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GeoTrackNet—A Maritime Anomaly Detector using Probabilistic Neural Network Representation of AIS Tracks and A *Contrario* Detection

Duong Nguyen, *Member, IEEE*, Rodolphe Vadaine, Guillaume Hajduch, René Garello, *Fellow, IEEE*, and Ronan Fablet, *Member, IEEE*,

Abstract—Representing maritime traffic patterns and detecting anomalies from them are key to vessel monitoring and maritime situational awareness. We propose a novel approach—referred to as *GeoTrackNet*—for maritime anomaly detection from AIS data streams. Our model exploits state-of-the-art neural network schemes to learn a probabilistic representation of AIS tracks, then uses a *contrario* detection to detect abnormal events. The neural network helps us capture complex and heterogeneous patterns in vessels’ behaviors, while the *a contrario* detection takes into account the fact that the learned distribution may be location-dependent. Experiments on a real AIS dataset comprising more than 4.2 million AIS messages demonstrate the relevance of the proposed method.

Index Terms—AIS, maritime surveillance, deep learning, anomaly detection, variational recurrent neural networks, a *contrario* detection.

I. INTRODUCTION

Nowadays, about 90% of the world trade is carried by maritime traffic, and it is growing consistently [2]. Maritime surveillance and Maritime Situational Awareness (MSA) are vital demands. In this context, anomaly detection is one of the most important tasks, because anomalies may involve accidents (loss of navigation, damages in engine, etc.) or illegal activities (smuggling, illegal transshipment, etc.). Initially designed for collision avoidance, the Automatic Identification System (AIS) has quickly become the main source of information for maritime surveillance thanks to its information richness. Roughly speaking, AIS messages contain the identification (the MMSI number), the GPS coordinates (latitude,

longitude), the current speed (Speed Over Ground—SOG) and course (Course Over Ground—COG), as well as other information about the vessel and the voyage. The potential of AIS is enormous, however, it is not fully utilized. AIS data are awash in noise, besides that, the massive amount of data quickly overwhelms human processing capacity. This emphasizes the need for a system that can automatically analyze and arise an alarm whenever there is an abnormal event. However, since AIS was originally created for collision avoidance only, no metadata (quality, reliability, uncertainty, etc.) are available, making the anomaly detection from AIS a very difficult task.

Here, we present *GeoTrackNet*—a new approach for maritime anomaly detection using a probabilistic RNN-based (Recurrent Neural Network) representation of AIS tracks and a *contrario* detection. This paper is an extended version of our previous work [1]. The first step in *GeoTrackNet* is to build a normalcy model that represents the characteristics of AIS tracks. Actually, at sea, either being enforced by law or for optimization issues (e.g. optimal fuel consumption, safety purposes, optimal patterns for fishing, etc.), vessels follow some specific patterns, and we expect to learn these patterns from data [1], [3]–[7]. In this work, we exploit sequential latent variational models, specifically the Variational Recurrent Neural Networks (VRNNs) [8] to create a probabilistic representation of vessels’ movement patterns. RNNs have been famous for their ability to capture long-term correlation in time series (here AIS tracks), VRNNs are an extension of RNNs where stochastic factors are added to improve the networks’ capacity of modeling data variabilities and uncertainties. This architecture is one of the state-of-the-art methods for text, speech and music analysis and generating [8]–[10]. In the proposed scheme, given the learned representation of the movement patterns of vessels, a “geospatial *a contrario*” detector evaluates how likely an AIS track segment is to state the detection of abnormal patterns. This detector exploits a geospatial prior depending on the location-dependent complexity of the patterns observed in the considered dataset. This prior also accounts for the strong geographical variabilities of vessels’ occurrences and movement patterns. We demonstrate the relevance of the proposed scheme with respect to state-of-the-art approaches on a real dataset comprising more than 4.2 million AIS messages.

The paper is organized as follows. In Section II, we give an overview of related work, and analyze the drawbacks of those models. The details of the proposed approach are

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This paper is an extension of the MultitaskAIS presented in [1]. While [1] presents the ability of handling noisy and irregularly sampled data as well as the computational benefit of this architecture for multiple tasks in maritime surveillance, this paper focuses on detailing the most important task: anomaly detection.

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presented in Section III. Section IV demonstrates the relevance of *GeoTrackNet* by experiments on real-life data. Conclusions, remaining challenges and future lines of work are discussed in Section V.

II. RELATED WORK

Recently, there has been a large number of publications related to maritime anomaly detection using AIS. Among them, we can cite [4], [5], [11]–[18] and references in [19], [20]. Those methods can be categorized into two groups: explicit anomaly detection and implicit anomaly detection.

The former group defines the abnormal behaviors explicitly and uses a set of rules to state the detection. A large list of such rules can be found in [21]. The advantage of this approach is its interpretability. Besides, it does not depend on historical data. However, it is difficult to define an exhaustive list of abnormal behaviors, and some terminologies such as fast/slow are relative and are hard to implement in operational systems, which may lower their usefulness for experts.

The latter is based on the assumption that the majority of events in the training set are normal. It detects anomalies by first building a normalcy model, then consider events that deviate from that model as abnormal. Most methods in this group rely on learning-based and unsupervised approaches [4]–[6], [11], [17], [18]. Learning frameworks provide us means to overtake the limitations associated with the definition of an exhaustive list of normal behaviors. Given the lack of labeled data for the anomalous class, unsupervised schemes naturally arise as the relevant learning strategies. Due to its flexibility and its ability to apply on a large scale, this second category of approaches has become the dominant approach in maritime anomaly detection.

There are two main stages in learning-based methods: i) representing learning for the normalcy, ii) the detection of deviations from the normalcy. In the first stage, density-based spatial clustering techniques, especially DBSCAN [22], have been very popular [5], [18], [23], [24]. Typically, DBSCAN is applied to cluster the critical points of AIS tracks into so-called Waypoints (WPs): ENs—where vessels enter the Region of Interest (ROI), EXs—where vessels exit the ROI, and POs—where vessels stop. From these WPs, these approaches build a graph whose nodes are the WPs and edges are the maritime routes. Using a probabilistic setting, e.g., Kernel Density Estimation (KDE) [5], Gaussian Mixture Models (GMM) [12], multiple Ornstein-Uhlenbeck (OU) processes [17], a normalcy model is fitted for each edge. The next stage aims to evaluate how likely a new AIS track is in order to state the detection of abnormal tracks. This is typically achieved using a thresholding on the distance to the centroid feature vector representing the route [18] or on the probability of the AIS track given the normalcy model [5], or through an adaptive hybrid Bernoulli filter [17].

