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Neural Networks for Vessel Monitoring Using AIS Streams

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Abstract—AIS data streams provide new means for maritime traffic surveillance. 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 deep learning model for AIS data using a stream-based architecture, which reduces storage redundancies and computational requirements. To deal with noisy and irregularly-sampled data, we explore variational recurrent neural networks. We empirically evaluate the performance 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.

Index Terms—AIS, vessel monitoring, deep learning, trajectory reconstruction, abnormal behaviour detection, vessel type identification, variational recurrent neural networks.

I. CONTEXT

Initially being designed for collision avoidance, but thanks to its wealth of information, Automatic Identification System (AIS) has been quickly exploited for several applications [1] and has become one of the most important sources of data in the maritime surveillance domain. However, vessel monitoring using AIS is not a trivial task. Every day, there are more than 500 millions AIS messages [2]; this massive amount of data, besides the irregular time sampling and the noise, makes it difficult to exploit all the power of AIS effectively and efficiently.

In this context, we propose a stream-based architecture which can handle the noise and irregular time sampling of AIS data. The process is executed once for multiple tasks, reduces storage redundancies and computational requirements.

This paper is structured as follow: first, we review the state-of-the-art in vessel monitoring using AIS in Section II. Section III presents the architecture of the proposed, followed by the results in Section IV. Finally, we give some conclusions and perspectives for future work in Section V.

II. STATE OF THE ART

A wide set of theories and algorithms have been applied to exploit the potential of AIS for different marine tasks. To predict or reconstruct the trajectory of vessels, besides simple methods such as linear velocity models or curvilinear interpolations, authors have also used Ornstein-Uhlenbeck processes [3] or Kalman filters [4]. Understanding vessels'

patterns and detecting anomaly is another important task in maritime surveillance. In [5], Rhodes used Normalcy box to detect abnormal speed patterns of vessels. Gaussian processes were used in [6] to model the relation between speed and heading of each type of vessels at each specific position. Other information such as weather condition, number of stops, major stopping points of vessels' tracks, etc. was also taken into account to build normalcy model in [7].

However, those models have limitations and have not successfully handled all the problems of AIS yet. Some are too simple to capture all the underlying explanatory factors of AIS data, others depend on strong assumptions or require too many sources of information which are not always available. [5] and [8] treated reported AIS messages of each AIS tracks independently, omitted the sequential property - a very important property of AIS data streams - and lack robustness to noise. Other Gaussian-processes-based models like those in [9], [10], [11] assumed that AIS series have the Markov property, which would lose the longterm behaviors of vessels' tracks. Besides that, these models do not deal with the irregularly time-sampling problem. Bayesian networks [12], [7] require explicit definitions of input features, but it is difficult to list out all the features that may effect the output, and some are not always available.

Recently, Deep learning [13] has emerged as a very promising approach for many data analysis and pattern recognition tasks. In this paper, we explore Recurrent Neural Networks (RNNs), which are currently the state-of-the-art methods in time series modeling and processing to create a multi-task system for vessel monitoring using AIS data streams. Our model is robust to noise, can deal with irregularly sampled data and reduce the storage redundancies and computational requirements.

III. PROPOSED MULTI-TASK RNN MODEL FOR AIS DATA

The proposed multi-task Recurrent Neural Network for AIS data streams is shown in Fig. 1. The key component of this model is the Embedding layer, which introduces a consistent and regularly sampled series of hidden states - called "*hidden regimes*". These regimes may correspond to specific activities of vessels (*e.g.*, at anchor, fishing, underway, etc.). The Embedding layer relies on a Variational Recurrent Neural Network (VRNN) [14]. 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 vessel trajectory reconstruction, the anomaly detection, the vessel type identifications, the identification of maritime routes, etc.

A. Embedding block

In our model, a AIS track is modeled by a time series $x_{1:T} \equiv (x_1, x_2, \dots, x_T)$ where x_i is a 4-D vector of reported dynamic information (latitude, longitude, Speed Over Ground-SOG and Course Over Ground - COG) of vessel at time t_i :

$$x_i \equiv [\text{lat}, \text{lon}, \text{SOG}, \text{COG}]^T$$

As the nature of AIS data streams, the interval between two consecutive reported AIS messages x_i and x_{i+1} is not constant (irregular sampling problem). We assume that $\{x_{1:T}\}$ is just an observation of the true hidden states - called regimes $h_{1:T} \equiv (h_1, h_2, \dots, h_n)$. These hidden regimes are regularly time sampled series and may correspond to the true activities of vessels.

