Decision Tree-Based Algorithms for Detection of Damage in AIS Data*

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Abstract. Automatic Identification System (AIS) is a system developed for maritime traffic monitoring and control. The system is based on an obligatory automatic exchange of information transmitted by the ships. The Satellite-AIS is a next generation of AIS system based on a satellite component that allows AIS to operate with a greater range. However, due to technical limitations, some AIS data collected by the satellite component are damaged, which means that AIS messages might contain errors or unspecified (missing) values. Thus, the problem of reconstruction of the damaged AIS data needs to be considered for improving performance of the Satellite-AIS in general. The problem is still open from research point of view. The aim of the paper is to compare selected decision tree based algorithms for detecting the damaged AIS messages. A general concept of detection of the damaged AIS data is presented. Then, the assumption and results of the computational experiment are reported, together with final conclusions.

Keywords: Damaged data detection · Multi-label classification · AIS data analysis · Decision Tree-based algorithms

1 Introduction

AIS (Automatic Identification System) has been developed to support the monitoring and control of maritime traffic,as well as collision avoidance. AIS messages can also be used for tracking vessels. An example of a system based on AIS messages is a vessel traffic services (VTS) system. Based on AIS data, VTS is a source of information of position of ships and other traffic data. The information provided by AIS can be classified as static (including vessel's identificafition number, MMSI) and dynamic (including ship's position, speed, course, and so on) [1].

The Satellite-AIS is a next generation of AIS system based on satellite component for extending range of AIS operationality. Due to technical limitations, resulting from lack of synchronization while receiving AIS packets from two or

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more so-called terrestrial cells at the same time, a problem of packet collision exists. Packet collision leads to the problem of the satellite component processing the AIS data that can be incomplete (missing) or incorrect, i.e. damaged. Of course, not all data is damaged, but the damage can be eliminated and not forwarded in an easy way.

When the damage of the data is detected in a form of missing data (i.e. a some part of AIS message being lost), the aim can be to predict proper values for missing fields and an elimination of data gaps. When the damage of the data manifests itself in the incorrectness of the data, the AIS data may be corrected. However, at first, this incorrectness must be detected. In literature, the problem of incorrect data detection is often discussed as a anomaly detection problem [2]. In this paper we called it as a data damage detection. One approach to this is to use statistical tools. Alternative approach is to use machine learning methods to the considered detection. Finally, at the last stage, the reconstruction of the damaged data is carried out.

This paper focuses on only one of these stages, i.e. the damage detection stage. A general concept for damaged AIS data detection (based on pre-clustering) is presented. After detecting of which AIS messages are damaged, the aim is to detect which parts of those messages are damaged and require correction. The main aim of the paper is to propose and evaluate the performance of decision tree-based algorithms, implemented to detect possible incorrections in individual parts of the AIS message. The role of these classifiers is to assign proper labels to each part of the AIS message, and thus indicate the damaged ones. Therefore, the problem of damage detections in AIS message fields is considered as a problem of multi-label classification[3].

The discussed approach is based on an ensemble of the decision tree models used for damage detection. Three different decision tree models have been compared, i.e. single Decision Tree, Random Forest and XGBoost [4],[5]. The decision tree based algorithms were chosen for evaluation because of their relatively low computational complexity, nevertheless, they are also powerful and popular tool for classification and prediction, being competitive to others [6]. On the other hand, the problem under consideration is related to its physical and engineering solution, where the mentioned attributes matter. The paper also extends research results presented before in [7].

The remainder of this paper is organized as follows. In the next section, there is a literature review regarding the considered topic, then the problem formulation is included. In Section 4, a general concept for the proposed approach is presented, with details on the process of anomaly detection and damage detection in the separate parts of the AIS message. Computational experiment results on evaluating the performance of the proposed method, together with their discussion, are included in Section 5. Finally, Section 6 concludes this paper.

[3] The multi-label classification problem and a review of different approaches for solving this kind of machine learning problem have been discussed in [3].

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2 Related Works

The topic of anomaly detection in AIS data is not entirely new in scientific literature. In most of works that can be found, existing frameworks consider "anomalies" as parts of ships' trajectories that do not fit to the expected trend of vessels' behaviour within a given area [8],[9]. The ships' typical trajectories are often extracted by analysing AIS data recorded during a long observation period: one way is to cluster collected trajectory points with the use of available clustering algorithms, such as DBSCAN [9], the other requires finding a specific trajectory points in a given area (called waypoints), where ships typically turn, speed up, etc [8],[10] — trajectories can be then expressed as egdes of graphs whose vertices are waypoints.