In all of the above mentioned methods, the extraction of the WPs is critical. However, the considered clustering techniques, such as DBSCAN, may be sensitive to hyper-parameters. Especially, different settings may lead to very different outcomes. Besides that, it is not always possible to link a track to an edge

of the normalcy graph, i.e. we can not assign the beginning point and the end point of a track to any WP. This is a common problem of any method based on a clustering step. Another issue of current state-of-the-art maritime anomaly detection methods is their assumption that the performance of the learned normalcy model is geographically-homogeneous. However, in some areas, there are a lot of vessels and their behaviors are similar, the maneuvering patterns in this areas can be learned easily to detect abnormal patterns. By contrast, other areas may involve few training data and/or highly-complex and multi-modal patterns, which result in poor performance of clustering-based normalcy models and of the associated anomaly detection schemes. The application of the same anomaly detection policy (threshold, filter) in these two types of areas cannot be relevant. Another important limitation of the above mentioned approaches is that they apply to cargo and tanker vessels but may not apply to other vessel types, For instance, fishing vessels whose AIS patterns do not involve route-like patterns. As AIS metadata may not be reliable, dealing with all vessel types in operational systems would require additional preprocessing steps to filter out these types.

In this paper, we present a new method, referred to as *GeoTrackNet* that exploits advances in probabilistic neural network representations for time series analysis and an *a contrario* detection framework for maritime anomaly detection from AIS data streams. Our method provides new means to address key issues of state-of-the-art approaches, both in terms of the extraction and representation of the normalcy and of the detection of the deviation from the normalcy for all types of vessels.

III. PROPOSED APPROACH

In this section, we present the proposed approach. *GeoTrackNet* relies on the architecture of the Embedding layer we introduced for the MultitaskAIS network presented in [1]. We first introduce this architecture, then detail the formulation of the proposed anomaly detection method.

A. Data representation

The most common way to represent an AIS message is a 4-D real-value vector (two dimensions for the position and the other two for the velocity, e.g. $[lat, lon, SOG, COG]^T$) [5], [15], [17], [25]. However, it is difficult for a neural network to disentangle the underlying meaning of these numbers. Instead, we represent each AIS point by a “four-hot vector” (Fig. 1). This bucketizing representation, which is inspired by the one-hot encoding in language modeling, is a concatenated vector of the one-hot vectors of the latitude coordinate, longitude coordinate, SOG and COG.

In addition to the classically-expected benefits of bucketizing representation [26], the four-hot vector helps disentangle the geometric features as well as the phase (time-space) patterns of AIS tracks. For example, Fig. 2 shows how this representation accentuates the geometric feature of an AIS track. Similarly, the phase feature appears when we sum up the one-hot vectors of the latitude, longitude coordinate and the speed in the resulting 3-D space (see [1]).

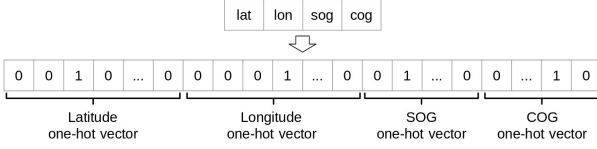


Fig. 1. “Four-hot” vector.

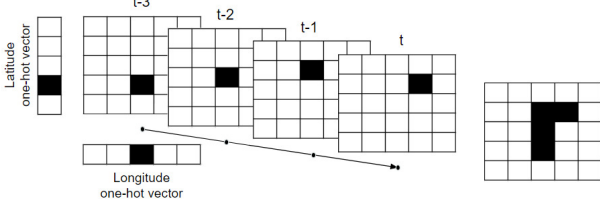


Fig. 2. Geometric feature obtained by concatenating the one-hot vector of the latitude and the longitude coordinate of AIS messages.

The hyper-parameters are the resolution of each bin in the one-hot vectors. If the resolution is too high, the whole network becomes too bulky and requires a high computational power to run, and may also lead to overfitting. If the resolution is too low, we may lose critical information. For anomaly detection, we may not need very accurate position and velocity features. For example, a speed of 10 knots or 10.1 knots is not expected to make any difference in the context of anomaly detection. Overall, our experiments suggest that resolutions of 0.01° for longitude and latitude, 1 knot for SOG and 5° for COG are relevant.

B. Probabilistic Recurrent Neural Network Representation of AIS Tracks

In this section we introduce a probabilistic neural network architecture that we use to represent AIS tracks: a Variational Recurrent Neural Network (VRNN) [8]. We detail the associated probabilistic formulation and the resulting; however, we present a different derivation which would clarify some terms used in the next sections of this paper.

For any contiguous AIS track¹, we can always apply an interpolation and sampling technique to create a sequence of T variables: $\mathbf{x}_{1:T} = \{\mathbf{x}_t\}_{t=1:T}$, with \mathbf{x}_t is the four-hot vector representation of AIS messages presented in Section III-A. The objective is to learn a distribution that maximize the log likelihood $\log p(\mathbf{x}_{1:T})$ which can factorize as:

$$\log p(\mathbf{x}_{1:T}) = \log p(\mathbf{x}_1) \sum_{t=1}^T \log p(\mathbf{x}_t | \mathbf{x}_{1:t-1}). \quad (1)$$

Recently, time series analysis has experienced the emergence of Recurrent Neural Networks (RNNs) as the state-of-the-art approach in many tasks [27], [28]. RNNs assume that at a given time t , the relevant historical information of $\mathbf{x}_{1:t-1}$ can be encoded in a deterministic hidden state \mathbf{h}_t : $p(\mathbf{x}_t | \mathbf{x}_{1:t-1}) = p(\mathbf{x}_t | \mathbf{h}_t)$. The dynamics of the series are modeled by a deterministic differentiable function f :

$\mathbf{h}_t = f(\mathbf{x}_{t-1}, \mathbf{h}_{t-1})$. f is usually parameterized by LSTMs [29] or GRUs [30]. The initial condition \mathbf{h}_1 is commonly set to $\mathbf{0}$. Eq. (1) becomes:

$$\log p(\mathbf{x}_{1:T}) = \sum_{t=1}^T \log p(\mathbf{x}_t | \mathbf{h}_t). \quad (2)$$

