synergies)[10]

12. **Estimation of Ship Performance in Ice:** For safe and efficient exploitation of ice-covered waters, knowledge about ship performance in ice is crucial. Recently, using AIS

data, two probabilistic, data-driven models that predict a ship's speed and the situations where a ship is likely to get stuck in ice have been developed.

Discussion

Various Machine learning processes used with AIS for analysis of Maritime Domain:

The AIS is intended to enhance safety of life at sea, the safety and efficiency of navigation, and the protection of the marine environment. This section describes how several machine learning techniques can be used on AIS data for various implementations:

1. **Support Vector Machines(SVMs):** The SVMs are a set of supervised methods that need some prior knowledge before classification. The SVMs method is implemented as a pattern classification technique that measures the similarity between input tracking data and the tracking data stored in the database [11].

2. **Neural Networks:** Neural networks methods can be used for maritime situational awareness at a variety of conceptual, spatial, and temporal levels. Various papers report successful learning for detection of anomalous vessel event behavior and to predict the future vessel location, both based on AIS data [12, 13].

3. **Bayesian Networks:** Bayesian Networks (BNs) are used as a tool for detecting anomalies in vessel tracks based on AIS data. BNs potentially have two substantial advantages in this domain over other types of models: 1) possibility to easily include expert knowledge into the model, and 2) possibility for non-specialists to understand and interpret the learned mode [14, 15].

4. **Gaussian Processes:** An advantage in GPs is that the model is non-parametric so it is not necessary to build in features of anomalous behavior. The model uses an Active Learning paradigm that allows selection of an optimal training sample from AIS data, which accurately represents the entire set [16].

5. **Gaussian Mixture Model:** Gaussian Mixture Model (GMM) is a common model for approximating continuous multi-modal distributions when knowledge regarding the structure is limited [17].

Machine Learning and AI based applications of AIS:

Machine learning based systems, are formulated to approach the human type of thinking and facilitate a human friendly environment during the decision making process. Hence, several Machine learning based decision making systems have been recently developed in the marine domain, based on the data provided by AIS. Some of these models have been discussed below briefly:

1. **Collision Avoidance:** Groundings, collisions and fires are the most frequent maritime accident types globally. However, on local sea areas with high traffic intensities, such as the Gulf of Finland and the Singapore Strait, ship–ship collision is one of the most frequently occurring accident types. We analyze some literature on this aspect:

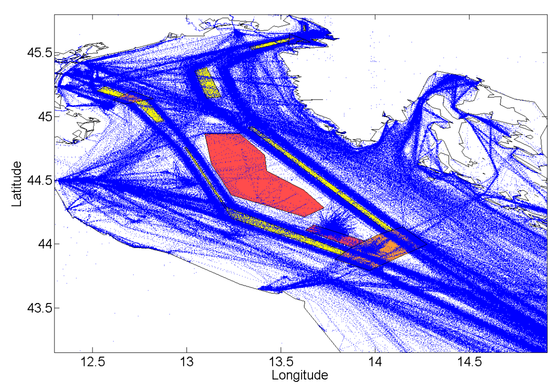
- In a paper published in Reliability Engineering and System Safety (2009) by Kujala et al the safety of the marine traffic in the Gulf of Finland area is analyzed. First a detailed accident statistics during the last 10 years are described and thereafter the risk of ship collisions is studied by theoretical modelling in two locations. Probability of error situations is found by application of a Bayesian Belief Network or by the use of a fault tree. Finally the results of the theoretical models are compared with actual accident statistics [18].
- The assessment by Perera et al.(2012) consists of a fuzzy theory based parallel decision making module whose decisions are formulated into sequential actions by a Bayesian-network-based module. It focuses on the formulation of a decision action execution model that can facilitate intelligent collision avoidance features in ocean navigation systems using AIS [19].
- In the paper by Haiqing Shen et al., an approach based on deep reinforcement learning (DRL) is proposed for automatic collision avoidance of multiple ships particularly in restricted waters. A training method and algorithms for collision avoidance of ships, incorporating ship maneuverability, human experience and navigation rules, are presented using AIS database [20].
- The paper by Bukhari et al. proposed vessel collision risk assessment system that is an intelligent solution which is based on fuzzy inference system and has the ability to design smart system which can take the data from RADAR and AIS and autonomously manipulate it, to calculate the degree of collision risk among all vessels from the VTS centre [21].
- Son et al. (2012) suggested a fuzzy algorithm to estimate collision risk among multiple ships in Korea using real-time AIS data, while Idiri and Napoli (2012) proposed a rule-based method applied to the movements of ships under changing sea conditions which would give an identification of the risks in real-time and potentially trigger an alarm to help prioritize interventions [3].

