Intelligent Anomaly Detection of Trajectories for IoT Empowered Maritime Transportation Systems

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***Abstract*— The convergence of Maritime Transportation Systems (MTS) and Internet of Things (IoT) has led to the promising IoT-empowered MTS (IoT-MTS). However, abnormal trajectories of maritime transportation ships can have highly negative impacts on the management of IoT-MTS. Therefore, anomaly detection of trajectories is important for the successful deployment of IoT-MTS. In this paper, we propose a Transfer Learning based Trajectory Anomaly Detection strategy, named TLTAD, for IoT-MTS. Specifically, a variational autoencoder is used to discover the potential connections between each dimension of the normal trajectory, while a graph variational autoencoder is used to explore the spatial similarity between normal trajectories. Based on internal connection of trajectories, a deep reinforcement learning algorithm, Twin Delayed Deep Deterministic policy gradient (TD3), is employed to train the trajectory anomaly detection model. To reduce the model training time, transfer learning is used to migrate the trained anomaly detection model between different regions of an ocean area or between similar ocean areas. Moreover, an efficient data transformation module is designed to improve the efficiency of model transfer. The experiments were conducted on a real-world automatic identification system (AIS) dataset. The results indicate that the proposed TLTAD can provide accurate anomaly detection on ships' trajectories in IoT-MTS with reduced model training times.**

***Index Terms*—Deep reinforcement learning, maritime transportation systems, anomaly detection, transfer learning.**

I. Introduction

MARITIME Transportation Systems (MTS) have become an indispensable part of modern economy and life [1]. At the same time, Internet of Things (IoT) can provide effective security monitoring and remote management for maritime transportation ships, thus leading to the IoT-empowered MTS (IoT-MTS). With the rapid development of ship positioning technology, communications technology, IoT [2], and big data [3], a large amount of ship trajectory data is generated during the ship's voyage. As time-series data, trajectories are presented in the form of temporal and spatial correlations, i.e., it records the location and time information of ship activities. Ship trajectory data is obtained from multiple data sources such as radar and automatic identification system (AIS). Due to the different positioning errors of various data sources, anomalies may appear in the trajectory data [4]. Therefore, it is important to have effective anomaly detection of trajectories for IoT-MTS [5], [6].

The IoT-MTS trajectory anomaly detection determines whether the ship's behavior is normal by analyzing the AIS information captured and sent back by IoT devices, as well as the ship's navigation information. In addition, the ship's trajectory characteristics can be used to predict its general behavior and perform abnormal trajectory detection. Specifically, by analyzing AIS information through data mining and machine learning [7], we can extract main characteristics of maritime transportation. If the ship's trajectory does not conform to the general law of motion, it could be regarded as abnormal [8].

However, the accurate detection of abnormal ship trajectory is still an open issue. The existing anomaly detection methods can be categorized into three categories, namely statistical analysis-based, prediction-based, and machine learning-based. Generally, methods based on statistical analysis use specific datasets to fit the statistical model of the ship's normal behavior, so as to obtain the probability that its trajectory may be abnormal. Prediction-based methods usually establish

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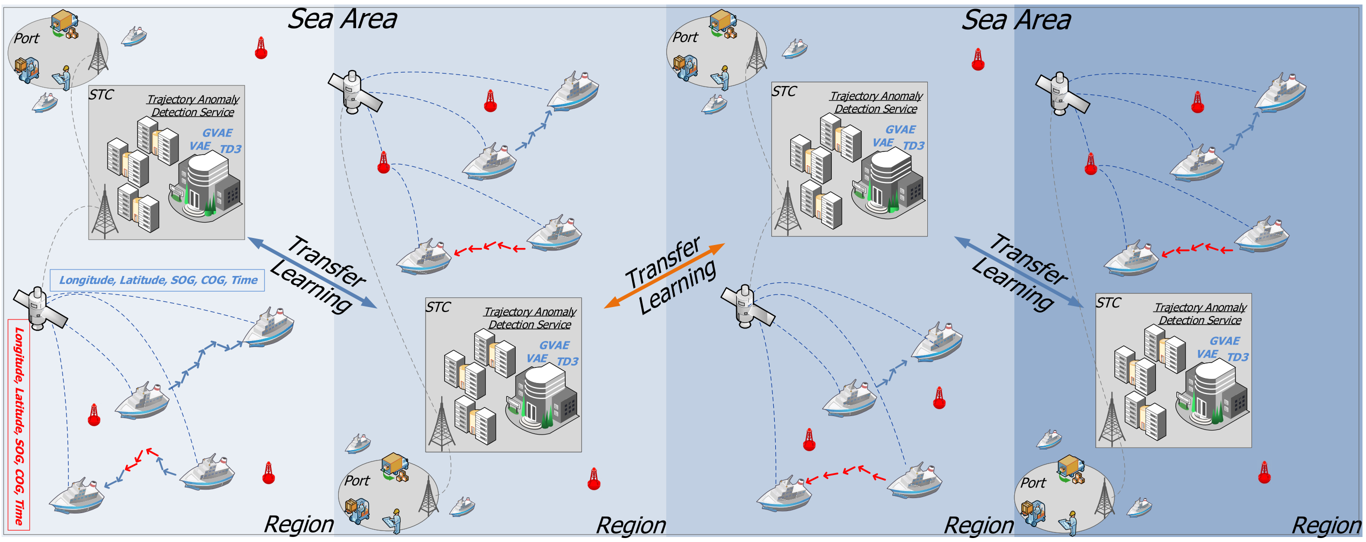