The fact that f is deterministic makes RNNs hardly capable of capturing all the variations and uncertainties in data. In our context, f can be interpreted as a representation of the maneuvering patterns of vessels from AIS tracks. Associated uncertainties may come from AIS data streams themselves as well as their discretization using four-hot vectors. Uncertainties in AIS data streams may relate to vessel types, weather conditions, AIS message corruption, etc. To account for such uncertainties, probabilistic RNNs relate to the introduction of latent stochastic variables, denoted as \mathbf{z}_t , which follow a prior distribution:

$$\mathbf{z}_t \sim p(\mathbf{z}_t | \mathbf{h}_t). \quad (3)$$

The dynamics and the generative distribution become:

$$\mathbf{h}_t = f(\mathbf{x}_{t-1}, \mathbf{z}_{t-1}, \mathbf{h}_{t-1}), \quad (4)$$

$$\mathbf{x}_t \sim p(\mathbf{x}_t | \mathbf{z}_t, \mathbf{h}_t). \quad (5)$$

At each time step t , the joint probability of \mathbf{x}_t and \mathbf{z}_t can factorize as:

$$p(\mathbf{x}_t, \mathbf{z}_t | \mathbf{h}_t) = p(\mathbf{x}_t | \mathbf{z}_t, \mathbf{h}_t) p(\mathbf{z}_t | \mathbf{h}_t). \quad (6)$$

Hence, $p(\mathbf{x}_t | \mathbf{h}_t)$ can be obtained by integrating out \mathbf{z}_t from Eq. (6):

$$p(\mathbf{x}_t | \mathbf{h}_t) = \mathbb{E}_{p(\mathbf{z}_t | \mathbf{x}_t, \mathbf{h}_t)} [p(\mathbf{x}_t | \mathbf{z}_t, \mathbf{h}_t) p(\mathbf{z}_t | \mathbf{h}_t)]. \quad (7)$$

However, this integral is usually intractable. Variational approach proposes that instead of maximizing $\log p(\mathbf{x}_t | \mathbf{h}_t)$, we maximize a lower bound of this distribution, called the Evidence Lower BOund (ELBO), by using an approximation $q(\mathbf{z}_t | \mathbf{x}_t, \mathbf{h}_t)$ of the posterior distribution $p(\mathbf{z}_t | \mathbf{x}_t, \mathbf{h}_t)$ [8], [31]:

$$\mathcal{L}(\mathbf{x}_t | \mathbf{h}_t, p, q) = \mathbb{E}_{q(\mathbf{z}_t | \mathbf{x}_t, \mathbf{h}_t)} [\log p(\mathbf{x}_t | \mathbf{z}_t, \mathbf{h}_t)] - \text{KL}[q(\mathbf{z}_t | \mathbf{x}_t, \mathbf{h}_t) || p(\mathbf{z}_t | \mathbf{h}_t)]. \quad (8)$$

where $\text{KL}[q(\mathbf{z}_t | \mathbf{x}_t, \mathbf{h}_t) || p(\mathbf{z}_t | \mathbf{h}_t)]$ is the Kullback-Leibler divergence between two distributions q and p .

Overall, given neural network parameterizations for function f , the generative distribution $p(\mathbf{x}_t | \mathbf{z}_t, \mathbf{h}_t)$ and the approximated posterior distribution $q(\mathbf{z}_t | \mathbf{x}_t, \mathbf{h}_t)$, the training step comes to maximize Eq.(2) where term $\log p(\mathbf{x}_t | \mathbf{h}_t)$ is approximated by $\mathcal{L}(\mathbf{x}_t | \mathbf{h}_t, p, q)$. This maximization is implemented using a stochastic gradient ascent using deep learning libraries, here Tensorflow. We further detail in the experiments the considered neural network parameterizations for the different building blocks of the model using LSTMs.

¹A contiguous AIS track is a track whose the time gap between any two successive messages is smaller than a threshold, here 4h.

C. A contrario detection

Once the distribution $p(\mathbf{x}_{1:T})$ is learned, we can simply apply a “global thresholding” rule to state the detection, i.e. AIS tracks whose $\log p(\mathbf{x}_{1:T}) < \epsilon$ are flagged as abnormal, like in our previous work [32]. However, as mentioned in Section II, vessels’ behaviors greatly vary depending on the considered geographical areas. In some areas, AIS tracks may involve multimodal but well-defined patterns such that the learned model precisely captures these patterns. As a result, normal AIS tracks shall be associated with high probability values, whereas tracks with low probability values shall relate to unusual and possibly abnormal ones. In other areas, due to the variabilities of the AIS tracks, limited AIS datasets and/or a lower ability of the model to represent AIS tracks, the learned model may result in low probability values whatever the tracks. In such cases, the use of a global thresholding approach might lead to poorly relevant detection results.

To address these issues, we introduce a new detection method, referred to as a “geospatial *a contrario*” detection. It takes into account the geographically-heterogeneous performance of the learned model. We rely on the division of the ROI into a grid. Let us denote by $l_{\mathbf{x}_t}^{C_i}$ the log probability $\log p(\mathbf{x}_t|\mathbf{h}_t)$ of AIS messages in a small geographical cell C_i (i.e., $\mathbf{x}_t \in C_i$) and p^{C_i} the distribution of $l_{\mathbf{x}_t}^{C_i}$:

$$l_{\mathbf{x}_t}^{C_i} \sim p^{C_i}. \quad (9)$$

An AIS message in cell C_i is considered as abnormal if its log probability is smaller than the lowest $\frac{1}{p}$ -quantile of p^{C_i} .

$$\mathbf{x}_t \text{ is abnormal} \Leftrightarrow p^{C_i}(L < l_{\mathbf{x}_t}^{C_i}) < p. \quad (10)$$

That means, if we randomly sample $l_{\mathbf{x}_t}^{C_i}$ from p^{C_i} (note that p^{C_i} is the distribution of the variable $l_{\mathbf{x}_t}^{C_i}$, and not \mathbf{x}_t), the probability that “ \mathbf{x}_t is abnormal” is p .

