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Predicting AIS reception using tropospheric propagation forecast and machine learning

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***Abstract*— The aim of this paper is to present a methodology for modelling and predicting the coverage of an Automatic Identification System (AIS) station based on tropospheric index forecast maps and modelling methods from machine learning. The aim of this work is to cartographically represent the areas in which the AIS signals emitted by ships will be received by a coastal station. This work contributes to the improvement of maritime situational awareness and to the detection of anomalies at sea [1], and in particular to the identification of AIS message falsifications [2] (ubiquity of a vessel by identity theft, falsification of GPS positions and deactivation of AIS).**

I. INTRODUCTION

The AIS (Automatic Identification System) is a system for the automated exchange of messages between ships via radio waves which allows ships and shore-based maritime surveillance systems to acquire a set of information (GPS coordinates, type of ship, ship registration, etc.) necessary for monitoring maritime traffic and analysing activities at sea. AIS messages are transmitted on the frequencies 162.025 MHz and 161.975 MHz (VHF). There are two classes of AIS: AIS-A and AIS-B. AIS-A is mandatory on vessels with 300 or more gross tonnage (1 gross tonnage = 2.83 m^3). AIS-B is reserved for smaller vessels but is not mandatory. In the context of this article only the reception of AIS-A will be addressed.

II. PROBLEM STATEMENT

The physical processes that affect the range of a radio wave vary with the distance between the transmitter and the receiver. Below a certain distance, propagation is considered direct (line of sight), and only the configuration of the antenna (the efficiency of the antenna, its power, its orientation, its height and the transmitter's height, the characteristics of the ground) and the obstacles that the wave may encounter can influence the antenna's masking and visibility zones. Beyond this distance, weather conditions may make it possible for the signals to propagate at great distances or, on the contrary, may slow it down. Here we study only the area beyond the radio horizon, since we can predict direct visibility using the curvature of the earth and a topographic data layer.

Many articles [3,4] explain the influence of meteorological conditions and in particular the refractive index of the atmosphere on the propagation of radio waves. However, the available forecast maps provide information on the quality of propagation within specific areas, but do not allow us to deduce the possibility of receiving a signal between two points on the map. We therefore propose a methodological approach to modelling and predicting the reception area of an AIS coastal station as a function of the atmospheric environment.

III. PROPOSED METHODOLOGICAL APPROACH TO MODELING AIS RECEPTION

In this paper, we propose a methodological approach to model and predict the reception coverage area of an AIS coastal station. Ship location data and tropospheric propagation forecast maps will be used in the training step and in the development of the prediction model. Supervised classification and in particular the XGBoost method will be used to model and predict the reception area of our AIS receiver. This method is efficient for prediction tasks and simple to implement [3].

A. Description of the AIS data acquisition system

In August 2018, the research Centre on Risk and Crises (CRC) at Mines Paris deployed a coastal station in Sophia Antipolis (south-eastern France) to receive AIS messages transmitted by ships. This device is constituted of a Yagi antenna installed at 188 m height, and a device for decoding AIS messages. The axis of the directional antenna is 100 degrees, and its beamwidth is 130 degrees. The beamwidth is the angular region where the received power is at least half of the power received in the antenna axis for the same transmission conditions.

B. Tropospheric propagation forecast maps

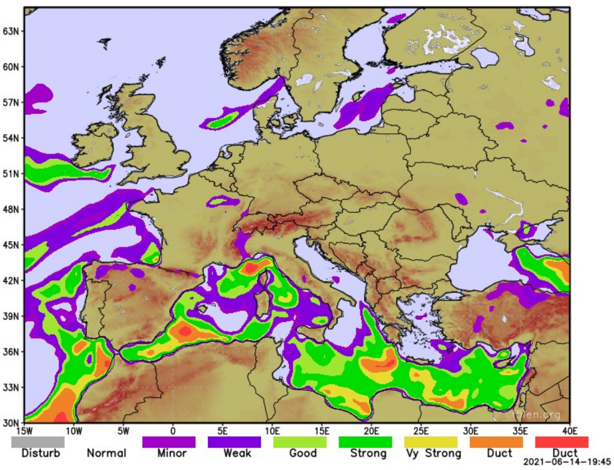

Figure 1. Tropospheric propagation forecast map (14/06/2021 at 15H UTC)

Pascal Grandjean uses NOAA meteorological data produced by the GFS 0.25 model to create forecast maps of VHF/UHF propagation conditions [4]. Many variables concerning the atmosphere or the ground are available, including temperature, pressure and humidity at different altitudes. For each of the pixels in the acquired data rasters, he calculates the average gradient of the atmospheric refractive index at different altitudes. Since the quality of wave propagation in the atmosphere depends directly on this gradient, he deducts a global map of the quality of radio wave propagation. The maps created in this manner are available to the interested public at a resolution of 0.035 degrees (Fig. 1).

