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On the possibility to use AIS and meteorological data to detect and characterize the drift of a ship

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ABSTRACT

The wealth of information that constitutes AIS database has been used extensively to produce approaches for anomaly detection. A specific type of anomaly that can be of interest is a ship going adrift. Spotting a ship adrift is important if it does not signal itself rapidly. It can then be useful to be able to predict its trajectory.

We thus propose a method to identify a ship going adrift based on its AIS data and to then use these AIS data together with meteorological data to determine the ship drift characteristics.

To determine a specific AIS signature corresponding to a drifting ship we used AIS data and intervention report from the French rescue centres to generate a reference base. Two approaches were then tested. The first was based on simple pre-processing using threshold rules on certain parameters such as speed and drift angle. The second was based on a neural network trained using the reference base previously generated. Both methods gave pertinent results, with the neural network achieving over 90% correct identification on a carefully constructed database. Application on a less refined database was less successful.

The AIS data were then used alongside current and wind data to determine drift characteristics. The results obtained were not satisfactory, presenting either too much dispersion or too much uncertainty.

Overall, we believe that this method is worth exploring further as it might provide valuable data regarding the drift of large ships.

Keywords: AIS ; Leeway drift ; neural network ; Search and Rescue.

NOMENCLATURE

a_C	Crosswind leeway coefficient [-]
a_D	Downwind leeway coefficient [-]
$\boldsymbol{u}$	Current speed [m s^{-1}]
$\boldsymbol{v}$	Ship speed [m s^{-1}]
$\boldsymbol{W_{10}}$	10-meter wind [m s^{-1}]
AIS	Automatic Identification System
CANSARP	Canadian Search and Rescue Planning Program
CROSS	Centre Régional Opérationnel de Surveillance et de Sauvetage
CWL	Crosswind Leeway
DWL	Downwinf Leeway
IMO	International Maritime Organization
LSTM	Long Short-Term Memory
MMSI	Maritime Mobile Service Identity
MOTHY	Modèle Océanique de Transport d'Hydrocarbures
SAROPS	Search and Rescue Optimal Planning System
SOLAS	Safety of Life at Sea
UNCTAD	United Nations Conference on Trade and Development

1. INTRODUCTION

Maritime transport is crucial for international trade in a globalised world. In 2020, over 80 percent of the volume of international trade was carried by sea (UNCTAD, 2021). With the notable exception of 2009 and 2020, the international maritime trade has been constantly growing for the last 50 years (UNCTAD, 2021). This leads to ever more ships at sea, thus increasing the need for efficient tools to monitor traffic and detect anomalies.

The AIS is a transceivers-based system that was introduced by the International Maritime Organization in SOLAS convention (IMO, 2015). It provides information pertaining to a ship such as its position, speed, or course. This allows ships to monitor traffic in their area and to be seen by said traffic for security reasons and especially collision avoidance. It also allows shore-based facilities to receive this information for traffic monitoring and maritime security in general.

The wealth of information that constitutes AIS database has been used extensively to produce approaches for anomaly detection (Wolsing *et al.*,2022). There are 3 main different ways to consider this problem. Some studies consider anomalies as a deviation from a "normal" pattern (Laxhammar, 2008). Other divide them based on the specific anomalous behaviour observed such as route deviation or zone entry (Lane *et al.*, 2010 ; Rong *et al.*, 2020). Some finally are aimed at detecting a specific source of anomalous behaviour such as illegal fishing (Singh and Heymann, 2020 ; Ford *et al.*,2012) or smuggling (Kowalska and Peel, 2012).

A specific source of anomaly that can be of interest is a ship going adrift. Spotting a ship adrift is important if it does not signal itself rapidly. It can then be useful to be able to predict its trajectory, especially in regions with intense maritime traffic. Operational models used to predict a drifting object trajectory such as MOTHY for the French CROSS (Daniel, 2019), CANSARP for the Canadian Coast Guards (Hillier, 2008) and SAROPS for the United States Coast Guards (Kratzke *et al.*,2010) are based on the Leeway method, formalized by Allen and Plourde (1999). This method requires field data regarding drifting objects, such as their speed, the 10-meter wind and the current, to then determine their drift characteristics. These data are costly and difficult to obtain for a large array of objects in a wide range of condition.

In this paper we will propose different methods to identify a ship going adrift based on its AIS data. We will then present two ways to use these AIS data together with meteorological data to determine the ship drift characteristics.