Assuming that the event “ \mathbf{x}_t is abnormal” of each AIS message \mathbf{x}_t in an AIS track $\mathbf{x}_{1:T}$ is independent, the probability that “at least k out of n AIS messages in an AIS segment of length n (denoted $\mathbf{x}_{t:t+n}$) of this track are abnormal” is a tail of a Binomial distribution:

$$\mathcal{B}(n, k, p) = \sum_{i=k}^n \binom{n}{i} p^i (1-p)^{n-i}. \quad (11)$$

The *a contrario* detection [33] detects whether such an AIS segment is abnormal based on the Number of False Alarms (NFA), defined as:

$$\text{NFA}(n, k, p) = N_s \mathcal{B}(n, k, p), \quad (12)$$

where $N_s = \frac{T(T+1)}{2}$ is the number of all possible segments. For example, if $T = 3$, there are 6 possible segments: 3 segments of length 1, 2 segments of length 2 and 1 segment of length 3. If the NFA of a track segment is smaller than a predefined threshold ξ , this segment will be considered as abnormal and an AIS track is abnormal if at least one of its segments is abnormal.

$$\mathbf{x}_{1:T} \text{ is abnormal.} \Leftrightarrow \exists(n, k), \text{NFA}(n, k, p) < \xi. \quad (13)$$

ξ is the the allowed expectation of “false alarm”, that means, i.e., if we run the detector on a series of random $l_{\mathbf{x}_t}^{C_i}$ $1/\xi$

times, there will be 1 segment detected as abnormal. Interested readers are referred to [33] for more details. To implement this *a contrario* scheme, we use two approaches to model distribution p^{C_i} : i) a simple Gaussian approximation and ii) a Kernel Density Estimation (KDE) [34], [35].

IV. EXPERIMENTS AND RESULTS

A. Experimental set-up

Datasets: We tested our model on AIS data received by an AIS station located in Ushant. The ROI is a rectangle from (47.5°N, 7.0°E) to (49.5°N, 4.0°E). The data were collected from January to March 2017, from July to September 2017 and from January to March 2018. In each period, there are more than 4.2 million AIS messages. For each period, we divided the data into three sets: a training set, from the first day to the 10th of the last month of this period (e.g. from January 1 to March 10); a validation set, from the 11th of the last month to the 20th of the last month (e.g. from March 11 to March 20) and a test set, from the 21st of the last month to the last day of this period (e.g. from March 20 to March 31). The basic idea behind this experimental setting is that for an operational application, we use historical data to train the model (i.e. to learn the distribution), then apply this model to current data. The validation sets are used to check for overfitting and for the estimation of distribution p^{C_i} . Fig. 3 shows an illustration of the training set, the validation set and the test set of the period from January to March 2017.

We removed erroneous position or speed messages in the considered AIS data streams. The SOG was truncated to 30 knots. Discontiguous voyages (voyages that have the maximum interval between two successive AIS messages longer than a threshold, here is 4 hours) were split into contiguous ones. Very long voyages were split into smaller tracks from 4 to 24 hours each. We re-sampled all tracks to a resolution of 10 minutes (i.e. , $\{t+1\} - \{t\} = 10\text{mins}$) using a linear interpolation.

Neural Network architectures: for the model reported in this paper, the resolutions of the latitude, longitude, SOG and COG were set to 0.01°(about 1km), 0.01°, 1 knot and 5°, respectively. We modeled f by a LSTM with one single hidden layer of of size 100 for datasets comprising only cargo and tanker vessels, and of size 120 for datasets comprising all types of vessels. \mathbf{z}_t is a real-valued variable of the same size of the hidden layer of the LSTM. $p(\mathbf{z}_t|\mathbf{h}_t)$ and $q(\mathbf{z}_t|\mathbf{x}_t, \mathbf{h}_t)$ are two Gaussian distributions parameterized by two fully connected networks with one hidden layer of size 100. $p(\mathbf{x}_t|\mathbf{h}_t, \mathbf{z}_t)$ is a multivariate Bernoulli distribution parameterized by a fully connected network with one hidden layer of size 100. The network was trained using Adam optimizer [36] with a learning rate of 0.0003.

A contrario detection: for the *a contrario* detector, we chose $p = 0.1$. ξ was initially set at a high value (in order to flag many tracks as abnormal), then was gradually decreased to reduce the false positive rate while keeping all the true detections.

The code, as well as the data that can replicate the results in this paper are available at: <https://github.com/dnguyengithub/MultitaskAIS>

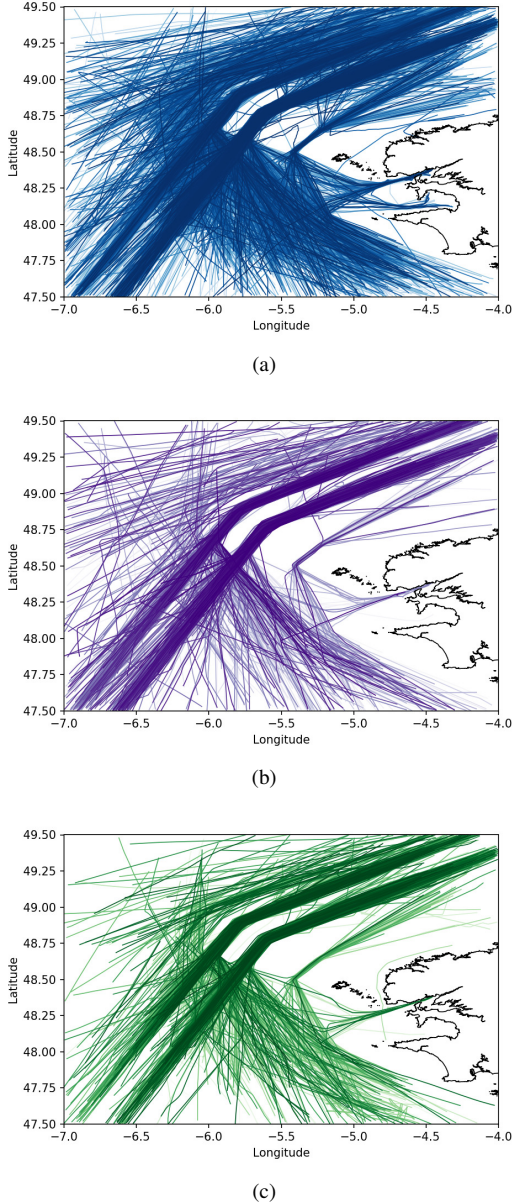


Fig. 3. All AIS tracks in the dataset from January 1 to March 31, 2017. (a) training set; (b) validation set; (c) test set.

Baseline: We used the Traffic Route Extraction and Anomaly Detection (TREAD) method, presented in [5] as the baseline. This model supposes that vessels following the same route have similar velocity in each small area. The hyper-parameters were set at the values suggested by [5] and [18] ($minPts = 10$, $eps = 2000$ (2km), the radius of each small area is 3km).