Fig. 1. The intelligent trajectory anomaly detection architecture for IoT-enabled maritime transportation systems.

a predictive model to predict the future state of the ship, including position, speed, and heading, and then compare the actual state with the predicted one to detect the ship's abnormal trajectory. Machine learning-based methods learn the model of the ship's normal behavior, if the ship's behavior deviates significantly from the learned model, it is considered that the ship's trajectory is abnormal.

Given that a ship's abnormal behavior is related to its trajectory, speed and position, if any of the following occurs, the ship's trajectory is considered to be abnormal: The trajectory is inconsistent with the normal operating characteristics of this type of ship, the ship has been in inappropriate positions for a period of time, or the course and speed of the ship is not consistent with its adjacent trajectory. Therefore, the anomaly detection process needs to be sensitive to the information hidden in data and the relationship between data samples, and analyze the root causes of abnormal ship behavior, such as environmental uncertainty, crew operations, and interactions between ships. This shows that it is not only necessary to discover the potential connections between each dimension of the normal trajectory, but also to explore the spatial similarity between the normal trajectories. In fact, these requirements can be met either by analyzing the ship trajectory data with the variational autoencoder (VAE) [9], or by using the graph variational autoencoder (GVAE) [10] to find the spatial correlation between ship trajectories. The emergence of deep reinforcement learning (DRL) [11] can help to combine these two, thereby greatly improving the accuracy of trajectory anomaly detection. However, deep reinforcement learning may bring about the problem of long training time for anomaly detection models. This can be solved by introducing transfer learning (TL) [12] to transfer the parameters of the trained model to others.

In this paper, we design an intelligent anomaly detection architecture (see Fig. 1) for IoT-empowered MTS, where different advanced machine learning technologies are employed and integrated. Based on this architecture, we propose a Transfer Learning based Trajectory Anomaly Detection strategy, named TLTAD, for IoT-MTS. The main contributions of this paper are summarized as follows:

1) We use the variational autoencoder to discover the potential connections between each dimension of a trajectory, and use the graph variational autoencoder to explore the spatial similarity between the trajectories. On this basis, a deep reinforcement learning algorithm, Twin Delayed Deep Deterministic policy gradient (TD3) is utilized to train an abnormal trajectory detection model.
2) We take advantage of the similarity of ship trajectories between different regions of each sea area, and use transfer learning to migrate the parameters of the trained anomaly trajectory detection model between regions, or between sea areas, thereby reducing the model training time. In addition, we designed an efficient dataset transformation module to improve the efficiency of model transfer.
3) The experiments were conducted using the real-world AIS dataset. The results show that the proposed TLTAD scheme can achieve a highly accurate ship trajectory anomaly detection in IoT-MTS and reduces the detection model training time.

We organize the rest of this paper as follows. The related work is presented in section II. The system model is introduced in section III. The implementation of the proposed TLTAD scheme is elaborated in section IV. The performance evaluation is conducted in section V. We conclude this paper in section VI.