This paper comports two main parts. The first is about drift detection and encompasses the creation of the reference database, the different methods that were tested and the results. The second shorter part is a work-in-progress about the possibility to use AIS-based drift detection in conjunction with meteorological data to infer the drift characteristics ships.

2. METHODS

The main objective of this work was to determine whether it was possible to identify when a ship goes adrift based on its AIS and to then evaluate the precision of this method.

2.1 Creation of the reference database

The first step was to create a reference database containing annotated AIS messages. The AIS data used for this work came from the SpatioNav database and roughly cover the Bay of Biscay, the Celtic Sea and the English Channel. They were then decoded using the software Envigis. In theory these data were sampled at a fixed interval, but many discrepancies were observed as highlighted in Figure 1. Overall, the sampling period appears to be closer to 500 seconds, with a mean of 498 seconds and a median of 504 seconds.

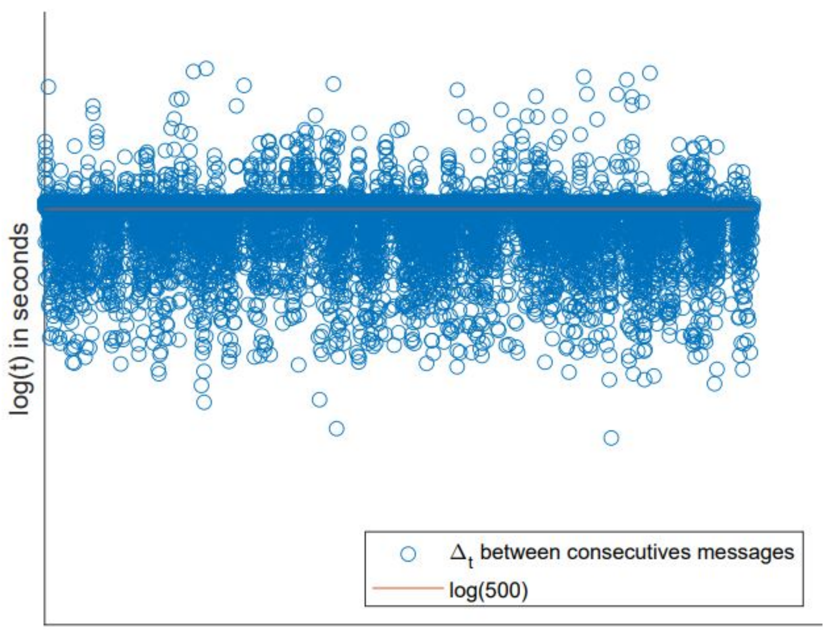

Figure 1: Distribution of the time between successive messages from the same ship in logarithmic scale.

We decided to break down the data in drift cases using the operation data made available by the French CROSS. Each drift case corresponds to the decoded and annotated AIS data for a single ship and a single incident. For each drift case we considered the entirety of the 24 hours period starting at midnight CET (or CEST) during which the report was made. For drift cases that spanned across two different 24h periods we simply considered a 48h period. Each individual AIS message within this time window was then labelled using the CROSS's intervention data. If the ship was considered adrift at the time a message was sent it is labelled with a 1, otherwise by a 0.

We filtered the intervention data based on the CROSS that received the alert, the type of event, and the type of object involved. We only kept interventions that were handled by the CROSS Griz-Nez, Jobour, Corsen and Etel as their intervention zone roughly corresponds to the area covered by our AIS data. We then discarded all interventions that were not labelled as either "propulsion system failure" or "electrical failure" as we deemed that only these types of events were likely to coincide with a ship going adrift. Finally, we only considered intervention concerning cargo or merchant ship, thus excluding fishing vessels and pleasure craft whose AIS data are often less complete.

After this was done, we had to manually sift through the data to exclude cases where or the AIS data were unexploitable or simply missing. We deemed as unexploitable data which were incomplete (e.g., missing the course over ground) or clearly incorrect (e.g., a cargo ship reporting a speed over ground over a hundred knot). For the period 2014-2019 this resulted in 663 annotated drift cases. Not all the information contained in the AIS message were exported. The values contained in the database are presented in Table 1.

Table 1: Database content with units.