Evaluation method: all the abnormal tracks detected by the proposed model were inspected manually. Since maritime anomaly is an ill-defined problem, it is difficult to make a fair comparison between our model and the state-of-the-arts. To our knowledge no groundtruthed datasets exist for abnormal behaviour detection, which prevents us from considering a quantitative benchmarking of different approaches. Instead, we analyze the types of anomaly can be detected by each model.

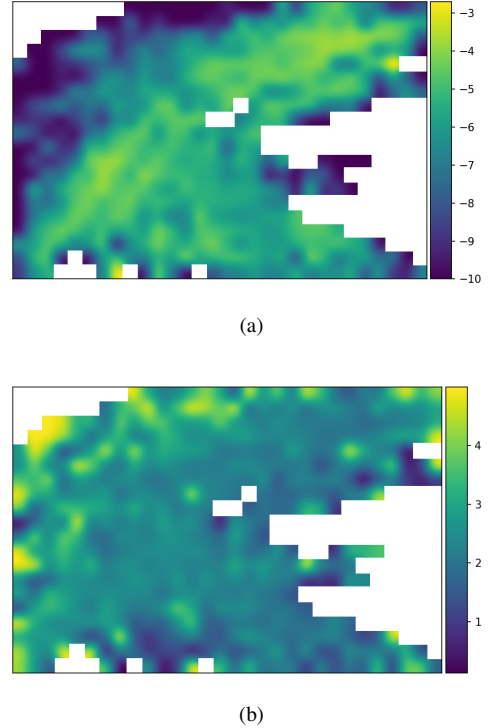


Fig. 4. The “performance” map displaying the mean (a) and the standard deviation (b) of the Gaussian approximation of distributions p^{C_i} from AIS messages in the validation set from January to March, 2017. On maritime routes, there are many vessels, mainly cargoes and tankers, their movement patterns can be learned easily, $\log p(\mathbf{x}_t|\mathbf{h}_t)$ is usually high and its variation is small. On the other hand, some areas depict few vessels or vessels’ behaviors are too complicated for the model to learn, $\log p(\mathbf{x}_t|\mathbf{h}_t)$ is usually low and highly variable. Blank regions are regions where we do not apply the detection (e.g., land areas or regions where we do not have enough data).

B. Experiments and results

Basic setting: For this test, we trained the model on the training set and evaluated the performance on the corresponding test set of each period. The dataset comprises only cargoes and tankers. Fig. 4 shows the mean and the standard deviation of distribution p^{C_i} . As expected, in some regions, there are many vessels and the learned distribution fits well the data with a mono-modal or multimodal distribution, such that the values of $\log p(\mathbf{x}_t|\mathbf{h}_t)$ are high. There are also regions where $\log p(\mathbf{x}_t|\mathbf{h}_t)$ is low on average. If an AIS track results in a low log probability in these regions, we do not know whether this track is unusual or the model does not approximate well the true distribution of \mathbf{x}_t . Applying a “global thresholding” rule like in [32] would lead to a bad outcome, as shown in Fig. 5b, where all the detections are in low log likelihood regions. By contrast, the proposed a contrario detector compares $\log p(\mathbf{x}_t|\mathbf{h}_t)$ of an AIS message \mathbf{x}_t with those in the same area, if it is significantly smaller than the others, then \mathbf{x}_t is regraded as abnormal. The results are shown in Fig. 5. In most of cases, the model using a Gaussian distribution approximation and the one using KDE gives similar outcomes. The proposed model can detect both: i) space-wise (geometric and geographic) anomalies, when vessels deviate from maritime routes, perform unusual turns, etc. and ii) phase-wise (kinetic) anomalies, when vessels have

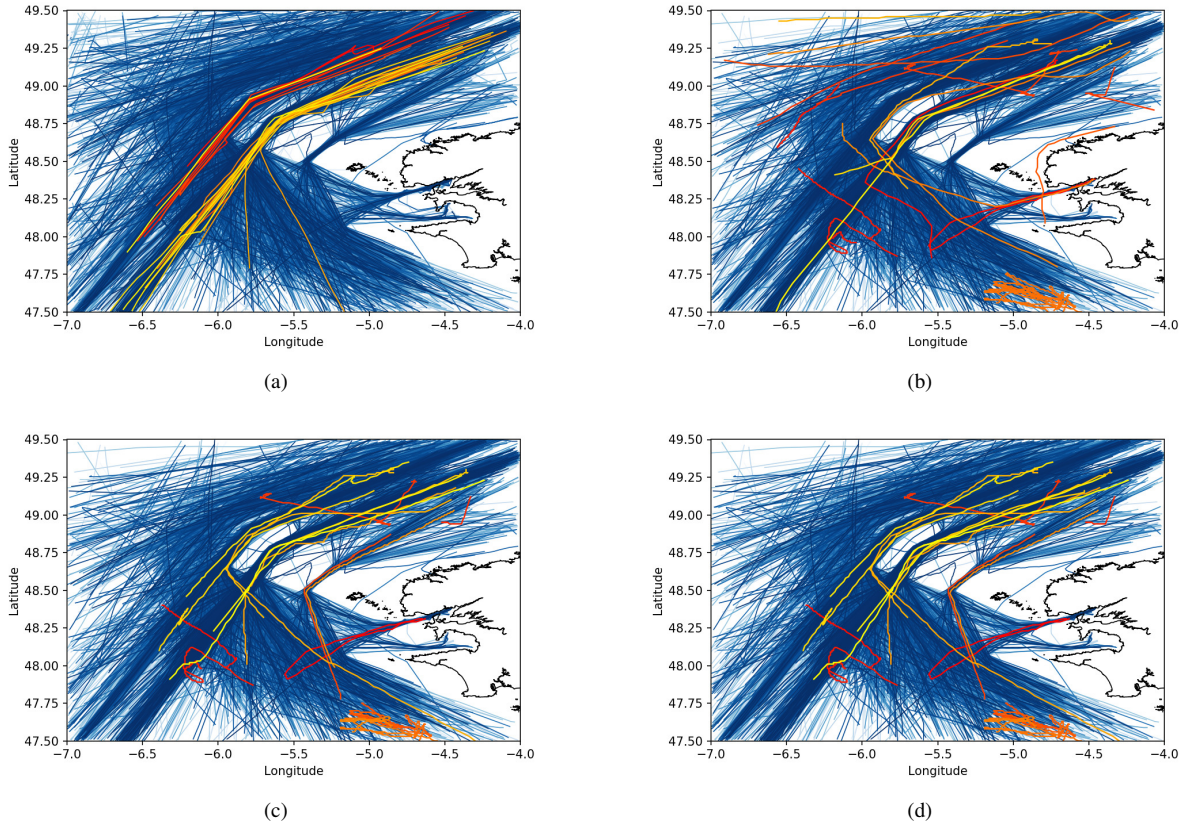


Fig. 5. Abnormal tracks detected by different models (the dataset comprises only cargo and tanker vessels, from January to March 2017). Blue: tracks in the training set; other colors: abnormal tracks in the test set. (a) TREAD (a DBSCAN-based method introduced in [5]). (b) Using a VRNN to learn the distribution of AIS tracks then applying a “global threshold” like in [32]; (c) *GeoTrackNet*, approximating each p^{C_i} by a Gaussian distribution; (d) *GeoTrackNet*, approximating each p^{C_i} by KDE.