2. **Estimation of Ship Performance in Ice:** Ship performance in ice has been given a lot of attention in the recent years, especially among northern maritime countries i.e. Canada, Finland, Norway, Russia and Sweden. However due to global warming resulting in the opening of the northern sea route in the Arctic, the issue becomes of global interest.

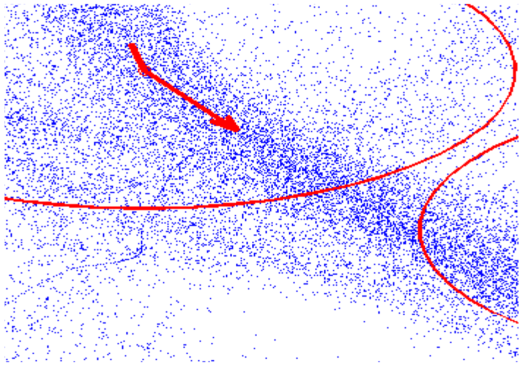
- Based on this topic a paper was published in Cold Regions Science and Technology (2015).This paper introduces two probabilistic, data-driven models that predict a ship's speed and the situations where a ship is likely to get stuck in ice based on the joint effect of ice features such as the thickness and concentration of level ice, ice ridges, rafted ice, moreover ice compression is considered. To develop the models, two full-scale datasets were utilized. First, the dataset about the performance of a selected ship in ice is acquired from the automatic identification system. Second, the dataset containing numerical description of the ice field is obtained from a numerical ice model HELMI, developed in the Finnish Meteorological Institute. The relations between ship performance and the ice conditions were established using Bayesian Belief Networks (BBN) and selected machine learning algorithms [22].

3. **Maritime Traffic Analysis:** Existing machine learning approaches to vessel traffic analysis can be divided in two categories: point-based and trajectory-based.

- In the paper by Vespe et al, an approach for maritime traffic analysis for anomaly detection is proposed. The proposed approach utilizes AIS data, historical or real-time, and is aimed at incrementally learning motion patterns without any specific apriori contextual description. This can be applied to a single AIS terrestrial receiver, to regional networks or to global scale tracking. The methodology was applied to data collected from i) coastal receivers over the Adriatic Sea and ii) Satellite AIS over the Red Sea and Gulf of Aden and following results were obtained [23].



Three months maritime traffic (blue) over the Adriatic Sea, areas to be avoided (red), traffic separation schemes (yellow) and precautionary areas (orange) [23].



Turning points automatically detected over the North Adriatic Sea [23].

4. **Fishing Fleet Monitoring and Control:** One of the notable study was conducted in 2015 by Cazzanti and Pallotta to identify and characterize main stationary areas for vessels. They created an algorithm to detect vessels' status as "sailing" or "stopped" using AIS data. Clustering methods are then used to determine the generalized stopping areas for vessels and/or to detect anomalies. If the identified stop area is not a port or harbour and it is far from coastline, it is asserted to be a fishing area [3, 24].

5. **Ocean Current Estimation:** The French eOdyn startup proposes a simple and inexpensive solution for the digital analysis of open data, including AIS data (Automatic Identification System), to measure the currents in real time and delayed time. This data allows ships to be operated as sensors collecting information on the currents [25].

6. **Ocean Ambient Noise Mapping:** Ambient noise in ocean is a complex combination of numerous types of natural and anthropogenic noise. The noise is dominant in all frequencies from 1 Hz to over 100 KHz with the various noise sources contributing in specific frequency bands as per their acoustic attributes. Various noise models have been developed for modelling the UW channel and for determining the nature sound propagates in such noisy environments. The primary objective of the paper by Roul et. al., is to establish a spatial ambient noise pattern in the territorial waters of the IOR region using the AIS data available with the Marine Traffic or the DGLL. The ambient noise spatial map, could be used for earmarking and establishing areas for conduct of tuning/calibration of underwater sensors, submarine sonar trials and various other UW applications irrespective of the backend noise model that has been used. The map can be generated real time for specific noise frequencies when updated AIS data is available for the region [9].