MMSI	[-]
Unix time	[s]
Navigation status	[-]
Rate of Turn	[degree s^{-1}]
Speed over Ground	[knot]
Longitude	[degrees East]
Latitude	[degrees North]
True Heading	[degrees North]
Course over Ground	[degrees]
Drift Status	[-]

2.2 Detection of a drift

This work is based on the idea that a ship going adrift presents a distinct AIS signature. Since ships going adrift are overall few and far between, we could not use approaches that were zone dependent like route deviation or zone entry. We thus decided to focus on 3 parameters that can be made independent of the zone where the drift occurred: the absolute speed of the ship, the difference between the heading and the course (or drift angle) and the navigation status. The basis for this was that a ship going adrift should experience a drop in absolute speed, and that unlike a ship under way using its engines, its heading might not be as close to its course. A direct observation of some drift cases (Figure 2) confirmed these first hypothesis.

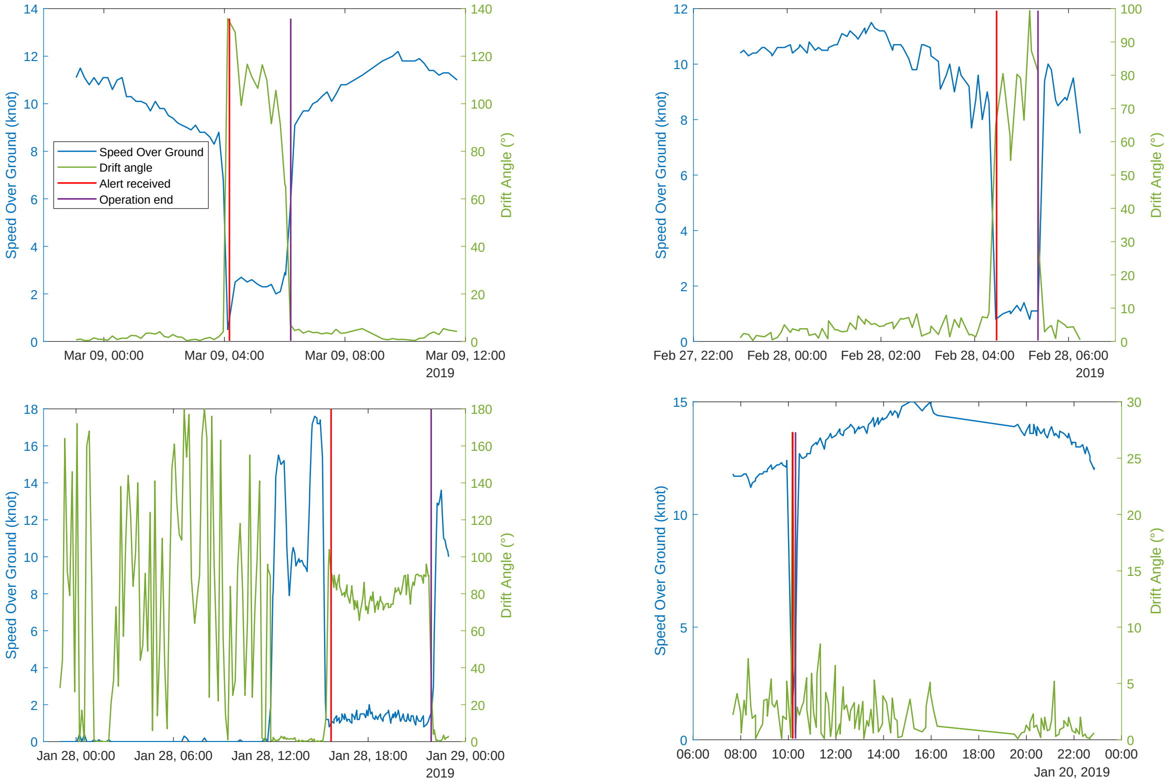

Figure 2: Overview of different cases.

2.2.1 Threshold

The first method consists in the superposition of 3 criteria relative to the speed over ground, the drift angle and the navigation status. As shown in Figure 3, ships that are adrift (in blue) and ships that are under way (in orange) have clearly different distribution regarding those 3 criteria.

