An AIS-based Deep Learning Model for Vessel Monitoring

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Abstract. AIS data streams provide new means for the monitoring and surveillance of the maritime traffic. The massive amount of data as well as the irregular time sampling and the noise are the main factors that make it difficult to design automatic tools and models for AIS data analysis. In this work, we propose a multi-task deep learning model for AIS data using a stream-based architecture, which reduces storage redundancies and computational requirements. To deal with noisy irregularly-sampled data, we explore variational recurrent neural networks. We demonstrate the relevance of the proposed deep learning architecture for a three-task setting, referring respectively to vessel trajectory reconstruction, abnormal behaviour detection and vessel type identification on a real AIS dataset.

Keywords: AIS · vessel monitoring · deep learning · abnormal behaviour detection · vessel type identification · recurrent neural networks

1 Context

In the modern world, maritime safety, security and efficiency are vital. For example, about 90% of the world trade is carried by sea, but only 2% of them is physically inspected. Vessel monitoring, therefore, becomes an essential demand. Besides that, the construction of a maritime situation map is also necessary for multiple purposes: security, smuggling detection, EEZ intrusion detection, transshipment detection, fishing activities control, maritime pollution monitoring, etc.

Over the last decades, the development of terrestrial networks and satellite constellations of Automatic Identification System (AIS) has opened a new era in maritime surveillance. Every day, AIS provides tens of millions of messages, which contain ships identification, their Global Positioning System (GPS) coordinates, their speed, etc. This massive amount of data would be very useful if the information contained inside could be extracted, analyzed and exploited effectively.

Several efforts have been conducted in order to create automatic/semi-automatic AIS analysis systems. The aims are to extract useful information from AIS data stream[9] [8], and use it for specific tasks such as maritime routes detection [7] [4], vessel trajectory prediction [1] [10] or anomaly detection [3] [5]. However, those models depend on strong assumption, and can not capture all the heterogeneous characteristic of noisy, irregularly sampled AIS data.

In this work, we propose a multi-task model which explores deep learning, and more specifically recurrent neural networks to process AIS data stream for multiple purposes: trajectory reconstruction, anomaly detection and vessel type identification.

2 Proposed multi-task RNN model for AIS data

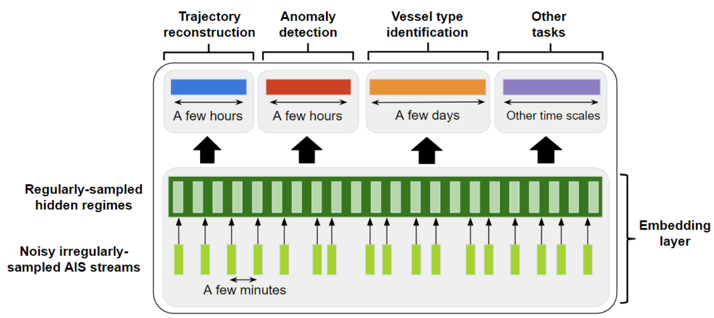


Fig. 1. Proposed RNN architecture.

As sketched in Fig. 1, we propose a multi-task Recurrent Neural Network (RNN) for the analysis of AIS data streams. The key component of this model is the embedding layer, which introduces hidden regimes. These regimes may correspond to specific activities (eg, under way using engine, at anchor, fishing, etc.). The embedding layer relies on a latent variable RNN [2]. It operates at a 10-minute time scale and allows us to deal with noisy and irregularly-sampled AIS data. Higher-level layers are task-specific layers at different time-scales (e.g., daily, monthly,...) to address the detection of abnormal behaviors, the automatic identification of vessel types, the identification of maritime routes,....

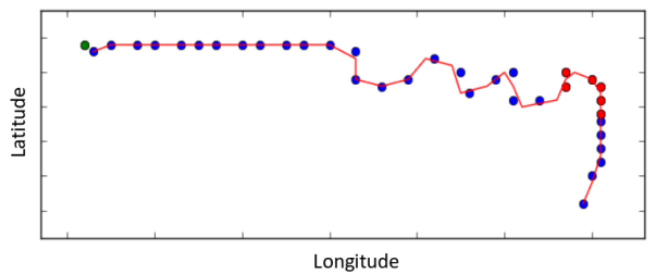
3 Results

We implemented the proposed framework for a three-task setting in the Gulf of Mexico to deal with vessel trajectory reconstruction, abnormal behavior detection and vessel type identification. Preliminary results are reported here for AIS data in January 2014, which amount to 10 154 808 AIS messages.