Other approaches for detecting anomalous trajectory points utilize neural networks [11],[12] or statistical models, like Bayesian model based on Gaussian processes in [13].

However, to the best of our knowledge, there are few frameworks that would reconstruct the AIS messages based on a single ship trajectory (in contrast to those mentioned above, relying on identyfing trajectory trends) and detect damages in AIS messages no matter whether the ship is following the trend or not.

There are also works that focus on the reconstruction of incomplete AIS data. What can be noticed is that deep learning is also widely seen in this task. For example, in paper [14] a classic neural network is used, in [15] — a convolutional U-Net, in [16] — recurrent neural network. Nonetheless, as mentioned before, there is still a need for developing algorithms for AIS data reconstruction that are as accurate as deep learning approaches, but requires less computational power and relatively small amount of time to execute — it is important for the ships not to wait long for the reconstructed data, otherwise they may collide.

3 Problem Formulation

Let T_i be a ship trajectory, described by a set of vectors $T_i^{t_m}$. Each $T_i^{t_m}$ represents ith ship's trajectory point observed in time (observation step) t_m, that can be expressed as [7]:

$$T_i^{t_m} = [x_{i1}^{t_m}, x_{i2}^{t_m}, x_{i3}^{t_m}, \ldots, x_{iN}^{t_m}], \tag{1}$$

where:

- $m = 1, ..., M$ and M denots the number of received AIS messages during a given observation time,
- N denotes the number of features of AIS message,
- $x_{in}^{t_m}$ represents nth feature of an AIS message from ith ship received in time t_m.

As it has been formulated in [1], typical data (features) of AIS message are as follows: message ID, repeat indicator, ship's ID (MMSI), navigational status, rate of turns, speed over ground, position accuracy, longitude, latitude, course

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over ground, true heading, time stamp, special manoeuvre indicator. They have either static or dynamic character.

Therefore, a trajectory of the ith ship can be defined as:

$$T_i = \{T_i^{t_1}, T_i^{t_2}, T_i^{t_3}, \ldots, T_i^{t_M}\}. \tag{2}$$

The data received by the AIS satellite may contain errors. After decoding the data, such a state of affairs will mean that the message could be damaged (totally or partially) or incomplete. Thus, the data received from ith ship (i.e. $T_i^{t_m}$ or elements of the vector, $x_{in}^{t_m}$) may be incorrect (or undefined), which can be expressed in the following way:

$$\exists_{t_m} T_i^{t_m}, \text{ that is missing/incorrect} \tag{3}$$

or

$$\exists_{n:n=1\ldots N} \quad x_{in}^{t_m} \text{ , that is missing/incorrect.} \tag{4}$$

In general, the authors' interest is to reconstruct each T_i, when the ith ship's trajectory points are partially damaged, i.e. there are incorrect or missing values within the vector $T_i^{t_m}$. Therefore, the reconstruction of missing or incorrect AIS data can be defined as a correction of detected incorrect/missing (damaged) messages, to the point where finally the following condition is fulfilled:

$$\forall T_i (\nexists T_i^{t_m} \vee \nexists x_{in}^{t_m}), \text{ that are not missing/incorrect.} \tag{5}$$

The important step in the reconstruction of missing or incorrect AIS data is a detection of the damaged AIS data. The problem of detection of the damaged AIS data (which is the main aim of the paper) can be considered as a classification problem. In that case, machine learning tools can be helpful in this process.

Considering the above, we can therefore associate each of the ship's trajectory point with a label c, where c is an element of a finite set of decision classes $C = \{0, 1\}$, where its elements are called "false" or "true", respectively. A true value means that the message is damaged, otherwise, it means that the message is proper (correct, no damage). Whereas, $|C|$ is equal to 2, the problem of detection of the damaged data is an example of a binary classification problem.

Thus, the one considered problem is to find a model (classifier) that describes and distinguishes data class for AIS messages and predicts whether ship's trajectory point is damaged or not. From the formal point of view and a considered binary classification problem, classification is the assignment of a class $c \in C$ to each trajectory point $T_i^{t_m}$.

The problem of detection of the damaged AIS data can be also considered with respect to the multi-label classification problem. In such case, each of ship's trajectory point is associated with a vector of labels, where each item in the vector refers to one feature of the ship's trajectory point. When the label is set to true, it means that the corresponding feature is damaged, otherwise, it is considered proper.

Thus, let now $C = [c_1, \ldots, c_N]$ be a vector of labels, where each element $c_{n:n=1,\ldots,N} \in \{0, 1\}$. The elements of C are related with elements of vector $T_i^{t_m}$.