abnormal evolution in speed and course (e.g. unusual slowing down, sudden changes in speed, etc.). When comparing our approach to TREAD [5], we note that some types of anomaly are detected by both approaches, like the double U-turn, abnormal turns, or abnormal speeds, as shown in Fig. 5a and Fig. 5d. However, while *GeoTrackNet* flags sudden changes in speed as abnormal, TREAD considers both sudden changes in speed and constant speeds that are higher or lower than other vessels’ in the same route as unusual (see Fig. 7).

A key advantage of *GeoTrackNet* over DBSCAN-based models is we can detect abnormal tracks which do not follow any maritime route like those in Fig. 6a. Because those tracks can not be mapped to any maritime route, DBSCAN-based methods have two options, either flag all of them as abnormal or do not monitor them. Since the number of those tracks is high (Fig. 8), neither of these options is relevant for maritime surveillance.

Vessel types: Another advantage of our model is the possibility to apply to any type of vessels. The first step of DBSCAN-based methods is to cluster AIS tracks into maritime routes and learn the signature of each route. Hence, those methods can only apply to vessels that follow maritime routes, i.e. cargo and tanker vessels. On the other hand, our method does not impose any hypothesis of this type, so it can apply to any type of vessels. We tested our model on a dataset that

comprises all kinds of vessels, the results are shown in Fig. 10. Since the number of vessels of other types than cargo and tanker is significant, applying the surveillance on all types of vessels is of interest. However, this is a difficult task. Unlike cargo and tanker vessels, some other types, for example fishing vessels, have very complicated moving patterns, the model can hardly learn all of them. Even when the model is able to capture all the dynamics of AIS tracks, unexpected results are still inevitable, when the statistical anomalies are actually not suspicious (see Fig. 10a). There is a trade-off between the monitoring capacity and the performance. When monitoring all types of vessels, it is possible that in a small area, there are some patterns that can be learned and others that can not. The distribution p^{C_i} is not unimodal anymore. Hence, it cannot be approximated by a Gaussian distribution (see Fig. 9). This explains the non-parametric density estimation using KDE gives better outcomes in those cases.

Hereafter in this paper, unless specified otherwise, the reported results are the outcome of *GeoTrackNet* using KDE. Results similar to those reported above for a dataset from July to September 2017 and from January to March 2018 can be found for models learned for these periods.

Seasonal effects: We conducted an additional test to demonstrate the consistency of *GeoTrackNet*. In this test, the models learned from the training set of one period were evaluated

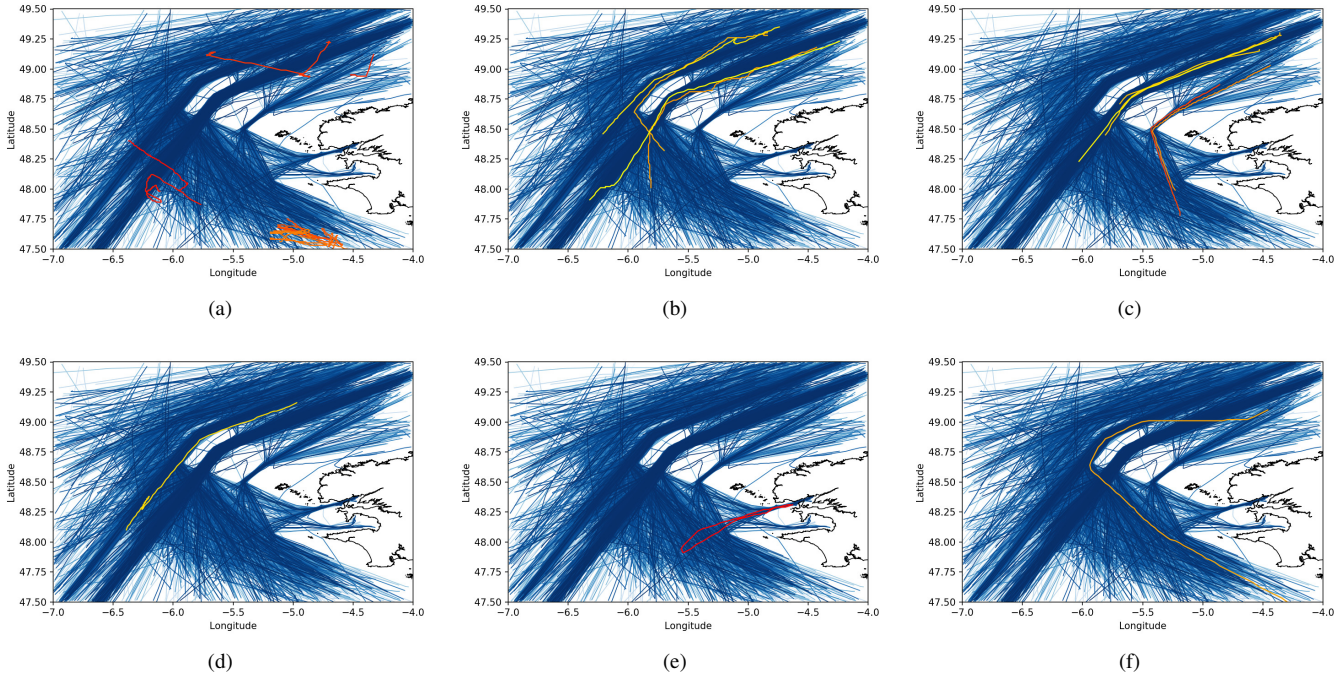


Fig. 6. Examples of anomalies detected by *GeoTrackNet* using KDE. (a) Vessels following abnormal routes. DBSCAN-based methods can not apply to these tracks because they can not be assigned to any common maritime route. (b) Geometrically or geographically abnormal tracks (e.g., deviating from maritime routes, unusual turns, etc.). (c) Abnormal speed tracks (e.g. suspiciously slowing down in a maritime route). (d) Double U-turns. (e) A cargo vessel steamed to sea then went back. (f) Each segment of this track is normal, however, it is unusual that a vessel follows this path. *GeoTrackNet* can detect this track because it has a memory (the memory of its LTSM).