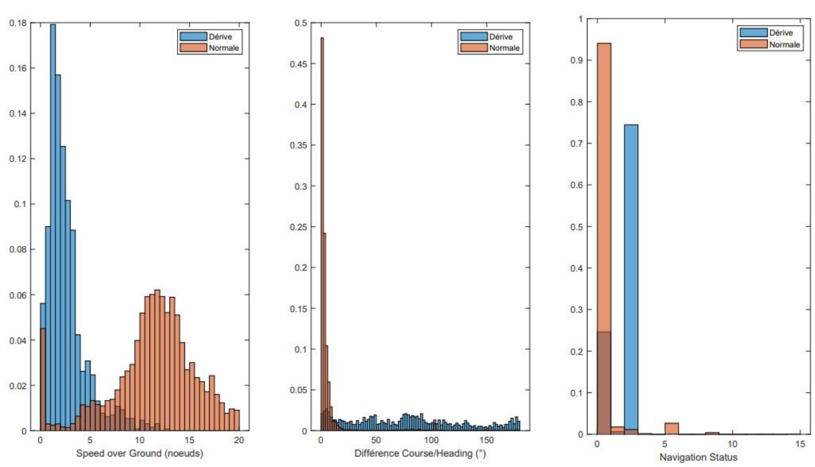

Figure 3: Repartitions of the ships along the 3 criteria depending on their drift status

It has to be noted though that the variety of conditions that can be encountered at sea results in some overlap between these two distributions. In addition, due to inertia, ships can sometime retain a relatively high speed at the onset of their drift. In the same way, when a ship regains control after a drift, it can take a few minutes to re-accelerate to its cruise speed.

We determined a speed threshold of 4 knots and a drift angle threshold of 10 degrees. They were chosen to maximize the probability that a ship under the speed threshold is adrift and the probability that a ship over the drift angle threshold is adrift. Finally we also accounted for the navigation status, considering that a ship that declares itself "not under command" is adrift.

This gave us 3 criteria, and we considered that a ship was adrift if it meets at least two of the three criteria.

2.2.2 Long Short-Term Memory Neural Network

The second method is based on the use of a Long Short-Term Memory Neural Network (Hochreiter and Schmidthuber, 1997). This architecture has already been used for AIS data (Gao *et. al*, 2018) as it is particularly well suited for the treatment of sequential data.

We used a sequence length of 3 messages and 3 informations were kept per message, the same as for the threshold method. The activation function for the hidden layer was an hyperbolic tangent and the output layer used a sïgmoide as activation function.

The neural network was then trained on the data from 2014 to 2018, which represents 587 drift cases and more than 50000 individual AIS messages.

2.3 Determination the Drift Characteristics

For search and rescue operations it is also important to possess an effective model to predict the trajectory of a ship going adrift. Such a model can be used to determine whether a ship that is drifting is at risk of crossing a major navigation route or entering a dangerous zone.

2.3.1 Leeway method

The Leeway field method is the method commonly used in SAR operational models such as MOTHY for the French CROSS (Daniel, 2019), CANSARP for the Canadian Coast Guards (Hillier, 2008) and SAROPS for the United States Coast Guards (Kratzke *et al.*,2010). The definition of the Leeway was given by Allen and Plourde (1999) and is as follow:

Leeway is the motion of the object induced by wind (10 m reference height) and waves relative to the ambient current (between 0.3 and 1.0-m depth).

The Leeway is then decomposed in its downwind component noted $\boldsymbol{DWL}$ and its crosswind component noted $\boldsymbol{CWL}$(Breivik *et al.*,2011). The speed $\boldsymbol{v}$ of a ship going adrift is thus

$$\boldsymbol{v} = \boldsymbol{u} + \boldsymbol{CWL} + \boldsymbol{DWL} \tag{1}$$

where $\boldsymbol{u}$ is the ambient current.

The $\boldsymbol{DWL}$ and $\boldsymbol{CWL}$ are supposed to depend linearly on the wind measured at 10 meters $\boldsymbol{W_{10}}$

which results in:

$$\boldsymbol{DWL} = a_D \boldsymbol{W_{10}} + b_D + \epsilon_D \tag{2}$$

$$\boldsymbol{CWL} = a_C \boldsymbol{W_{10}} + b_C + \epsilon_C \tag{3}$$

where a_D and a_C are dimensionless coefficients called the leeway coefficients, b_D and b_C are offset coefficients which can be considered null, so that there is no Leeway in the absence of wind and ϵ_D and ϵ_C are error terms.

In this case, assuming the speed of the drifting object is known as well as the wind and current, determining the leeway coefficients is then done by performing linear regressions (Breivik *et al.*,2011).

Our method simply consists in using AIS data for the speed of the ship and data for meteorological model for the wind and current. While these data are inherently less precise than data stemming from a field trial, they are also easier to collect.

2.3.2 Wind and Current Regression

This method is a slight variation on the Leeway method. It abandons the hypothesis that the drift speed is equal to the ambient current plus a component that depends on the wind and instead considers that it depends linearly on both the wind and current.