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Then, in case of any element $x_{in}^{t_m}$ being damaged, a respective c_n is set to be 1, otherwise to 0. It also means that the vector of labels can have one or more than one true values, and in the extreme case all true values, which means that all features (fields) of the AIS message are damanged. Finally, the role of a classification model (classifier) is to assign a vector of labels C to each trajectory point $T_i^{t_m}$.

4 Proposed Approach for Damage Detection

4.1 Anomaly Detection

To successfully reconstruct the damaged fragments of AIS data, it is necessary to first find the AIS messages and their parts that actually require correction — this is exactly the purpose of the anomaly detection stage.

Algorithm 1 Framework of AIS data reconstruction using machine learning

Require: D — dataset;
K (optional, according to the chosen clustering algorithm) — number of clusters (equal to the number of individual vessels appearing in a dataset)

begin
  $D_c = D$
  Map messages from D into K clusters
  (1 cluster = messages from 1 ship) using a selected clustering algorithm.
  Let $D_1, \ldots, D_K$ denote the obtained clusters and let $D = D_1 \cup D_2 \cup \ldots \cup D_K$.
  for all $i = 1, \ldots, K$ **do**
    Search for anomalies (potentially damaged messages) in D_i.
    Let $\hat{D}_i$ denote cluster with detected anomalies.
    Predict the correct values of damaged fields for $\tilde{D}_i$.
    Update D_c using $\tilde{D}_i$.
  end for
  return D_c — corrected dataset.
end

To accomplish this, during the very first step of the reconstruction, a clustering stage is provided. During the clustering stage, the analysed AIS data is divided into groups, such that (ideally) one group consists of messages from one and only one vessel. DBSCAN algorithm [17] was used in this task. Although AIS messages contain a field with the transmitting ships' identifier (which is called MMSI, Maritime Mobile Service Identity) we decided not to sort the data accoring to the MMSI because, as other fields in AIS messages, this value might contain errors and clustering algorithms should recognize the similarity between messages from the same vessel despite those errors or mark the message as clearly outlying. Only then, when the individual trajectories have been distinquished, they can be further processed to find datapoints that somehow do not fit to the

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rest (we will call them outliers, which in other words are potentially damaged messages) and reconstructed.

The desired algorithm, as mentioned before, should require low computational complexity and manage to detect damages in AIS messages no matter whether the ship is acting typically or not.

We focused to find anomalies in MMSI, navigational status, speed over ground, longitude, latitude, course over ground and special manouvre indicator fields (unfortunately, the data that we was working on contains mostly default values in rate of turns and true heading fields). Also, we decided not to reconstruct values in fields such as message type, repeat indicator, position accuracy, since they describe the message itself rather than vessel's trajectory.

The whole proposed reconstruction algorithm (including the damage detection stage) is presented as Algorithm 1. In next sections, the two-step process of anomaly detection part (including searching for both standalone and proper, multi-element clusters) is discussed.

4.2 Detection of Damage in Standalone Clusters

Background. To find AIS messages that are potentially outliers, it is advisable to search for messages that after the clustering stage became a part of standalone, 1-element clusters. If a clustering algorithm decided to place those messages that far from any other points, it might suggest that the fields inside such message contain anomalous values, i.e. are damaged.

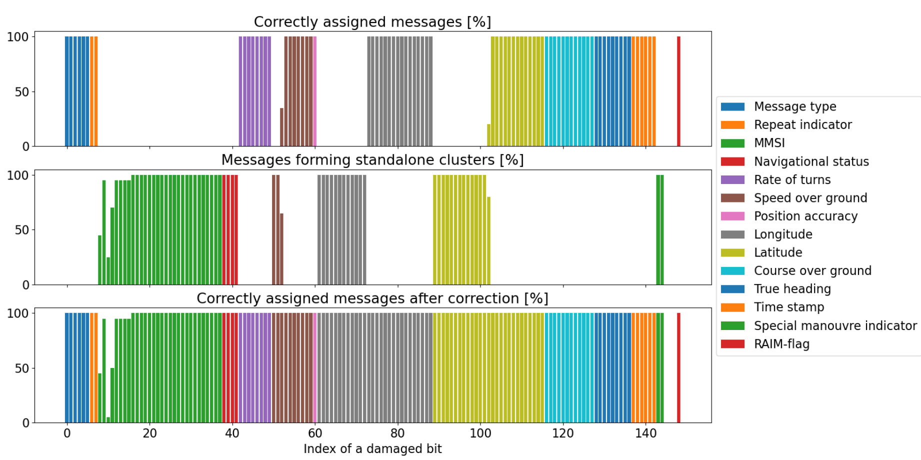

Fig. 1. The motivation behind the analysis of standalone clusters for AIS data damage detection