II. Related Work

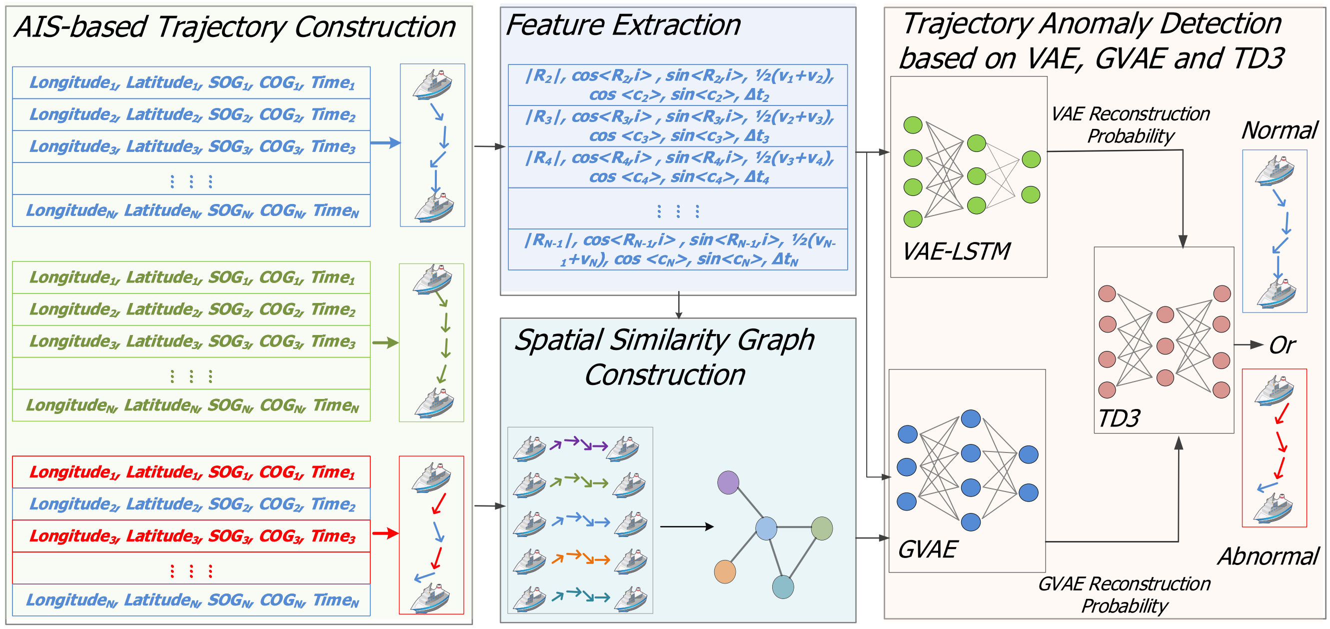
It is an open question to detect abnormal trajectory points or abnormal behavior from ship trajectory data. In response to this problem, a large number of scholars have proposed corresponding solutions.

There exist some statistical analysis based methods for abnormal trajectory detection. Pallotta *et al.* [13] uses traffic route extraction and anomaly detection to acquire maritime traffic knowledge to detect low-probability behaviors and predict the future location of ships. In addition, for low-likelihood detection, Weibull model and sliding time window technology can be used to avoid incomplete and segmented trajectories. Rong *et al.* [14] characterize typical vascular behavior and calculate the Gaussian function value of the lateral distribution of ships to detect deviation behavior. If the value is lower than the threshold, it is detected that the ship is not traveling along the specified route. Shuai *et al.* [15] use the k-order multivariate Markov chain and multiple related parameters to establish a state transition matrix, and only predict the next time of the ship's trajectory based on the state of the last time with the highest probability, but insufficient consideration is given to the ship' s historical track status at each moment. Wang *et al.* [16] analyze the distribution characteristics of maritime traffic hazards, draw ship trajectory diagrams based on AIS information and made statistics using the distance to closet point of approach and kernel density estimation. The choice of statistical method mainly involves calculation cost, fitting accuracy and so on. Due to different model requirements, each model has different fitting effects on different data anomalies. Different statistical models can be used to detect ship behavior in combination with specific application scenarios, and the changes in specific statistical variables and the correspondence of specific behavior abnormalities can be analyzed through experiments. If the abnormalities in the sample are uniformly distributed, the statistical method is invalid. In addition, the statistical method is still a challenge for processing high-dimensional data.