7. **Maritime Anomaly Detection:**

- Lane et al. identify five anomalous ship behaviors that can be monitored using AIS transmissions: deviation from standard routes, unexpected AIS activity, unexpected port arrival, close approach and zone entry [26].
- Mascaro et al. in produced networks at two different time scales, in the form of the time series and track summary models. They did so by using the machine learner CaMML on AIS data combined with additional real world data such as weather and time, as well as vessel interactions. The models demonstrated distinct and complementary strengths in identifying anomalies, paving the way to an improvement in the field of anomaly detection by combining their assessments [27, 28].
- Laxhammar proposed and implemented unsupervised clustering of normal vessel traffic patterns using multivariate GMM as cluster model in [17].

Future Scope

1. **Data Quality:** The value of the AIS system is limited to the quality of the information which it can provide. In particular, elements of the system which require user input (vessel particulars, destination, etc.) may suffer from widespread data entry errors, limiting their utility and also favouring illegal actions, a detailed analysis of which has been presented by Cyril Ray.et.al 2015 in their work [3]. Three major cases of bad data quality can be distinguished:
   - The errors (when false data in non-deliberately broadcasted),
   - The falsifications (when false data is deliberately broadcasted) and
   - The spoofing (when data is created or modified and broadcasted by an outsider) [2].

2. **Anomaly detection:** Anomaly detection is used in the field of data analysis, with the three elementary steps that are:
   - The identification of the “normality” characteristics by computation and determination of data classical signatures (for instance trajectory clusters in the AIS messages case),
   - The determination of metrics for the computation of the distance of the studied behaviour from the standard behaviour and
   - The determination of threshold criteria for the distance to the standard behaviour, allowing the normality, the abnormality, the magnitude of normality and the magnitude of abnormality for a datum.

The determination of a normal behavioural pattern can be done using neural networks or machine learning which depends on the data in hand. Statistical methods are fitted with the data in which extreme values are anomalous (the speed for instance), and do not work in the cases where the anomalies are evenly distributed. Neural networks are fitted for the discovery of hidden patterns with complex boundaries, but their black box behaviour and their need of a learning phase. The principle of machine learning is to automatically learn complex structures and take data-based decisions.

The distance determination will depend on the type of data and distances such as Euclidian distance in dimension 1 (in the case of speed), Euclidian distance in dimension 2 (in case of localization coordinates with small distance), orthodromic distance (in case of long distance localization coordinates), mean, Hausdorff or Fréchet distances (in the cases of computation of distance between trajectories), or edition distance (in the case of distance with textual data, for the field “destination” for instance). The choice of the right distance for each field is of major importance in the anomaly detection process.

The third step in this anomaly detection is the thresholding for outlier determination in different cases, among which those aforesaid. This will be the purpose of future work measures.

3. **Attempt to improve efficiency of Donald Ross Formula for radiated ship noise:** The underwater acoustic output generated by commercial ships contributes significantly to ambient noise in the ocean. The determination of noise radiated by the ship is one of the important aspects of study of underwater acoustics.

The source level of each ship depends upon the length and speed of the ship. The length and speed of a ship are calculated based on uniform distribution function but forcing limits to speed and length. Donald Ross formula computes the radiated ship noise based on this concept [29, 30]:

$$L_s \ (f, v, l_s) = L_{so} \ (f) + 60 \ \log(v/12) + 20 \ \log(l_s/300) + df * dl + 3.0 \ ,$$

Using normal programming, the time complexity of algorithm employing D Ross formula is O(n), where n is the number of ships. However, there are as many as twenty five million ships in the world ocean. Computing radiated noise for so many ships using this algorithm is practically impossible. Hence, we try to device a machine learning based algorithm to reduce the complexity of the algorithm and to analyze the behaviour of Donald Ross formula.

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