Indeed, an auxilary test that was conducted confirms this logic. For each bit, we randomly selected 20 messages, artificially corrupted the given bit (swapped its value from 0 to 1 or from 1 to 0) and repeat the clustering stage. It turned out that for some bits, its corrruption makes the message become a 1-element cluster j, as can be seen in Fig. 1 — those fields are mainly ships' identifier MMSI, navigational status, special manouvre indicator and most significant bits from speed over ground, longitude and latitude. Therefore, when a standalone, 1-element cluster is found, we can assume that the message in it is an outlier that should be further examined.

However, it is not enough to find a corrupted message $\hat{T}_j^1$ — we would also like to know which part (or parts) of it is actually damaged. In order to accomplish this, the origin of such message must be established — in other words, the message must be assigned to a right cluster together with other messages that were transmitted by the same ship. We decided to use a k nearest neighbour classifier [18] for this task. The index of a cluster assigned to a message by the clustering algorithm becomes a classifying label and then $k = 5$ messages closest to the outlying one are found — the cluster that most of messages found this way is assigned to becomes the new group for the outlying message.

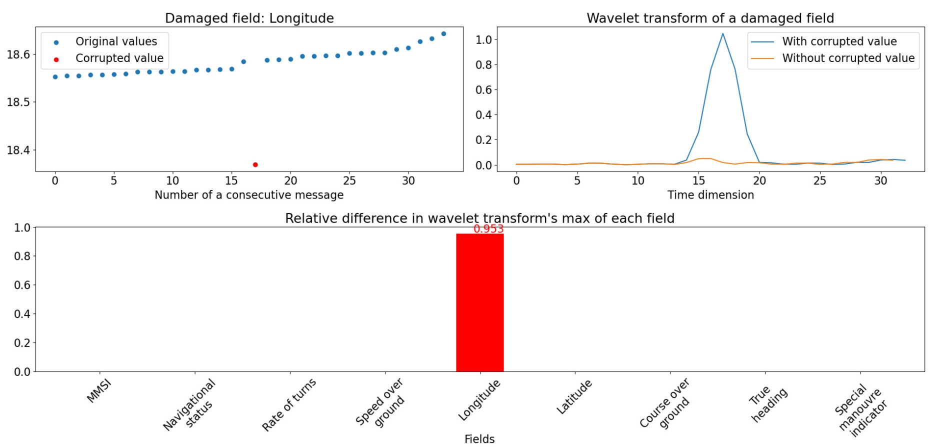

Fig. 2. The intuition behind the usage of waveform transform in AIS data damage detection

After the origin of an outlying message is established, its trajectory can be evaluated and the fields that contain wrong values can be detected. If we take a look at a waveform consisting of consecutive values from a given AIS message field, i.e. how the values from a given field change over time (Fig. 2), we can see that the (exemplary) outlying value changes much from the rest and the whole waveform starts to resemble a specific mathematic function called a wavelet, basically speaking, in the form of a sudden value change. A wavelet $\psi(t)$ is a function that meets the following criterium [19]:

$$\int_{-\infty}^{\infty} \frac{|\hat{\psi}(\omega)|^2}{\omega} \, \mathrm{d}\omega < \infty \tag{6}$$

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where $\hat{\psi}(\omega)$ is a Fourier transform of a wavelet $\psi(t)$. Wavelet transform [19] is a transformation that measures how much a given signal $f(t)$ is similar to a wavelet $\psi(t)$. Wavelet transform can be described as [19]:

$$F_{\psi}(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) \cdot \psi\left(\frac{t-b}{a}\right)\ \mathrm{d}t \tag{7}$$

where:

- $F_{\psi}(a,b)$ is a wavelet transform of a signal $f(t)$ computed for wavelet $\psi(t)$,
- t is time,
- a denotes a scale parameter,
- b is a time-shift parameter.

