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RECONSTRUCTING DAMAGED DATA IN AIS AND OTHER TELECOMMUNICATIONS SYSTEMS: A SURVEY

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Abstract: AIS (Automatic Identification System) is a telecommunication system created to enable ships to transmit information regarding their trajectories (such as their position, speed, course, etc.) to other ships and shore stations. With the use of AIS, collisions between ships can be avoided. Unfortunately, AIS suffers from some technical issues that lead to part of the transmitted data being damaged (incorrect or missing). This paper contains a review of machine learning based methods of reconstructing this damaged AIS data as well as examples of inspiration from other telecommunication systems for dealing with this kind of a problem. Finally, after analysing frameworks available in the relevant literature, a novel algorithm for AIS data reconstruction is briefly presented.

Keywords: AIS data analysis, trajectory reconstruction, machine learning, telecommunication.

1. INTRODUCTION

AIS (*Automatic Identification System*) is a telecommunication system that enables ships to transmit information regarding their trajectories to other ships and marine equipment, such as shore stations. For example, messages called position reports (messages of types 1-3 out of all 27 types that AIS can carry) contain fields such as the ship's position (longitude and latitude), speed and course over ground, navigational status, ID (*Maritime Mobile Service Identity*, MMSI) etc. [ITU 2014; ESA 2019].

There are two segments of AIS. Terrestrial AIS [ITU 2014] enables line-of-sight communication (ship-to-ship, ship-to-shore) and utilises two VHF (*Very High Frequency*) frequencies: 161.975 and 162.025 MHz with a 25-kHz bandwidth. Its most appreciated feature is its ability to synchronise the communication between many AIS transponders sharing the same wireless medium (using *Self-Organized*

Time Division Mutliple Access, SOTDMA). Nonetheless, its main drawback is its range of up to 74 km. To overcome this limitation, a satellite segment of AIS (SAT-AIS) has been introduced [ESA 2019]. SAT-AIS enables communication within a much broader area thanks to the satellite (mostly on Low Earth Orbit) mediating the transmission between ships from many terrestrial cells. Unfortunately, even SAT-AIS suffers from its own technical limitations – the most crucial of these being the fact that communication between terrestrial cells is not synchronised, and a satellite may therefore receive messages from many ships at the same time (packet collision [Wawrzaszek et al. 2019]). Naturally, if so, it is not able to correctly process them, which causes some parts of AIS data to be damaged (incorrect or missing).

There are some approaches to dealing with the issue of packet collision. Statistical modelling [Seta et al. 2016] or the Viterbi algorithm [Prevost et al. 2012] are two examples. However, with the recent increase of available computational power, the popularity of modern computational methods such as machine learning has also grown, and these can be seen in a wide range of literature dealing with missing AIS data imputation.

Machine learning [Shai and Shai 2014] (ML) offers algorithms that can enhance their performance by being exposed to more and more data: they model some phenomena by defining a structure (or relationships) within the data and are able to update the parameters describing the model as more data are available, rather than being explicitly programmed and following some pre-defined rules. Machine learning approaches can be divided into two main groups: approaches involving supervised learning (where each data record provided contains the expected output, called a label) and approaches involving unsupervised learning (when data labels are not included, and algorithms need to find the expected output by themselves).

Since ships using AIS transponders transmit numerous AIS messages, AIS is a great source of data that machine learning algorithms can learn from, not only for analysing maritime traffic, but also for defining correct/incorrect trajectory points and reconstructing the wrong ones. Here, in the next two sections of this paper, a review of such ML-based approaches for reconstruction of AIS and other telecommunication systems data is presented. After an analysis of existing methods, in Section 4 a novel framework is proposed for quick, real-time AIS message reconstruction, while Section 5 concludes the findings.

2. RECONSTRUCTION OF AIS DATA USING MACHINE LEARNING

2.1. Prediction of ships' trajectories

The issue of predicting the ship's trajectory is crucial for maintaining safety on the sea and for ship collision prevention [Zhang et al. 2015]: to know exactly where a vessel is, either when there is a connectivity failure or data received from a vessel might be damaged and we cannot fully trust them, then there is a need for data reconstruction.