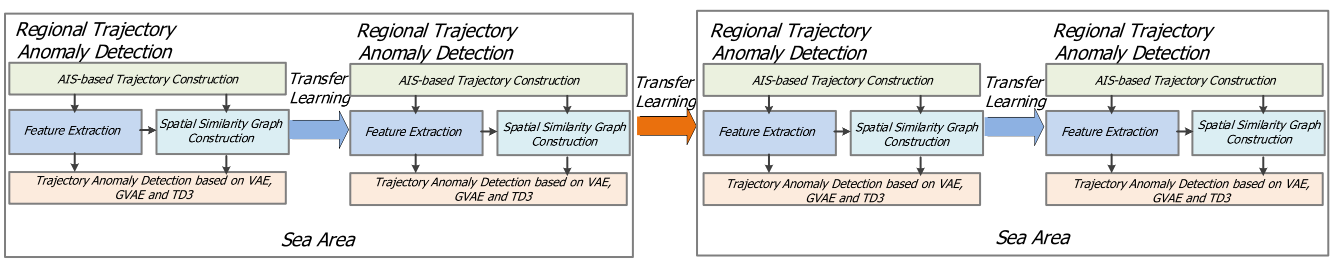
Some prediction based abnormal trajectory detection methods are proposed. Laxhammer and Falkman [17] use Hausdorff distance to measure trajectory similarity, and generates a prediction set through shape-preserving prediction. Aiming at the improvement of the normal trajectory pattern learning algorithm, the sequence Hausdorff nearest neighbor conformal anomaly detection is proposed and studied, which is used for online learning and trajectory sequence anomaly detection. Nouretdinov *et al.* [18] introduced a multi-level conformal clustering method MLCC. Without making any assumptions about the data distribution, there will be a clear statistical result with the help of conformal prediction in clustering. MLCC combines clustering and anomaly detection to provide statistical robustness, and clustering and anomaly detection can be performed at the same time. Mazzarella *et al.* [19] use the k-nearest neighbor algorithm and Mahalanobis distance measurement method to cluster AIS data to eliminate the influence of redundant data, and propose a knowledge-based velocity model and particle filter for ship motion track prediction. The method based on the prediction model is to establish a prediction model when familiar with the historical situation, and judge whether it is abnormal by comparing the actual value with the predicted value. For example, by extracting historical ship motion data, predicting future ship motion. But this is also a limitation. The choice of forecasting method and the acquisition of historical conditions have a certain impact. Whether the grasp of historical conditions is comprehensive and accurate is not well judged.

Machine learning methods are widely used in abnormal trajectory detection. Yin *et al.* [20] proposed an anomaly detection model combining convolutional neural networks and recursive autoencoders. Through the first stage sliding window, the original time series containing abnormal points is expanded into a fixed-length series with normal or abnormal labels. Then through another smaller sliding window, each sequence is converted into a continuous time-related subsequence. Injadat *et al.* [21] used Bayesian optimization to find the global minimum of the objective function, and set the parameters of three traditional classifiers with Gaussian kernel, support vector machine, random forest, and K nearest neighbors to improve the performance of the anomaly detection method. Wang and Ahn [22] cascaded the autoregressive integrated moving average model and the artificial neural network, established an independent detection process, and analyzed the correctness of the data. The use of Bayesian information criteria effectively reduces the impact of over-fitting or non-fitting on real-time prediction and improves prediction accuracy. Pozi *et al.* [23] proposed a classifier method based on support vector machines. Through a new post-SVM optimization algorithm, the intrusion detection rate for rare attacks is improved without reducing the overall accuracy, and it can be extended to hidden data with different input and attack distributions. Zheng *et al.* [24] used a density-based spatial clustering algorithm to obtain the density distribution of ship berthing points in the Waigaoqiao port area, and clustered all berthing ships, and finally used the historical trajectory of ships to identify abnormal ships. To identify normal data patterns and different types of anomalies, Liu *et al.* [25] constructed auxiliary feature vectors of each condition variable for clustering, and proposed a parameter selection method for database scanning in an unsupervised environment based on a threshold curve based on the number of clusters. The methods based on machine learning mainly include classification, nearest neighbor, and clustering. The classification method has strong robustness and fault tolerance, and requires plenty of parameters for calculation with results difficult to interpret. The premise for nearest neighbors to be effective is to have enough neighbors, no need to estimate parameters, no training, but the calculation is more complicated. The principle of clustering algorithm is simple, the calculation speed is fast, and it can handle clusters of any shape and size, but the effect is not ideal when processing clusters with large differences in density, high-dimensional data, or when the clustering distance is very different.

Although these works provide various good solutions to the problem of ship trajectory anomaly detection, there are still the following two problems: (i) How to analyze the difference in time and space between the normal trajectory and the abnormal trajectory to improve the anomaly detection (Ii) How to reduce the training time of anomaly detection model while ensuring detection accuracy. To address these problems, this paper proposes an intelligent trajectory anomaly detection strategy for IoT-MTS.



(a) Anomaly detection model construction.



(b) Detection model transfer.

Fig. 2. The system model of the proposed TLTAD.

III. System Model

To realize the accurate and efficient trajectory anomaly detection of IoT-MTS, two entities are mainly considered, namely the ship and the ship traffic center (STC).