C. XGBoost

Gradient boosting is a method that consists of training several classifiers. Each classifier learns from the mistakes of the previous ones by giving more weight to the observations that the latter did not classify correctly. The resulting classifier makes its prediction based on the most predicted class of each classifier [5].

IV. Learning Process and Predictions

We trained a gradient boosting algorithm by cross-validation on 6 month of data. The confusion matrices, the rate of correct classification, the precision and the recall, will allow us to assess the performance of the algorithm used.

A. Model inputs

The input data for the model are vectors derived from tropospheric forecast maps. The vectors contain the values of the propagation quality between a pixel of a grid constructed with Grandjean maps and the receiving station. If this pixel contains a ship, then it is given a "reception" label, otherwise it is given a "no reception" label. The learning algorithm will then learn the link between the vectors and the labels in order to establish a classification model.

B. Supervised learning

We applied the XGBClassifier from the Python xgboost library on our dataset with a forest of 10 decision trees of depth 8 and 100 boosting rounds. The dataset labels were unbalanced so we used random subsampling. The classification results are presented in the confusion matrix below (Table 1).

TABLE I. CONFUSION MATRIX ON TEST SET WITH XGBOOST CLASSIFIER.

	Classification matrix	
	Predicted "no reception'	***Predicted "reception"***
"no reception" true label	1508	325
"reception" true label	513	1320

This corresponds to a correct classification rate of 77.1% and accuracy on class "reception" of 80.2%.

C. Prediction maps visualisation

Fig. 2 shows an example of AIS reception prediction for our antenna, limited to a range of 600 km. The model provides relevant predictions. On this map we observe that the predicted reception area includes all the AIS-A vessels. The reception coverage is large due to the good tropospheric conditions.

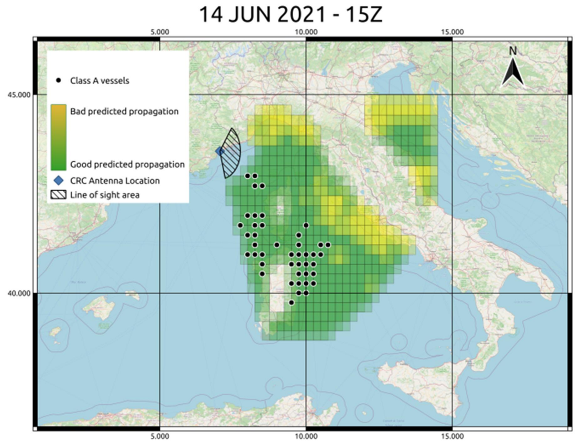

Figure 2. Reception prediction from our antenna (14/06/2021 at 15H UTC)

V. Conclusion et Discussion

The classification results for the prediction of propagation in the area beyond the radio horizon show promising results. However, some improvements can be made.

The input data of the model can be improved. Indeed, the label 0 assigned to a location could be divided into two classes: a class 0 for no ship and a class -1 for no reception despite the presence of a ship in the location. This classification could be obtained by crossing our data with those of other receiving stations in the neighbourhood of ours.

Recalculating the different refractive indices using the data sources of the maps would allow us to obtain vectors of propagation conditions of better accuracy. Recalculating these conditions would also allow the timeframe of the study to be extended, as we are currently limited by the availability of propagation maps, whereas we have AIS data over several years.

On the algorithm side, improvements can be made on dataset subsampling, hyperparameters optimization, model architecture and resolution scale.

Acknowledgment

We would like to thank Pascal Grandjean for providing the VHF propagation forecast maps on his website: https://tropo.f5len.org/forecasts-for-europe/.

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