A special algorithm for detecting anomalies in AIS message fields, based on wavelet transform, is proposed. For each analysed field, we compute the wavelet transform (based on a Morlet wavelet) for two waveforms: $\Delta\hat{w}_{in}$ consisting of differences between the consecutive values in a given field (8) and Δw_{in}, very much alike, but excluding the possibly outlying value $\hat{x}_{jn}^{t_m}$ (9) (both scaled with the use of maximum value from $\Delta\hat{w}_{in}$):

$$\begin{gathered} \Delta\hat{w}_{in} = [x_{in}^{t_2} - x_{in}^{t_1}, \quad x_{in}^{t_3} - x_{in}^{t_2}, \quad \dots \quad x_{in}^{t_M} - x_{in}^{t_{M-1}}] \\ \Delta\hat{w}_{in} = \frac{\Delta\hat{w}_{in}}{\max(\Delta\hat{w}_{in})} \end{gathered} \tag{8}$$

$$\begin{gathered} \Delta w_{in} = [x_{in}^{t_2} - x_{in}^{t_1}, \quad \dots \quad x_{in}^{t_M} - x_{in}^{t_{M-1}}]^{x_{in}^{tm} \neq \hat{x}_{jn}^{tm}} \\ \Delta w_{in} = \frac{\Delta w_{in}}{\max(\Delta\hat{w}_{jn})} \end{gathered} \tag{9}$$

Then, the relative difference between the maximum values from two computed wavelet transforms $\hat{W}_{\psi}^{in}(a=1,b)$ and $W_{\psi}^{in}(a=1,b)$ is calculated:

$$\Delta\psi_{in} = \frac{|\max(\hat{W}_{\psi}^{in}(a=1,b)) - \max(W_{\psi}^{in}(a=1,b))|}{\max(\hat{W}_{\psi}^{in}(a=1,b))} \tag{10}$$

The higher the difference $\Delta\psi_{in}$, the more impact to the wavelet transform was given by introducing the potentially damaged value $\hat{x}_{jn}^{t_m}$, indicating higher chance for this value to require further correction.

Based on the same logic, the relative difference of standard deviation of values from the two given waveforms $\hat{w}_{in}$ and w_{in} can be calculated:

$$\begin{gathered} \hat{w}_{in} = [x_{in}^{t_1}, \quad x_{in}^{t_2}, \quad \dots \quad x_{in}^{t_M}] \\ w_{in} = [x_{in}^{t_1}, \quad x_{in}^{t_2}, \quad \dots \quad x_{in}^{t_M}]^{x_{in}^{tm} \neq \hat{x}_{jn}^{tm}} \\ \Delta\sigma_{in} = \frac{|\sigma_{\hat{w}_{in}} - \sigma_{w_{in}}|}{\sigma_{\hat{w}_{in}}} \end{gathered} \tag{11}$$

Again, the higher the difference $\Delta\sigma_{in}$, the more change to the distribution of the values from a given field n was introduced by the damaged value $\hat{x}_{jn}^{t_m}$.

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Algorithm 2 Detection of damage in AIS data

Require: $D_1,\ D_2,\ \ldots\ D_K$ — subsets of the AIS dataset (groups obtained during the clustering phase);
N — number of fields in AIS messages.

begin
  for $j = 1, 2, \ldots K$ **do**
    if $|D_j| == 1$ **then**
      Add index of T_j^1 to *idx_list*.
      Run k-NN algorithm to find group i ($i \neq j$) — the one that the message T_j^1 should be assigned to.
      Add i to *i_list*.
      for $n = 1, 2, \ldots N$ **do**
        Compute the wavelet transform $\hat{W}_\psi^{in}$ of normalized sequence of differences between the consecutive values of field n in group i.
        Compute the wavelet transform W_ψ^{in} of the same sequence, excluding the value from the potentially damaged message T_i^1.
        Compute $\Delta\psi_{in}$, the relative difference between the maximum values of both wavelet transforms.
        Compute $\Delta\sigma_{in}$, the relative difference between the standard deviation of values of field n from group i and those values excluding the one from the potentially damaged message.
        Run classification algorithm to classify vector $[\Delta\psi_{in}, \Delta\sigma_{in}]$.
        if classification result == 'field n is damaged' **then**
          Add n to *n_list*.
        end if
      end for
    end if
    for $n = 1, 2, \ldots N$ **do**
      if $n = 2, 3, 12$ **then**
        Run Isolation Forest to detect outlying values from nth field and jth ship.
      else
        for $m = 1, 2, \ldots M$ **do**
          Create vectors consisting of field values (longitude, latitude, speed over ground, course over ground, timestamp) from previous, given and next message.
          Run classification algorithm to classify those vectors.
        end for
      end if
      if classification/anomaly detection result == 'field n is damaged' **then**
        Add index of T_j^{tm} to *idx_list*.
        Add j to *i_list*.
        Add n to *n_list*.
      end if
    end for
  end for
  return *idx_list* — list of indices of AIS messages that require correction,
  i_list — list of indices of groups that those messages should be assigned to,
  n_list — list of indices of AIS message fields that require correction.
end