- Ships: The ship is responsible for transporting the goods to the destination. In the transportation process, due to the changeable ocean weather, the shipping routes are often affected by bad weather, causing the problem of the goods cannot be delivered on time or even cannot be delivered. Therefore, in the process of cargo transportation, it is necessary to adjust the ship's route according to the ocean weather conditions, the location of the reef and the location of the ship. The position of the ship can be directly sent to the STC through low-orbit satellites. After the reef position and sea surface conditions are sensed by the buoys, they can be sent to the STC through multi-hop between buoys or buoy-satellite transmission.
- Ship Traffic Center (STC): The STC guides ships to avoid dangerous areas and reach their destination safely based on AIS data. Considering that the sensing equipment of ships and buoys may malfunction, which may cause abnormal problems in data such as ship position, reef position and sea surface conditions, STC should detect abnormal trajectories based on the internal connection of the trajectory.

Note that the trajectory of the ship can be obtained from the AIS data, while the trajectory features extracted from the original trajectory data can be used by the STC for abnormal trajectory detection. However, the accuracy of this detection mechanism needs to be improved, because the internal connection between the various dimensions of the ship's trajectory is the key to judging whether the trajectory is abnormal, which can be discovered through a variational autoencoder. In addition, the normal trajectories may have a certain degree of similarity, which indicates that the spatial similarity between the normal trajectories helps the detection of abnormal trajectories, which can be found by the graph variational autoencoder. On this basis, STC can transform the problem of abnormal trajectory detection into a 01 decision problem. As an efficient decision-making algorithm, the DRL algorithm TD3 will be used by STC to detect abnormal trajectories. The framework of the abnormal trajectory detection strategy TLTAD is given in Fig. 2.

IV. The Implementation of the TLTAD

The proposed TLTAD consists of two modules, namely trajectory preprocessing and TL-based anomaly detection. Among them, trajectory preprocessing includes AIS-based trajectory construction, trajectory feature extraction and trajectory spatial similarity graph construction, while TL-based anomaly detection includes intelligent abnormal trajectory detection and TL-based detection model transfer.

A. Trajectory Pre-Processing

1) AIS-Based Trajectory Construction: The trajectory of the ship over a period of time according to the AIS data can be presented as

$$\begin{bmatrix} Longitude \\ Latitude \\ SOG \\ COG \\ Time \end{bmatrix} = \begin{bmatrix} long_1 & long_2 & \cdots & long_N \\ lat_1 & lat_2 & \cdots & lat_N \\ v_1 & v_2 & \cdots & v_N \\ c_1 & c_2 & \cdots & c_N \\ t_1 & t_2 & \cdots & t_N, \end{bmatrix} \tag{1}$$

where $long_i$, lat_i, c_i, s_i and t_i represent the longitude, the latitude, the course over ground, the speed over ground and the receiving time of the ship in the ith AIS message, respectively.

2) Trajectory Feature Extraction: Considering that the sending frequency of AIS messages is related to the sailing speed of the ship itself, that is, ships of different speeds send data at different frequencies, while the same ship sends different frequencies at different speeds. Since AIS messages have different time intervals, and a ship's displacement is determined by the speed and time interval between two adjacent messages, the ship's true movement cannot be obtained by using AIS data directly [4]. Therefore, we use the ship's displacement R, i.e., $R_i = [Long_i - Long_{i-1}\ Lat_i - Lat_{i-1}]$, and the deviation in time of two adjacent AIS data Δ, i.e., $\Delta t_i = t_i - t_{i-1}$, to indicate the movement of the ship. Specifically, the displacement R_i is represented by the modulus of the displacement, i.e., $|R_i|$, the sine and cosine values, denoted by $\sin\langle R_i, \vec{i}\rangle$ and cosine $\cos\langle R_i, \vec{i}\rangle$, of the angle between the x-axis and the displacement vector R_i. In addition, the speed over ground v_i is replaced by the average speed of the ship between two adjacent AIS messages, i.e., $\frac{v_{i-1}+v_i}{2}$, and the course over ground c_i is replaced by the cosine and sine values, i.e., $\cos c_i$ and $\sin c_i$, of the ship's course. Therefore, a more accurate ship trajectory in a continuous period of time is given by a matrix composed of $N-1$ trajectory points, and each trajectory point is represented by a vector, that is, $[|R_j|, \cos\langle R_j, \vec{i}\rangle, \sin\langle R_j, \vec{i}\rangle, \frac{v_{j-1}+v_j}{2}, \cos\langle c_i\rangle, \sin\langle c_i\rangle, t_j]$, $2 \le j \le N$. Generally speaking, if the ship's motion law is satisfied for each element in the matrix, the ship's trajectory is normal.