The distribution of $x_{1:T}$ is then estimated by the Evidence Lower Bound (ELBO):

$$\log p(x_{1:T}) \geq \mathcal{L}(x, p, q) = \mathbb{E}_{z_{1:T} \sim q} [\log p(x_{1:T} | z_{1:T})] - \mathcal{KL}[q(z_{1:T} | x_{1:T}) || p(z_{1:T})] \quad (1)$$

where $q(z_{1:T} | x_{1:T})$ is an approximation of the posteriori distribution $p(z_{1:T} | x_{1:T})$ (variational approach [14], [15], [16], [17]) and $\mathcal{KL}[q || p]$ is the Kullback-Leibler divergence between two distributions q and p .

The Embedding block is a VRNN [14] and will learn the distributions:

$$p(x_{1:T} | z_{1:T}) = \prod_{t=1}^T p(x_t | x_{1:t-1}, z_{1:t}) \quad (2)$$

$$q(z_{1:T} | x_{1:T}) = \prod_{t=1}^T q(z_t | x_{1:t}, z_{1:t-1}) \quad (3)$$

$$p(z_{1:T}) = \prod_{t=1}^T p(z_t | x_{1:t-1}, z_{1:t-1}) \quad (4)$$

The introduction of the hidden regimes $h_{1:T}$ brings us two benefits: i) they are a data representation that can disentangle the underlying factors of AIS data and provide necessary information for task-specific submodels. ii) the hidden regimes provide consistent and interval-regular series, which would facilitate the construction of higher blocks.

B. Trajectory reconstruction block

Our Trajectory reconstruction submodel shares the idea with methods in the literature: vessels tend to perform similar trajectories in a specific area [18]. This maritime contextual information is inferred through the the probability $p(x_t | x_{1:t-1}) = \mathbb{E}_{z_{1:t}} p(x_t | x_{1:t-1}, z_{1:t})$ of a set of AIS tracks in a region of interest, learned by the Embedding layer.

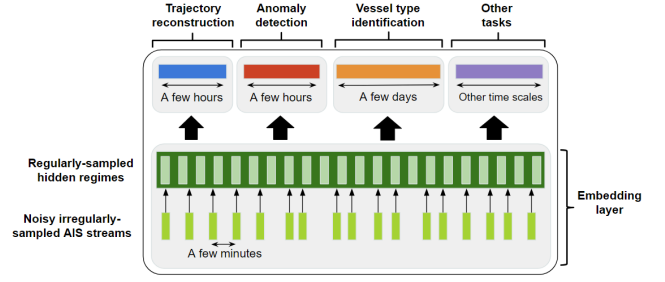


Fig. 1. Proposed RNN architecture.

Concretely, we estimate the position of vessel at a given time t by sampling from $p(x_t | x_{1:t-1})$ using a variational particle filter [17].

C. Anomaly detection block

This layer addresses the detection of abnormal vessel behaviors at a 4-hour time scale. Our model learns the distribution of vessels' tracks from the training set, both in terms of geometrical patterns, space-time distributions as well as speed and heading angle features. Any track in the test set that does not suit this distribution will be considered as abnormal. In other words, for any AIS track $x_{1:T}$, we evaluate $\log p(x_{1:T})$ (the parameters of this distribution have already been learned by the Embedding block), if this likelihood is smaller than a threshold, this track will be considered as abnormal.

D. Vessel type identification block

Sometimes some vessel do not send their static information, sometimes some vessel send purposefully a false vessel type in static AIS messages. This block aims to identify the true type of vessel from their activities. We use a Convolutional Neural Network (CNN) to build a classifier, operating at a 1-day time scale. The input of the network is the concatenation of the hidden regimes along time axis.

IV. 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 58,268,981 AIS messages.

A. Vessel trajectory reconstruction

To simulate the missing data phenomenon (e.g. AIS switch-off), we delete a 2-hour segment from each AIS track then try to reconstruct it.

This contextual maritime route information gave our model the ability to reconstruct complicated patterns like those shown in Fig. 2. Those constructions out-perform methods in literature. However, to obtain such an impressive result, the model requires a high vessel density in the training set, i.e. it works only in busy traffic regions.

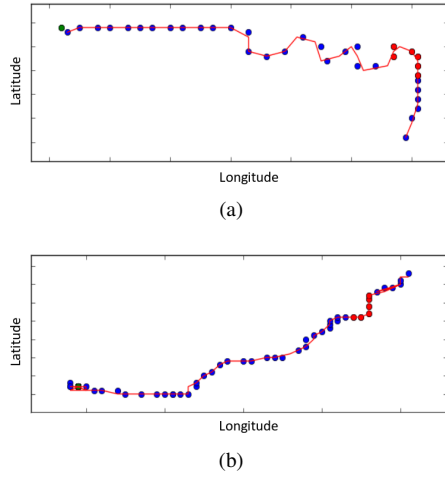


Fig. 2. Two examples of the vessel trajectory reconstruction. Blue dots: received AIS messages; red dots: missing AIS messages; red line: reconstructed trajectory. The model could predicts these turns because others vessels in this regions did the same.