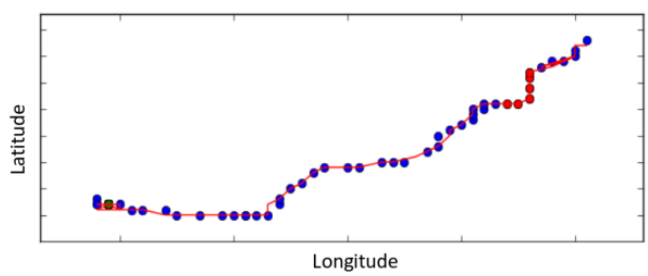
3.1 Vessel trajectory reconstruction

The trajectory reconstruction layer is a particle filter, estimates the position of vessel where data are missing. We follow [6] and take into account maritime contextual information to build this filter. Instead of using TREAD [8] to extract maritime routes, the contextual information in our case is here learned by the embedding layer.

We test the trajectory reconstruction by deleting 2-hours segments in vessel tracks, then reconstruct these missing segments. The model is able to perform some surprising good results like those shown in Fig. 2.



(a)



(b)

Fig. 2. Two examples of vessel trajectory prediction. Blue dots: received AIS messages; red dots: missing AIS messages; red line: estimated trajectory. The model could predicts these turns because others vessels in this regions did the same.

3.2 Abnormal behaviour detection

This layer addresses the detection of abnormal vessel behaviors at a 2-hour time scale. Our model learns the distribution of vessels' trajectories from the training set, both in terms of geometrical patterns, space-time distribution as well as speed and heading angle features. Any trajectory in the test set that does not suit this distribution will be considered as abnormal. An example of the outcome of the detector is shown in Fig. 3.

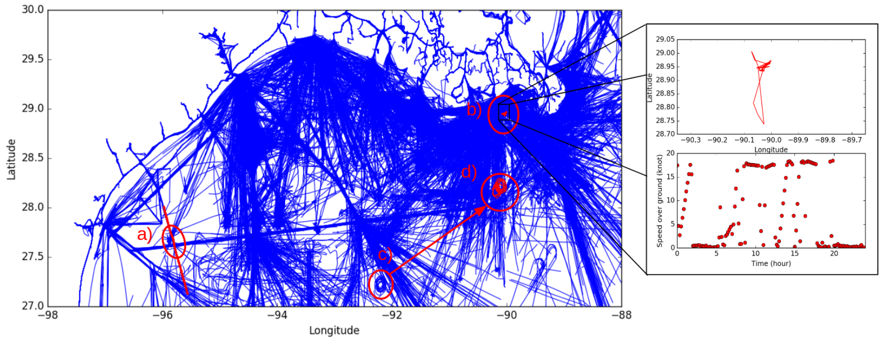


Fig. 3. Three examples of detected abnormal tracks: Tracks in the training set (which itself may contain abnormal tracks) are presented in blue. Abnormal tracks detected in the test set are presented in red; a) this track diverges from the usual maritime route in this area. b) example of abnormal speed pattern, c) example of simulated geometric pattern correctly detected as abnormal (this example was simulated by translating behaviors observed in zone C to zone D.

3.3 Vessel type identification

Using a Convolutional Neural Network (CNN) on top of the RNN, we design a vessel type classifier. This layer operates at a 1-day time scale. The targeted classification task comprises 4 classes of vessel: cargo, passenger, tanker and tug. We reach a relevant f1-score of **88.01%**.

4 Conclusions and perspectives

We introduced a deep learning model that can process the AIS stream on-the-fly for multiple purposes. The use of variational recurrent neural networks provide our model the ability to deal with irregular time sampling and noisy AIS data streams. Three tasks have been tested with successful outcomes. Other tasks (fishing detection, AIS on-off switching detection, etc.) can be added by simply plugging in other task-specific layers on top of the current ones.

Future work could involve benchmarking experiments with current state of the art methods, including the evaluation of the ability of the proposed approaches to scale up to global AIS data streams. The fusion with other sources of information in the maritime domain could be a promising solution.

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