What can be seen by analysing the available literature regarding this topic is that deep learning is widely used here. Deep learning is a subset of machine learning which utilises neural networks – special algorithmic architectures based on many layers of activations (neurons) and connections between them (with corresponding weights), which can model sophisticated phenomena, such as the behaviour of a sailing vessel. For instance, in one paper [Zhang, Ni and Xu 2020], a classic neural network is used, in [Li et al. 2020], there is a U-Net convolutional network, in [Jin et al. 2020] there is a recurrent, LSTM (*Long Short Term Memory*) neural network and in [Liang et al. 2019] an ensemble of LSTMs is utilised to perform the task of ship trajectory prediction. In those approaches, neural networks were trained on AIS data and learned the relations between the features describing trajectories, such as the ships‘ position, speed and course, to be able to predict (in the form of a regression task) the current or missing position of a moving ship.

However, it must be emphasised that training a neural network in general requires a lot of data, memory and computations. Therefore, other methods of reconstructing ships‘ trajectories were also investigated: based on cubic spline interpolation [Zhang et al. 2018] or Fermat spiral fitting [Shi et al. 2019].

2.2. Establishing trajectory trends and anomaly detection in AIS data

Many existing works focus not necessarily on the entire process of ship trajectory reconstruction, but more heavily on one step of that process, which is determining which parts of recorded AIS (trajectory-related) data actually require reconstruction. Such data is often considered an anomaly, hence, we will call this step anomaly detection.

Usually, to decide if a trajectory point seems valid (not an anomaly), there is a need to analyse the available data first to distinguish how the correct trajectories look like. One popular method of doing so is to model the vessels’ trajectories using what is called *waypoints*, that is to say, by defining characteristic points in a given area where usually ships’ trajectory changes: vessels tend to turn, speed up, start or stop. Those points form a graph (they are its vertices), whose edges are the actual trajectory steps. A sophisticated system that uses waypoints is TREAD, described in [Pallotta, Vespe and Bryan 2013]. Other works doing so are, for instance, [Kontopoulos, Varlamis and Tserpes 2019] or [Machado et al. 2019]. In [Dobrkovic, Iacob and van Hillegersberg 2016], waypoints are identified using a genetic algorithm.

Naturally, defining waypoints is not the only possible method of determining trajectory trends. For instance, other approaches involve using Gaussian processes [Kowalska and Peel 2012] or decision trees [Wang et al. 2020].

There are also many ways of identifying outlying trajectory points (as mentioned before, we will call them outliers) or even parts of trajectories, mostly those that do not find the defined trend. In [Singh and Heymann 2020], a 3-layer artificial neural network performs anomaly detection, while in [Xia and Gao 2020], a Bayesian recurrent network does so using binary classification (outlier/not outlier). Paper [Lei and Mingchao 2018] proposes a different approach, based on calculating distances between datapoints (using different metrics): a datapoint that is far away from the other should be considered an anomaly. On the other hand, according to [Kontopoulos, Varlamis and Tserpes 2019], an anomalous datapoint is one that is not assigned to any cluster with other datapoints. Finally, a masked autoregressive normalising flow for trajectory data anomaly detection (not AIS but based on Microsoft GeoLife dataset) was described in [Dias et al. 2020].

2.3. Clustering in AIS data analysis

Clustering algorithms (which are used for dividing dataset into clusters so that datapoints in one cluster are more similar to each other than to any point from other clusters), which belong to the unsupervised learning class, are often found helpful in analysing AIS data and vessels' trajectories.

When it comes to finding trajectory waypoints (described earlier) for determining trajectory trends for anomaly detection, this is often initially done by clustering the available trajectory points [Pallotta, Vespe and Bryan 2013]. Moreover, even if a trajectory trend is not described by waypoints, clustering often assists in determining it by collecting similar trajectories [Lei and Mingchao 2018] or even finding isolated points that could be potential outliers [Li, Zhang and Zhu 2016]. Here, it seems as though DBSCAN is a popular choice of clustering algorithm [Pallotta, Vespe and Bryan 2013; Li, Zhang and Zhu 2016; Lei and Mingchao 2018], since it manages to create clusters of different shapes (not only a sphere-like shape in a given dimension), as long as the clustered datapoints are connected (in a sense of data density) to each other [Ester et al. 1996].