B. Abnormal behaviour detection

An example of the outcome of the detector is shown in Fig. 3 and Fig. 4. An AIS track can be characterized by the shape of its trajectory (geometric pattern), its speed/course pattern and the zone where it is in (geographical pattern). Our model has the ability to detect whether one or some of these patterns of a track significantly deviate from the corresponding ones of AIS tracks in the neighborhood.

We also believe that some specific patterns should appear in some specific areas. To verify this argument, we ran our anomaly detection model on a synthetic test set, where we translated some normal tracks out of their area (to create anomalies). The result are shown in Fig. 5. The translated track were detected as abnormal, as expected.

C. Vessel type classification

The Vessel type classifier was tested with 4 classes of vessel: cargo, passenger, tanker and tug. We empirically evaluated the model against state-of-the-art models for time series classification: CNNs and LSTMs. For each type of networks, we tested several configurations and report the best result. We also tested these models in the case of missing data where we deleted a part of 2 hours randomly in each AIS stream.

The results are shown in Table. I, the missing data cases are reported by the symbol *. Our model obtained comparable results with those of the state-of-the-art methods, especially when a part of AIS tracks is missing. It is because the Embedding layer can provide a consistent and regularly sampled hidden regimes series with necessary explanatory factors for the task despite irregular time sampling in AIS streams. Although the improvement of the classification performance is slight (from 87.43% to 87.72%), the proposed model is highly beneficial in big data context because it significantly reduces storage requirements and the computational costs when doing each task separately.

TABLE I
CLASSIFICATION RESULTS.

Model	Precision	Recall	F1-score
LSTM	89.06%	89.22%	89.13%
CNN	85.64%	85.11%	85.09%
VRNN-CNN	88.90%	88.50%	88.66%
LSTM*	88.04%	87.16%	87.43%
CNN*	83.83%	84.06%	83.75%
VRNN-CNN*	88.00%	87.67%	87.72%

V. CONCLUSIONS AND PERSPECTIVES

We introduced a deep learning model that can process the AIS stream on-the-fly for multiple purposes. Variational Recurrent Neural Networks showed their ability to deal with irregular time sampling and noisy AIS data streams. In comparison to other models in the state-of-the-art, our method brings several benefits:

- We relax strong assumptions like the Markov property [9], [10], [11], the finite number of Gaussians [19].
- By using VRNN, we successfully deal with noisy and irregularly time-sampling of AIS data streams.
- The Embedding block helps our model reduce the storage redundancies and computational requirements.

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 [17] and [8], as well as evaluating ability to scale up to global AIS data streams. The fusion with other sources of information such as weather condition and time could potentially improve the performance of the proposed model.

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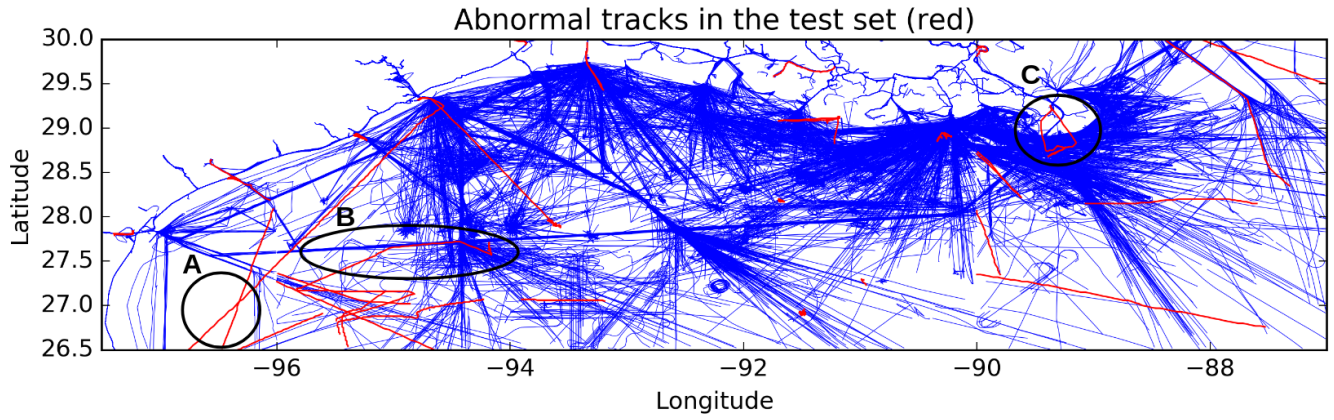


Fig. 3. Example of anomaly detection on the real data: Tracks in the training set (which itself may contain abnormal tracks) are presented in blue. Abnormal tracks detected in the test set are presented in red. An AIS track will be considered as abnormal if: i) it appears in an abnormal zone (zone A); ii) it has an abnormal shape (zone B) or iii) it performs an unusual speed pattern (zone C).