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Multi-Label Field Classification. For each element of $T_i^{t_m}$, 2-element vectors $[\Delta\psi_{in}, \Delta\sigma_{in}]$ is computed using the equations presented in the previous section. Based on the values of the 2-element vectors it is possible to predict whether a given field $x_{jn}^{t_m}$ from $T_i^{t_m}$ is damaged or not. The higher the values $[\Delta\psi_{in}, \Delta\sigma_{in}]$, the more likely the field n can be considered anomalous (damaged). The prediction process is here associated with solving multi-label classification problem. For each analysed field, independent classifier is build.

4.3 Detection of Damage Inside Proper Clusters

After examining the AIS messages that formed standalone clusters, also messages from proper, multi-element clusters must be checked — the damage might be so slight that the clustering algorithm manages to assign the corrupted message along with other messages from the same vessel.

For dynamic data: speed over ground, longitude and latitude fields, we created vectors consisting of values from the current, previous and next AIS message from the following fields: longitude, latitude, speed over ground, course over ground, timestamp: $[x_{i7}^{t_m} - x_{i7}^{t_{m-1}}, x_{i7}^{t_{m+1}} - x_{i7}^{t_m}, x_{i8}^{t_m} - x_{i8}^{t_{m-1}}, x_{i8}^{t_{m+1}} - x_{i8}^{t_m}, x_{i5}^{t_{m-1}}, x_{i5}^{t_m}, x_{i5}^{t_{m+1}}, x_{i9}^{t_{m-1}}, x_{i9}^{t_m}, x_{i9}^{t_{m+1}}, t_{m+1} - t_m, t_m - t_{m-1}]$. For course over ground, $\arctan\left(\frac{x_{i8}^{t_{m+1}} - x_{i8}^{t_m}}{x_{i7}^{t_{m+1}} - x_{i8}^{t_m}}\right)$ and $\arctan\left(\frac{x_{i8}^{t_m} - x_{i8}^{t_{m-1}}}{x_{i7}^{t_m} - x_{i8}^{t_{m-1}}}\right)$ was put instead of values related to speed, longitude and latitude differences to help the algorithm deal with the trigonometric functions that field relies on. To some of those fields in a training data, we introduced an artificial damage, those were labelled as 1 ("damage"), to some we did not (labelled 0, "no damage"). Here, we again used the dedicated classifier (such as Decision Tree, Random Forest or XGBoost) to make a prediction of whether a given field is corrupted or not.

For static fields, values from a given nth field and given ith ship $(x_{i2}, x_{i3}, x_{i12})$ were analysed by Isolation Forest [20] to distinguish anomalies.

The entire proposed damage detection process in presented as Algorithm 2.

5 Computational Experiment

5.1 Overview

The Goal of the Experiment. The computational experiment focuses on validation of the performance of the tree-based algorithms, i.e. Decision Tree, Random Forest and XGBoost — as base classifiers in the ensemble approach, in proposed machine learning based framework for detecting damaged AIS messages and their fields.

Environment. The framework and all algorithms have been implemented in Python programming language using Sci-kit learn [20] and XGBoost [5] libraries in Visual Studio Code.

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Quality Metrics. The following quality measures [20] have been used in order to evaluate the performance of the proposed approach for AIS data damage detection: recall (percentage of detected positive instances among all truly positive instances) and precision (percentage of true positive instances among those classified as positive).

Hyperparameters. During some initial tests, we found the optimal hyperparameters for our Random Forest [7] for analysing standalone clusters: max_depth, indicating how deep the tree can be, was set to 5, and $n\_estimators$, indicating the number of trees in our Forest, was set to 15 (for XGBoost classifier, those parameter are 3 and 15, respectively).

Also the values of hyperparameters for analysing proper clusters have been discovered: for Random Forest $max\_depth = 15$ and $n\_estimators = 15$; for XGBoost $max\_depth = 7$ and $n\_estimators = 15$; as a tradeoff between good performance on validation set (in the sense of classification F1 score) and overfitting to the training set. Note: only for the speed over ground field the max_depth was set to 12 and 5, respectively.

For Desision Trees, the same max_depths were used as for Random Forests.

Data. In this experiment, data from a real, operational AIS was used. Recorded AIS messages of types 1-3 (those that carry the information regarding the vessels' movement) were divided into 3 datasets:

1. 805 messages from 22 vessels from the area of Gulf of Gdańsk,
2. 19 999 messages from 524 vessels from the area of Gibraltar,
3. 19 999 messages from 387 vessels from the area of Baltic Sea.