On the other hand, other clustering algorithms also appear in the literature, as a support for AIS data analysis. For example, in [Hanyang, Xin and Zhenguo 2019], the use of *k*-means as the algorithm for AIS data clustering and trajectory extraction was examined, together with the elbow method for determining the optimal number of clusters in a dataset; hierarchical clustering [Wang, Gao and Yang 2017] or even neural networks (in the form of a convolutional auto-encoder) [Wang et al. 2020] were also researched. In [Theodoropoulos, Tritsarolis and Theodoridis 2019] a sophisticated algorithm called EvolvigClusters was proposed, which imposes both spatial and temporal restrictions on the clusters obtained.

3. PROBLEM OF DAMAGED DATA IN OTHER TELECOMMUNICATION SYSTEMS

To investigate the methods of dealing with damaged AIS data more broadly, it is advisable to examine which machine learning based approaches are used in relation to other telecommunication systems – for example, computer networking.

It appears that, in most cases, the existing frameworks focus more on reconstruction of the payload of the data unit (either frame or packet) damaged during transmission, rather than attempting to reconstruct the whole data unit (since the data headers contain mostly information relevant to the transmission only, such as source and destination address). The works that can be found describe predicting missing images [Zhang et al. 2018], video frames [Yu et al. 2020] or audio samples [Hsu et al. 2012]. What can be seen is that in most cases, it is multimedia payload that is the object of an attempted re-creation. The explanation lies within the specification of how the networking protocols work. It is worth remembering that there are the two main network protocols on the transport layer of the OSI model: *Transmission Control Protocol* (TCP) and *User Datagram Protocol* (UDP) [PyNetLabs 2022]. TCP provides sophisticated mechanisms for ensuring transmission reliability: acknowledging successful reception of data and retransmission parts of transmitted data which reception was not acknowledged. Therefore, TCP is mainly used for transmission of sensitive data: e-mails, website content, files, etc. Actually, the need for reconstruction of data carried by TCP is minimal. The other protocol, UDP, does not ensure such transmission reliability. Moreover, it is UDP that is usually used for transmission of multimedia streams – hence, that is why we often find works about multimedia data being reconstructed. For example, in [Yu et al. 2020], a complex convolutional neural network architecture is designed to reconstruct missing video frames. Some works focus on re-creation of damaged speech samples: in the literature, we can find approaches based on old methods, such as interpolation and extrapolation [Husain and Cuperman 1995], but also modern ones – for instance, in [Hsu et al. 2012], a SVM classifier helps classify speech samples (into voiced or voiceless samples, for example) to make further reconstruction easier.

Other researchers attempted to bypass the reconstruction problem by focusing more on predicting the network overload to be able to counteract and, consequently, reduce the amount of lost data packets or frames. Authors of [Faten and Elbiaze 2009] proposed a neural network (using fuzzy logic) for this purpose. They have also examined several autoregressive models which, by analysing captured network traffic, try to predict its peak in the future. Similarly, in [Balaji, Duraisamy and Umapathi 2010], an approach based on clustering is presented.

Aside from analysing network using the TCP/IP stack, there are also attempts for reconstruction of data flowing through other telecommunication systems. In [Zhang et al. 2018], a reconstruction of satellite images is examined; here, again, the convolutional neural network is used, which learns through relationships between existing data in a spatial, spectral and time domain. Research published in [Alippi, Boracchi and Roveri 2012] and [Pan and Li 2010] deals with the problem of reconstructing data from a network of sensors using machine learning. The first work presents the usage of the *K* Nearest Neighbour algorithm, while in the latter a recurrent neural network was trained to find spatial and temporal dependencies between data from neighbouring sensors to reconstruct the missing parts.

Inspirations from these works can be helpful in the problem of AIS data reconstruction. Here, we should also focus on prediction of the actual payload of AIS messages (i.e. the corresponding message fields: longitude, latitude, speed, course, ship identifier, etc.) rather than trying to recover the entire message bitwise. Moreover, the search for finding spatial and temporal relations between consecutive messages might be helpful: knowing where the analysed ship was in the past and how it moved might be crucial for predicting its current position.