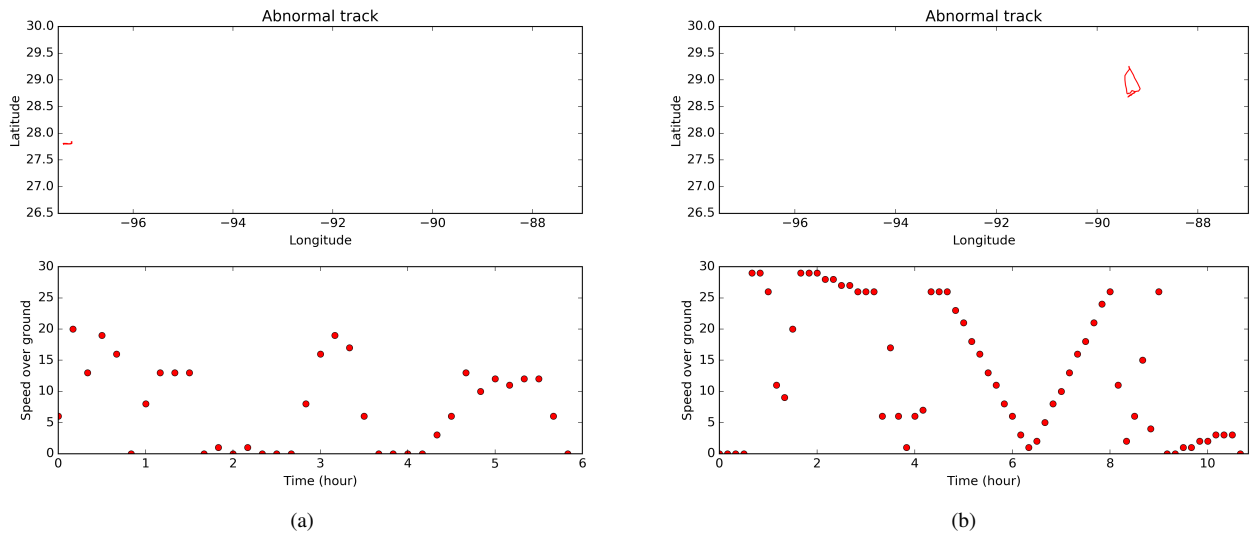


Fig. 4. Abnormal speed patterns detected by the model.

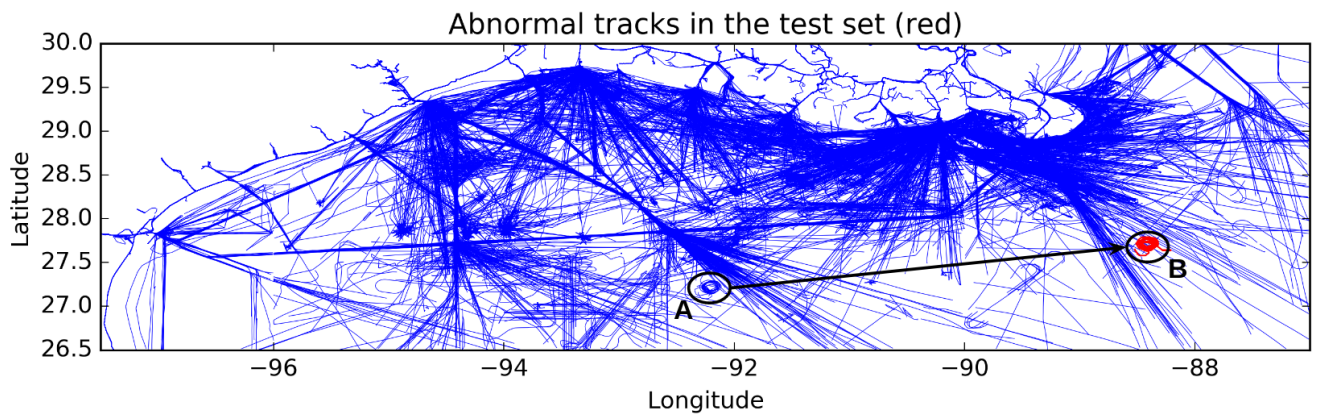


Fig. 5. Example of anomaly detection on synthetic data. The circle-shaped abnormal tracks were simulated by translating tracks in zone A to zone B.

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