3) Trajectory Spatial Similarity Graph Construction: The graph structure can reflect the spatial correlation between objects, so it can be used to explore the spatial similarity between trajectories. Considering that the trajectory of a ship in a period of time is represented as a $7 \times (N-1)$ matrix, if we regard it as a $7 \times (N-1)$ dimensional vector, then the similarity $sim_{i,j}$ between two trajectories $\mathcal{T}_i$ and $\mathcal{T}_j$ can be measured by the cosine of the angle between them, that is, $sim_{i,j} = \frac{\mathcal{T}_i \cdot \mathcal{T}_j}{|\mathcal{T}_i||\mathcal{T}_j|}$. In fact, the similarity of each pair of adjacent trajectories can be used to construct a spatial similarity map of the trajectories. Specifically, we take the trajectory of the ship in a fixed time period as a node on the spatial similarity graph, and then combine the grid division of the channel to fit the similarity distribution. If the similarity of the two trajectories deviates too far from the expectation, then there are no edges between the nodes representing these two trajectories in the graph.

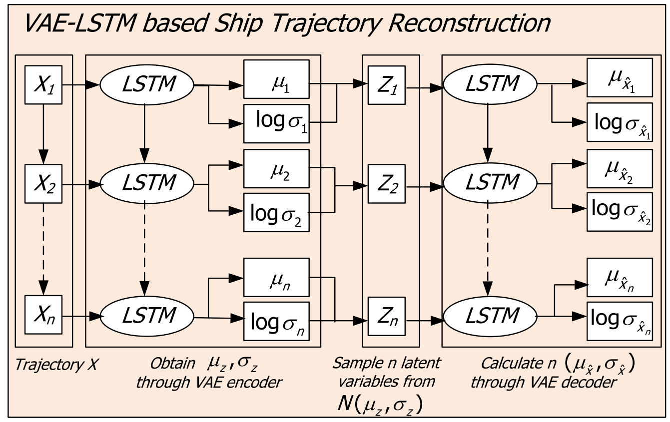


Fig. 3. VAE-LSTM based ship trajectory reconstruction.

It is worth to mention that the choice of ship trajectory length will affect the accuracy of anomaly detection. The reason for that is as follows. If we choose a relatively short trajectory length, then the difference between adjacent trajectories may be small. Thereby, it is difficult to accurately judge whether a trajectory is abnormal regardless of the relationship between the dimensional data of the trajectory or the spatial similarity between the trajectories. Otherwise, there may be differences in length between adjacent trajectories. This is because different ships have different voyages, which causes the problem of incomparable trajectories.

B. TL-Based Anomaly Detection

1) Intelligent Trajectory Anomaly Detection: In this paper, we will use VAE, GVAE and TD3 to discover the relationship between the dimensions of the trajectory and explore the spatial similarity between the trajectories, so as to achieve abnormal trajectory detection.

In VAE, each input x can be mapped to a hidden variable z_k, and the final output $\hat{x}$ can be generated by a Gaussian distribution $p_\theta(x_k|z_k)$. The parameters of the latent variable distribution $q_\phi(z_k|x_k)$ generated by the encoder function $f_\theta(z_k)$ and the decoder function $g_\theta(x_k)$ are all subject to a set of constraints on the parameter θ. Note that the purpose of variational inference in VAE is to find an approximate distribution $p(z_k)$ to replace the distribution $q_\phi(z_k|x_k)$. And Kullback-Leibler (KL) divergence is used to measure the similarity between these two distributions. Then, the following loss should be minimized as the objective.

$$\mathcal{L}(\theta, \phi; x_k) = \mathcal{D}_{KL}[q_\phi(z_k|x_k)||p(z_k)] - \mathbb{E}_q[\lg p_\theta(x_k|z_k)], \tag{2}$$

In order to take the advantages of LSTM in processing time series data and improve the accuracy of abnormal trajectory detection, this paper will implement the ship trajectory anomaly detection based on VAE-LSTM (see Fig. 3). Specifically, we take the VAE model as the main structure and replace the BP neural network with LSTM.

A fixed-time sequence of trajectory point feature vectors, i.e., $[|R_j|, \cos\langle R_j, \vec{i}\rangle, \sin\langle R_j, \vec{i}\rangle, \frac{v_{j-1}+v_j}{2}, \cos\langle c_i\rangle, \sin\langle c_i\rangle, t_j]$, $2 \leq j \leq N$, is the input. The LSTM encoder will automatically extract the time series features of the input data and encode the data into a series of hidden variables. Another LSTM decoder completes the reconstruction of the hidden variables. For each sample from the encoder, the probability decoder will output the mean and variance, and use these mean and variance to calculate the probability of generating the original data from the distribution. The average value of the probabilities obtained, named p^{VAE}, is used as the reconstruction probability.

$$p^{VAE} = \frac{1}{n}\sum_{i=1}^{n} p_\theta(x|\mu_{\hat{x}_i}, \delta_{\hat{x}_i}) \tag{3}$$

In general, trajectory points with low reconstruction probability might be considered as abnormal, and the trajectory with abnormal trajectory points will be judged as an abnormal trajectory.