4. PROPOSED APPROACH FOR DAMAGED AIS DATA RECONSTRUCTION

While analysing the findings of the literature review, it can be noticed that there is still a need for creating a fast and reliable AIS message reconstruction framework for detecting damaged parts of AIS data (not only containing position information) and predicting their correct form in real-time operation (otherwise two ships may eventually collide), without the time-consuming process of analysing long-term ship trajectory trends within a given area (on the contrary, we would like to focus on determining the correct relations between AIS message fields to find those that do not correspond to the relations and, consequently, reconstruct their values, regardless of whether the trajectory itself corresponds to the overall trend or not).

Our attempt to fulfil these assumptions is presented (in the form of charts) in Figure 1. In short, the proposed framework can be divided into 3 stages:

1. **Clustering stage.** In this stage, AIS position reports recorded from a given area and given time interval are divided into separate groups (clusters) by using clustering algorithms, such as DBSCAN [Ester et al. 1996]. The goal of this step is to distinguish individual ships' trajectories, regardless of whether the MMSI field value received is correct or not (as a reminder, MMSI is transmitted as a part of AIS message and may also be damaged). Trajectories obtained this way can be further analysed to find abnormal points within them. If a point is so distant from other points from a given dataset that the clustering algorithm puts it into a standalone, 1-element cluster, it should also be considered an anomaly. The performance of using DBSCAN algorithm in this stage, as well as hyperparameter tuning, is presented in [Mieczyńska and Czarnowski 2021].

2. **Anomaly detection stage**. During the second stage, each cluster (i.e. ship trajectory) is analysed to find potentially damaged datapoints (AIS messages), which we call anomalies. Not only do the whole damaged messages need to be identified, but also the exact location where the damage occurred (corrupted field) and, if MMSI is corrupted/unknown, also the ship that the given message originated from. The proposed anomaly detection stage is a 2-step process. At first, we take a look at the inside of the aforementioned 1-element clusters [Szarmach and Czarnowski 2022]. Since the origin of such messages is unknown (as they are not related to any other messages to form a trajectory cluster, and moreover, we cannot be certain if its MMSI field is correct or not), we use the *K* Nearest Neighbour algorithm [Altman 1992] to decide which other cluster seems the most similar to that message. Then, we analyse the values from each message field (of the following: dynamic – longitude, latitude, speed and course over ground, static – MMSI, navigational status and special manoeuvre indicator) and we compute the wavelet transform [Debnath 1998] of the waveform of consecutive values from the given field and ship (more precisely, we calculate the relative difference between the maximum values of the wavelet transforms and standard deviations of such waveforms with and without the potentially damaged fields). The damage can be recognised by a sudden value change, thus, the differences calculated should be high. The pre-trained classifiers (such as Random Forest [Ho 1998] or XGboost [Chen and Guestrin 2016], one for each field) analyse the differences obtained and decide whether to consider them (and their corresponding AIS message field) anomalous or not – see this method's performance results in [Szarmach and Czarnowski 2022]. Then, we examine the proper, multi-element clusters. For dynamic fields of such messages, we create specific vectors (containing the values and their differences from the analysed, previous and next message in a batch from the given ship) and again, let pre-trained Random Forest or XGboost classifiers decide if these vectors contain correct relations between their features or not. In the latter case, they must be reconstructed. For static fields, we use an Isolation Forest [Liu, Ting and Zhou 2008] to find anomalous values directly. We believe that this method deals with finding damage even when the control sum field fails to do so (such as GPS drift) – see [Szarmach and Czarnowski 2023] for more details and results.
3. **Prediction stage**. After the AIS message fields that require correction are found, the process of actual reconstruction of their correct values has to be executed, possibly using prediction algorithms. However, this stage is yet to be implemented and researched.

We find the results presented in given references promising (the proposed algorithm managed to find 90%-95% messages and 58%-74% of their fields with 2 bits artificially damaged [Szarmach and Czarnowski 2023]).Therefore, we will continue our work on developing this framework in the future.