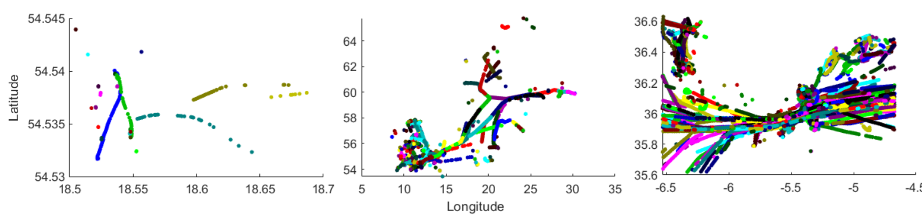

Fig. 3. Visualisation of vessels' trajectiories from each dataset used in this experiment

Each dataset was later divided into training (50%), validation (25%) and test (25%) sets. For each, a matrix X was build, serving as an input to the machine learning algorithms and consisting of the following fields of AIS messages type 1-3: longitude, latitude, MMSI, navigational status, speed over ground, course over ground, true heading (not used in anomaly detection phase), special manouvre indicator. In clustering stage, some features being the identifiers (MMSI, navigational status, special manouvre indicator) were additionally one-hot-encoded and the whole data was standarized.

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5.2 Results

Performance of the Proposed Method. In the first part of the experiment, we checked how well our framework of detecting false values in AIS data works (in terms of the quality metrics described earlier).

Table 1. Performance of the proposed method in AIS data damage detection

Algorithm	Damaged messages	Metric	1. dataset	2. dataset	3. dataset
Decision Tree	5%	Recall (mess.)	90.77%	91.00%	93.51%
		Precision (mess.)	05.78%	06.02%	05.50%
		Recall (field)	58.46%	69.38%	60.60%
		Precision (field)	55.73%	49.82%	50.89%
	10%	Recall (mess.)	90.74%	91.20%	92.82%
		Precision (mess.)	11.84%	11.83%	10.87%
		Recall (field)	60.74%	69.24%	61.17%
		Precision (field)	50.89%	47.67%	45.23%
Random Forest	5%	Recall (mess.)	95.38%	91.68%	93.35%
		Precision (mess.)	06.01%	06.20%	05.73%
		Recall (field)	72.31%	73.74%	64.00%
		Precision (field)	58.46%	49.93%	49.00%
	10%	Recall (mess.)	93.70%	92.20%	92.88%
		Precision (mess.)	12.29%	12.06%	11.32%
		Recall (field)	71.85%	74.00%	64.99%
		Precision (field)	51.87%	48.04%	46.07%
XGBoost	5%	Recall (mess.)	92.31%	91.88%	93.43%
		Precision (mess.)	06.56%	06.50%	05.68%
		Recall (field)	71.54%	72.76%	63.80%
		Precision (field)	58.08%	51.71%	49.97%
	10%	Recall (mess.)	91.85%	92.24%	92.72%
		Precision (mess.)	13.67%	12.60%	11.21%
		Recall (field)	71.85%	73.30%	64.77%
		Precision (field)	53.48%	49.92%	46.30%

The performance was examined in two scenarios: when 5% or 10% of messages were artificially corrupted (2 randomly chosen bits of randomly chosen messages of given amount were swapped) for each of the three available datasets. The corrupted bits were chosen among the features of our interest. The test was executed 10 times for each percentage and the mean value of the following metrics were calculated: recall and precision in detecting messages, recall and precision in detecting fields. During the test, Decision Tree, Random Forest and XGBoost were examined. The results are presented in Table 1.

It can be noticed that a single Decision Tree underperforms in most cases, while both enseble methods give better and similar results. The recall (of both message and field detection) looks promising, however, we find precision values slightly unsatisfying. It seems like the proposed method marks more messages as "damaged" that it should (high false positive rate), but when it does, it predicts