As another variant of the self-encoder, GVAE can use a graph convolutional network (GCN) as an encoder and a simple inner product as a decoder to learn the latent representation Z of an undirected graph $\mathcal{G}$ of N nodes, where the adjacency matrix $\mathcal{A}$, node degree matrix $\mathcal{D}$ and node features matrix $\mathcal{X}$ of $\mathcal{G}$ are required [10]. The inference model used in GVAE is parameterized by a two-layer GCN, i.e., $GCN(\mathcal{X}, \mathcal{A}) = \tilde{\mathcal{A}}ReLU(\tilde{\mathcal{A}}\mathcal{X}W_0)W_1$ with the weight matrices W_i and $\tilde{\mathcal{A}} = \mathcal{D}^{-\frac{1}{2}}\mathcal{A}\mathcal{D}^{-\frac{1}{2}}$ is the symmetrically normalized adjacency matrix, such that $q(Z|\mathcal{X}, \mathcal{A}) = \prod_{i=1}^{N} q(z_i|\mathcal{X}, A)$ and $q(z_i|\mathcal{X}, \mathcal{A}) = \mathcal{N}(z_i|\mu_i, diag(\sigma_i^2))$. And $\mu = GCN_\mu(\mathcal{X}, \mathcal{A})$ and $\log_\sigma = GCN_\sigma(\mathcal{X}, \mathcal{A})$ share the first-layer parameters W_0. The inner product between latent variables is used as the generative model of GVAE. Similar to VAE, GVAE takes the variational lower bound as the optimization target w.r.t the variational parameters W_i. To detect abnormal trajectories, we use the symmetrically normalized adjacency matrix $\tilde{\mathcal{A}}$ of the spatial similarity map of normal ship trajectories and its trajectory characteristics $\mathcal{X}$ as the input of GVAE, and the output reconstruction probability $p^{GVAE} = p(\mathcal{A}|Z)$, which is calculated by

$$p(\mathcal{A}|Z) = \prod_{i=1}^{N}\prod_{j=1}^{N} p(A_{ij}|z_i, z_j), \tag{4}$$

where $p(A_{ij} = 1|z_i, z_j) = sigmoid(z_i^T z_j)$, can be used to measure the spatial similarity of trajectories. Theoretically, the spatial similarity between each pair of normal adjacent trajectories is close, while the spatial similarity between the abnormal trajectory and the adjacent normal trajectory is quite different.

Relying solely on the reconstruction probability of the trajectory or that of the trajectory spatial similarity graph is difficult to improve the detection accuracy, which means that these two need to be deeply integrated. As an efficient deep reinforcement learning algorithm, by comprehensively considering a variety of factors, the Twin Delayed Deep Deterministic policy gradient algorithm (TD3), which consists of critic networks Q_{θ_1}, Q_{θ_2}, target critic networks Q'_{θ_1}, Q'_{θ_2}, a actor network π_ϕ, and a target actor network π'_ϕ with parameters θ_1, θ_2, θ'_1, θ'_2, ϕ and ϕ' respectively, can be used for decision-making. To be specific, similar to the attention mechanism [26], we use TD3 to generate a pair of optimal coefficients, i.e., (α, β) with $\alpha + \beta = 1$, to combine these two reconstruction probabilities in depth, thus realizing the accurate and efficient abnormal trajectory detection. To be specific, for each STC, the state s, action a and reward r of the abnormal trajectory detection using TD3 are defined as follows:

- *State*: To maximize the detection accuracy, we let the false negative rate (FNR) (5) and false positive rate (FPR) (6) consist of the state s, i.e., $s = (FNR, FPR)$, where FPR and FRN are calculated by

$$FNR = \frac{FN}{TP + FN}, \tag{5}$$

$$FPR = \frac{FP}{TN + FP}. \tag{6}$$

- *Action*: Obviously, the pair of coefficients (α, β) compose of the action a.
- *Reward*: In anomaly detection, we aim to achieve the maximum detection accuracy. That suggests the detection accuracy should be chosen as the reward r to measure the choice of coefficients, i.e.,

$$\begin{aligned} r &= Accuracy \\ &= \frac{TP + TN}{TP + FP + TN + FN}, \end{aligned} \tag{7}$$

where FP, FN, TP and TN represent false positive, false negative, true positive, true negative, respectively.