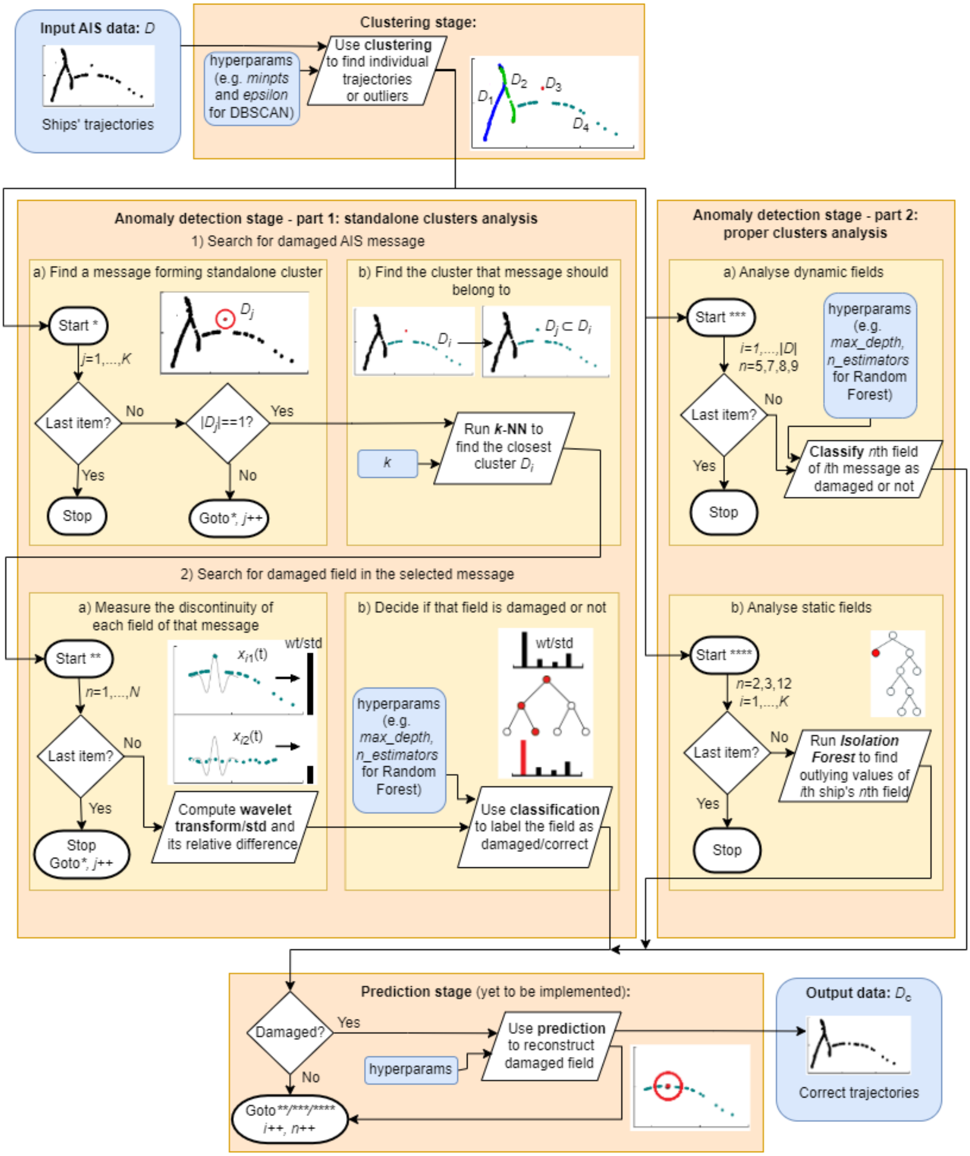

Fig. 1. Proposed general algorithm

Source: own study.

5. CONCLUSIONS

AIS is an important telecommunication system for maintaining the safety of the maritime transport. Unfortunately, due to some technical issues, it struggles against some parts of its data being damaged during transmission. Many researchers around the globe are attempting to use advanced and modern machine learning algorithms to reconstruct the lost or incorrect trajectory points to make AIS data clean. The proposed approaches varies, from those focusing on detecting trajectory trends (usual ship trajectories) to find outlying datapoints that require correction (often supported by clustering algorithms), to those conducting real reconstruction, often by using neural networks. Both supervised and unsupervised learning algorithms can be observed in the literature.

In this work, we gathered the necessary knowledge of existing AIS data reconstruction frameworks (and we are also seeking similar methods in other telecommunication systems) and proposed our own, 3-step ML-based algorithm, which we find promising. In the future, we will complete our framework mainly by creating a satisfying algorithm in the final (prediction) stage which, at the time of writing this publication, is yet to be done.

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