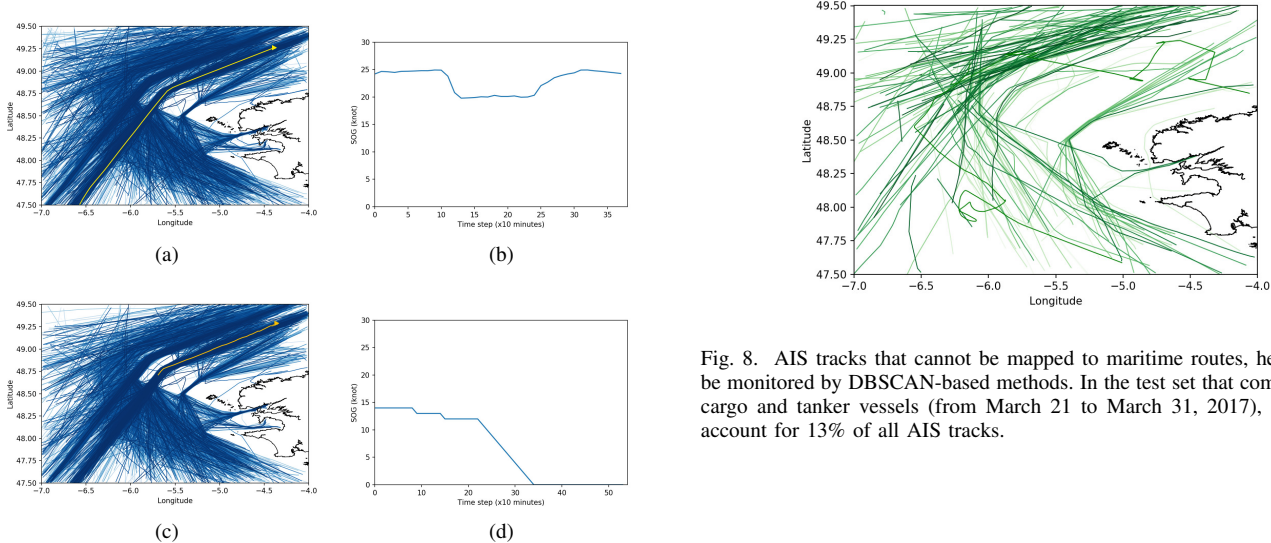


Fig. 7. Examples of abnormal speed tracks detected by TREAD and *GeoTrackNet*. (a) An example of a track flagged as abnormal by TREAD and its speed (b), the speed of vessels in this route is almost from 10 to 18 knots, this vessel was moving at around 20 to 25 knots, higher than the average. (c) An example of a track flagged as abnormal by KDE *GeoTrackNet* and its speed (d).

on the test set of another period². Table I shows the average log likelihood on different test sets of models trained on data from January 1 to March 10, 2017. The test sets are data

²In real-life applications, we always train the model on recent data. This setting is just to test the consistency of the model

Fig. 8. AIS tracks that cannot be mapped to maritime routes, hence cannot be monitored by DBSCAN-based methods. In the test set that comprises only cargo and tanker vessels (from March 21 to March 31, 2017), such tracks account for 13% of all AIS tracks.

from the 21st to the end of the corresponding month. Seasonal effects are small for cargo and tanker vessels. Over seasons, most of the changes are in speed. While for other types of vessels, especially for fishing vessels, the behaviors change completely. That explains why the log likelihood of the model trained on all vessels, from January 1 to March 10, 2017 is considerably low on the test set of September 2017. As shown in Fig. 11, between winter and summer, the fishing patterns are very different. A model trained on data in one season may not apply to data in another season. These experiments suggest to consider season-specific models and/or training a general model which also takes into account a seasonal information.

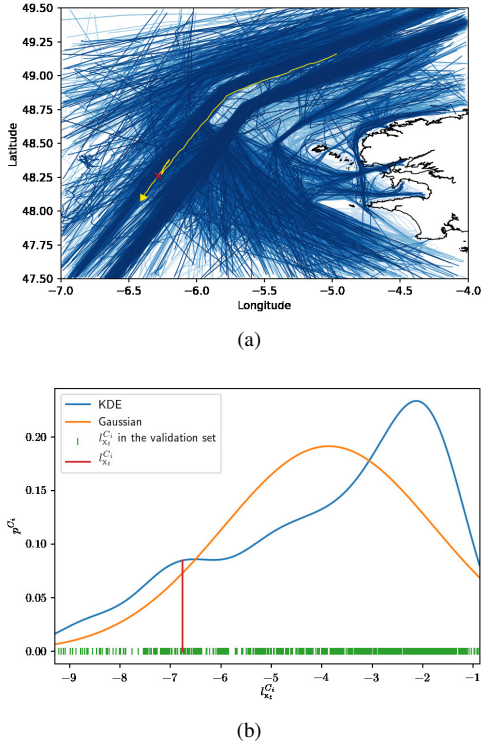


Fig. 9. Comparison between the Gaussian approximation and KDE for distribution p^{C_i} . (a) a track detected as abnormal by KDE *GeoTrackNet*, and not by Gaussian *GeoTrackNet*. (b) p^{C_i} of the area around the point “x” in (a). $p_{KDE}^{C_i}(L < l_{x_t}^{C_i}) = 0.128$ while $p_{Gauss}^{C_i}(L < l_{x_t}^{C_i}) = 0.082$. Overall, when the data comprises all types of vessels, p^{C_i} is not unimodal and KDE shall be preferred.

TABLE I

AVERAGE LOG LIKELIHOOD OF THE KDE *GEOTRACKNET* FOR DIFFERENT TEST SETS WHEN TRAINED ON AIS DATA FROM JAN 1 TO MAR 10, 2017.