The speed $\boldsymbol{v}$ of an ship going adrift is thus

$$\boldsymbol{v} = \boldsymbol{DWD} + \boldsymbol{CWD} + \boldsymbol{DCD} + \boldsymbol{CCD} \tag{4}$$

where $\boldsymbol{DWD}$ is the component of the drift attributed to the wind in the downwind direction, $\boldsymbol{CWD}$ is the component of the drift attributed to the wind in the crosswind direction, $\boldsymbol{DCD}$ is the component of the drift attributed to the current in the downcurrent direction and $\boldsymbol{CCD}$ is the component of the drift attributed to the current in the crosscurrent direction.

As before, the $\boldsymbol{DWD}$, $\boldsymbol{CWD}$, $\boldsymbol{DCD}$ and $\boldsymbol{CCD}$ are supposed to depend linearly respectively on the wind and current, hence:

$$\boldsymbol{DWD} = \alpha_{DWD} \boldsymbol{W_{10}} + \epsilon_{DWD} \tag{5}$$

$$\boldsymbol{CWD} = \alpha_{CWD} \boldsymbol{W_{10}} + \epsilon_{CWD} \tag{6}$$

$$\boldsymbol{DCD} = \alpha_{DCD} \boldsymbol{u} + \epsilon_{DCD} \tag{7}$$

$$\boldsymbol{CCD} = \alpha_{CCD} \boldsymbol{u} + \epsilon_{CCD} \tag{8}$$

with α_{DWD}, α_{CWD}, α_{DCD}, α_{CCD} dimensionless drift coefficients.

Our hypothesis is that this approach will allow a better consideration of the impact of the current on large ships, as there can be non negligible current variations over their immersed height. For smaller ships it is expected that α_{DCD} be close to 1 and α_{CCD} be close to 0, which will then coincide with the classical formulation of the Leeway drift.

In this case determining the drift coefficients is less straightforward. For each timestep this results in the following system :

$$M_i x = V_i \tag{9}$$

with $M_i = \begin{bmatrix} w_x & -w_y & u_x & -u_y \\ w_y & w_x & u_y & u_x \end{bmatrix}$, $x = \begin{bmatrix} \alpha_{DWD} \\ \alpha_{CWD} \\ \alpha_{DCD} \\ \alpha_{CCD} \end{bmatrix}$ and $B_i = \begin{bmatrix} v_x \\ v_y \end{bmatrix}$

If we then pose : $A = \begin{bmatrix} M_1 \\ \vdots \\ M_n \end{bmatrix}$, $x = \begin{bmatrix} \alpha_{DWD} \\ \alpha_{CWD} \\ \alpha_{DCD} \\ \alpha_{CCD} \end{bmatrix}$ and $B = \begin{bmatrix} V_1 \\ \vdots \\ V_n \end{bmatrix}$

We obtain the following system:

$$Ax = B \tag{10}$$

Which can be solved using the ordinary least square (OLS) method.

3. RESULTS

3.1 Drift Detection

Both methods produced reasonably good results with over 92% correct identifications for the threshold method and 98% for the neural network. As the database was highly unbalanced, with only around 10% of drift cases (or positives), it is best however to consider confusion matrix as in Figure 4.

Both methods then have a true positive rate of 90%, meaning that 90% of the time, an AIS message corresponding in the database to a ship that is adrift was correctly identified. The main difference was the rate of false positive which was significantly higher for the threshold method. For the neural network, around 10% of the messages that were predicted to be coming from a ship that is adrift were false positive, and this rate was of 37% for the threshold method.

In both cases these results are highly encouraging, although the rate of false positives remains too high for a direct application in traffic surveillance. Considering the number of ships that each CROSS has to watch, even a 1% false positive rate would still mean a dozen false alert per hour which is not acceptable.