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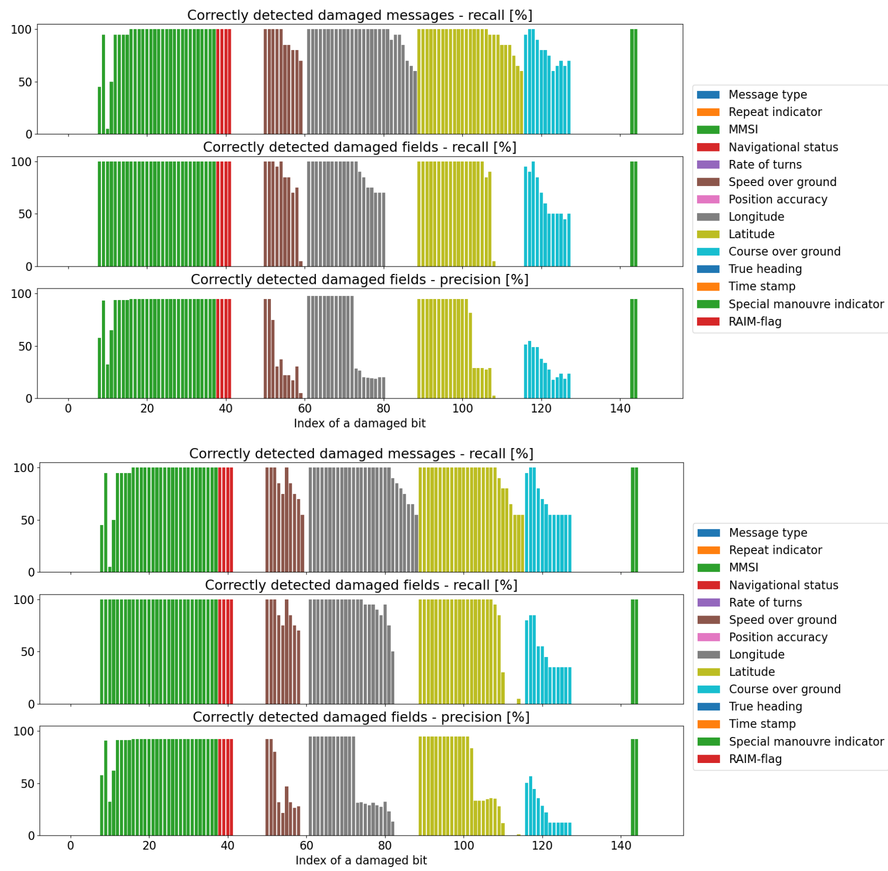
only a few fields to be corrupted in those messages. In fact, this is not that big issue since it is more important to detect all damaged messages (their appearance in the dataset might eventually result in two ships colliding) than bother with the false positive instances (which would be handled during the last, prediciton stage). What also can be noticed is that the increasing of number of damaged messages has only a little impact on the performance.

Impact of the Damaged Bit Position. In another part of the experiment, the impact of where exactly the damaged bit is on the performance of the proposed method of AIS data damage detection was examined.



a)

b)

Fig. 4. Impact of damaged bit position on damage detection: a) RF, b) XGBoost

While iterating over each of the AIS position report bit (excluding the bits related to fields that we decided not to investigate), the value of that exact bit was swapped in 20 randomly selected messages (only from the first dataset) and the performance (in the form of recall and precision) of detecting that the selected message and the field corresponding to the damaged bit were indeed corrupted was calculated.

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The results are presented on Fig. 4. While using Random Forest, the average recall of detecting corrupted AIS messages was 92.26%, the average recall and precision of detecting fields were 78.98% and 61.28%, respectively. For XGBoost, the same results are 89.87%, 81.42% and 61.47%, respectively. It can be noticed that the precision is slightly lower than the recall (a part that still can be improved). Moreover, the proposed method struggled to detect damage placed in least significant bits of some of the fields (speed over ground, longitude, latitude and course over ground).

6 Conclusions

In this paper the framework designed for finding anomalies (damage, considered as incorrect values in AIS messages) is proposed. The effectiveness of usage of decision tree based algorithms (Decision Tree, Random Forest, XGBoost) in this framework was evaluated.

The comparison between the effectiveness of AIS data damage detection method proposed in this paper and others existing in the literature may be ambiguous due to the fact that (as mentioned before) some existing frameworks consider "anomalies" as parts of trajectories that do not fit to the pattern of a usual vessels' behaviour in a given area, while our approach focuses more on identyfing false values in AIS messages fields. Our method managed to correctly mark 90% - 95% damaged messages and 60% - 74% damaged fields as "damaged". TREAD framework proposed in [8] correctly identifies 40% - 80% (depending on the analysed area) trajectories as "normal", while framework described in [2], based on masked autoregressive normalizing flows (not working on AIS data, but trajectory data from Microsoft GeoLife set) receives 0.055 - 0.6 false positive rate (for fixed 80% true positive rate). Therefore, we find our results promising.

In the near future, the further development of the proposed method by establishing the optimal observation time from the damage detection point of view will be considered. Also, the methods for reconstruction of the detected damaged elements of the AIS messages will be examined.

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