Test set	Cargoes and tankers	All types
March 2017	-5.83	-6.53
September 2017	-5.97	-7.43
March 2018	-5.84	-6.76

V. CONCLUSIONS AND FUTURE WORK

We introduced a new approach for maritime anomaly detection using AIS data. To our knowledge, this is the first model which relies on a normalcy model of AIS tracks using a deep learning generative scheme. More precisely, we exploit Variational Recurrent Neural Networks to represent AIS tracks probabilistically. Once the approximate distribution of the data is learned, a geographical *a contrario* detection is used to evaluate how likely an AIS track is. This detector takes into account the fact that the performance of the learning is geographically dependent. The general idea is that if an AIS message has its log probability lower than other messages’ in the same region, it should be flagged as abnormal. An AIS track is abnormal if there are many abnormal messages in this track.

Our approach have several advantages:

- It requires minimal prior knowledge about the data. The model can be applied in different regions without major modifications.

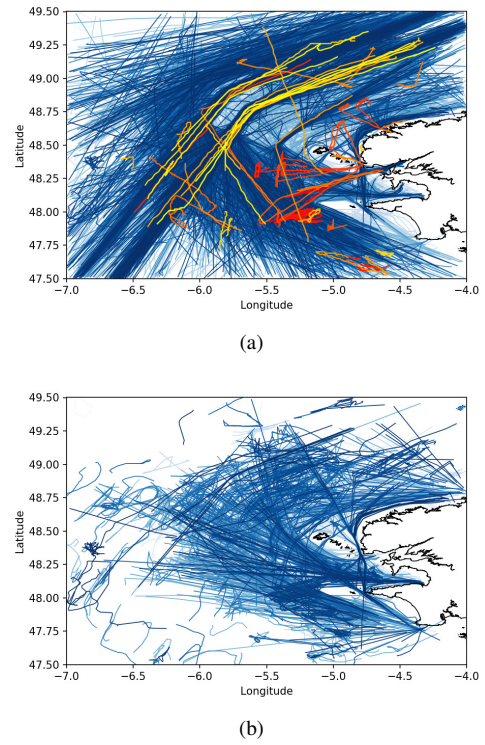


Fig. 10. Anomaly detection examples of KDE *GeoTrackNet* with AIS data comprising all vessel types from January to March 2017. (a) AIS tracks that are flagged as abnormal by KDE *GeoTrackNet*. Some tracks are statistically abnormal, however, their behaviors are not suspicious. For examples, the red tracks that steam from land are fishing vessels went fishing; they were detected as abnormal because there were not enough similar AIS tracks in the training set. (b) AIS tracks of fishing vessels in the training set (about 13% of tracks in the training set).

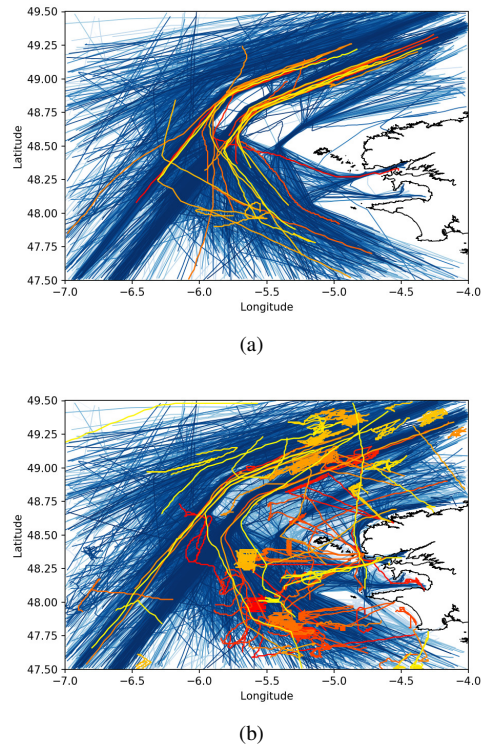


Fig. 11. Anomaly detection examples for a the model trained on the same data as Fig. 10a and tested on data from July 21 to September 30, 2017. (a) When the data comprise only cargo and tanker vessels. (b) When the data comprise all kind of vessels.

- It does not require important hyperparameters such as the number of points in a cluster when using DBSCAN, the number of modes in mixture models, etc.
- We can control the percentage of the activities we want or are allowed/willing to flag as abnormal by simply changing the value of ψ in Eq. 13.
- DBSCAN-based models cannot monitor AIS tracks that do not follow maritime routes. Fig. 8 and Fig. 10b show that the number of those tracks are significant³. Our method applies to all AIS tracks in the ROI.
- The proposed model can detect both geometric/geographic and speed-related anomalies.
- The nature of VRNN provides additional means to condition the output onto external control inputs or other sources of information. Hence, our model could further benefit from complementary information such as weather conditions, ocean current situations, etc. Mathematically, it comes to modeling $p(\mathbf{x}_t|\mathbf{x}_{1:t-1}) = p(\mathbf{x}_t|\mathbf{h}_t, \mathbf{u}_t)$ with \mathbf{u}_t the control inputs and additional information.
- It is worth noting that anomaly detection is one task (and the most important one) in maritime surveillance. A model that can be integrated into a bigger system would optimize computational and storage resources. The proposed model is naturally a part of a bigger system—the MultitaskAIS [1], makes it more preferable.

Although deep learning has recently grown extremely fast and has become the state-of-the-art approach in many domains [27], its achievement in MSA is surprisingly limited. To the best of our knowledge, this work is the first one that applies deep neural networks to maritime anomaly detection. This work may open new avenues to explore new research directions to complement and/or outperform DBSCAN-based approaches. In this respect, future work may address the following issues:

- As any unsupervised learning-based model, the proposed approach detects events that are statistically unusual. These events may not involve suspicious actions.
- We manually inspected all the detections presented in this paper to check whether there were false detections; however, the amount of AIS data overwhelms our capacity to make sure that no missed detections exist. The creation of a reference groundtruthed dataset would be highly beneficial to advance the state-of-the-art and make benchmarking experiments quantitative.
- The proposed neural network representation provides a flexible and powerful means to learn the distribution of AIS tracks, yet uninterpretable. The model is more suitable for a computer-assisted system (where the final decision is still on the human operator) than a fully automatic system. We may emphasize that this representation is also of interest for other tasks, e.g., AIS track interpolation, vessel type identification, as shown in our preliminary work [1]. Future work might benefit from such multi-task settings.

³The original paper [5] reported the fraction of processable AIS messages varied from 40 to 95%

- Reported experiments involve a region off Brittany, which is representative of a ROI for surveillance activities of local authorities. Future work shall also consider the application or adaption of the proposed scheme on a global scale.

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