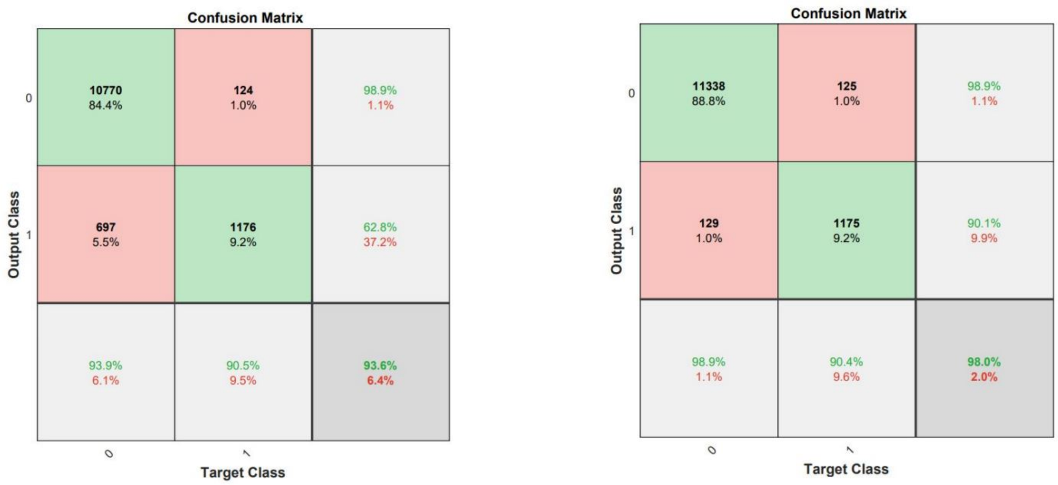

Figure 4: Confusion matrix for the threshold method (on the left) and the LSTM (on the right)

3.2 Drift Characteristics

The first method was applied to 27 drift cases that were identified for the month of september 2022. As each drift case was relatively brief, we grouped them all together, which is not ideal as the ships concerned were not all identical. We found a mean a_D of 0.032 with a median at 0.044 and a mean a_C of 0.016 with a median at 0.02. The values are relatively in line with those available in the reference databases for ships. However, as shown in Figure 5, the dispersion is important, resulting in significative uncertainties once the method is used to predict a ship drift speed.

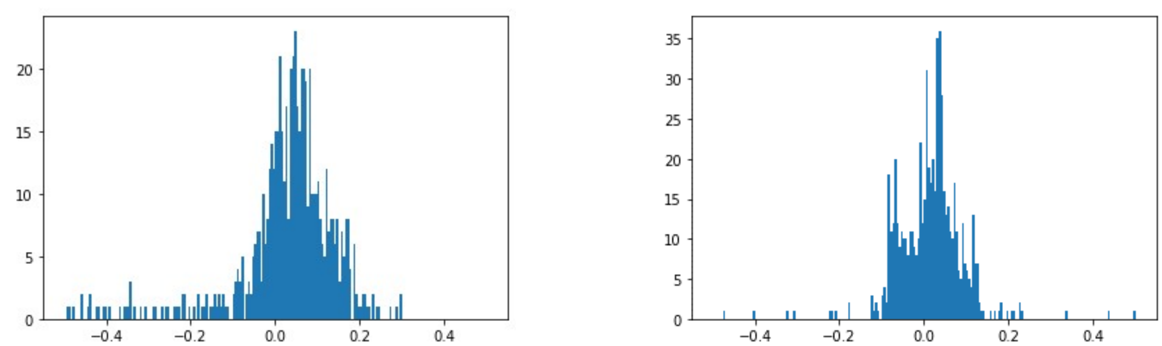

Figure 5: Repartition of the DWL coefficients (right) and CWL coefficients (left) for the drift cases.

The second method was only applied on a handful of drift cases as it is less straightforward to interpret the coefficients in regard with the literature available. The results proved to be highly innacurate in with relative errors of up to 200% in certain cases. Due to the small number of cases studied, we were not able to determine whether this was because of the quality of the data or because of problems in our model.

Although these initial results are quite poor, we believe it is worthwhile to continue exploring these methods as conducting Leeway field tests on large merchant ships is impractical at best.

4. CONCLUSIONS

We have given an overview of three methods to identify a ship going adrift based on its AIS and two approaches to exploit this information in conjunction with meteorological data to infer the drift characteristics of a ship.

While on most aspects this is still a work in progress, we believe it may already prove useful for some applications. In their current state, the drift detection methods can reach over 90% correct identification. Although they still produce too much false positives to be used directly for traffic surveillance, they can be used as a basis for statistical analysis.

The determination of the drift characteristics however is not yet ready for any applications due to the uncertainties in the results and more work still needs to be done, mostly by analysing a larger amount of data to be able to regroup the ships in homogeneous groups.

The next steps in this project will be to increase the amount of AIS data processed. First by exploiting a longer time period, and in a second time by including AIS data from other sources covering different areas. This will also be the occasion to confirm where these methods are truly independent on training in a specific zone. In a second time we would also like to increase the quality of the AIS data used, mainly by reducing the time step between messages in our database, as it would open new possibilities in term of analysis.

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