According to the literature [27], the TD3 is trained in episodes until it reaches the convergence. In each episode, an action $a \sim \pi_\phi(s) + \epsilon$ is selected with exploration noise $\epsilon \sim \mathcal{N}(0, \sigma)$ and reward r is calculated using Eq. (7) and the new state s' is observed. Then, the transition tuple (s, a, r, s') is stored in the replay buffer B. Next, a mini-batch of N transitions (s, a, r, s') is randomly sampled from B to update critics and the actor. For critics, the update is implemented by

$$\theta_i \leftarrow \arg\min_{\theta_i} \frac{1}{N}\sum (y - Q_{\theta_i}(s, a))^2, \tag{8}$$

where $y \leftarrow r + \gamma \min Q_{\theta'_i}(s', \tilde{a})_{i=1,2}$, $\tilde{a} \leftarrow \pi_{\phi'}(s') + \epsilon$ and $\epsilon \sim clip(\mathcal{N}(0, \tilde{\sigma}), -c, c)$. For the actor, the update is conducted every d episodes using the deterministic policy gradient, i.e.,

$$\nabla_\phi J(\phi) = \frac{1}{N}\sum \nabla_a Q_{\theta_1}(s, a)|_{a=\pi_\phi(s)} \nabla_\phi \pi_\phi(s). \tag{9}$$

And the target networks are updated by

$$\theta'_i \leftarrow \tau\theta_i + (1 - \tau)\theta'_i, \tag{10}$$

$$\phi'_i \leftarrow \tau\phi_i + (1 - \tau)\phi'_i, \tag{11}$$

where $\tau \in (0, 1)$.

2) TL-Based Detection Model Transfer: Given that the abnormal trajectory detection model should be trained for each region of each sea area, the difference between the AIS datasets in different sea areas may result in completely different model training times. To solve this problem, we transfer the trained anomaly detection model between different regions of each sea area using transfer learning, or between different sea areas. That is, we transfer the parameters of the trained anomaly detection model to another model to be trained. In addition, in order to improve the efficiency of model transfer, we designed two dataset transformation methods for the above two different cases. Specifically, for the first case, the dataset transformation $\mathcal{T}_1$ should satisfy Eq. (12), i.e.,

$$\min_{\mathcal{T}_1} ||AIS_S^R - AIS_T^R \mathcal{T}_1||_2^2 + \lambda ||\mathcal{T}_1||_2^2, \tag{12}$$

where AIS_S^R and AIS_T^R denote the source region and target region of a sea area in the transfer learning respectively, and λ is the regularization parameter. Then, we compute $\mathcal{T}_1$ by

$$\mathcal{T}_1 = ((AIS_T^R)^T \cdot (AIS_T^R) + \lambda \mathbf{I})^{-1} \cdot (AIS_T^R)^T \cdot (AIS_S^R). \tag{13}$$

For the second case, the data transformation $\mathcal{T}_2$ should satisfy Eq. (14), i.e.,

$$\min_{\mathcal{T}_2} ||AIS_S^A - AIS_T^A \mathcal{T}_2||_2^2 + \lambda ||\mathcal{T}_2||_2^2, \tag{14}$$

where AIS_S^A and AIS_T^A denote the source sea area and the target sea area in the transfer learning, respectively. Similarly, we calculate $\mathcal{T}_2$ by

$$\mathcal{T}_2 = ((AIS_T^A)^T \cdot (AIS_T^A) + \lambda \mathbf{I})^{-1} \cdot (AIS_T^A)^T \cdot (AIS_S^A). \tag{15}$$

In addition, for the model transfer between different regions and different sea areas, the dataset transformation needs to be realized by using the Eq. (15) and the Eq. (13) sequentially.

V. Performance Evaluation

A. Experiment Setup

We verify the performance of the proposed TLTAD scheme in Python on a computer of 32G running memory, 2.7GHZ Intel Core i7 processor and 64-bit win7 system. This experiment uses the real-world AIS dataset of the Wuhan-Shanghai section of the Yangtze River (May 2019-August 2019) [4]. This dataset is a manually labeled dataset and contains 800 abnormal AIS data. We roughly divide these abnormal AIS data into three types: abnormal position, abnormal speed and abnormal course.

- *Position Abnormality:* If some trajectory points of a ship deviate significantly from other points, the AIS data is considered abnormal data.
- *Speed Abnormality:* According to the latitude and longitude of the AIS data, it is easy to obtain the distance R_i between the i-th and $(i+1)$-th ship position point, and then divide R_i by the time interval to get the average ship speed V. If $V > 2v_i$, then the i-th AIS data is considered abnormal.
- *Course Abnormality:* According to the latitude and longitude of the AIS data, the bearing is defined as the relative position of the ship's positions in the i-th and $(i+1)$-th AIS data. If the bearing is between the course c_i and the course c_{i+1}, the course c_i is considered normal.

In addition, we divide the AIS data of a ship over a period of time into multiple AIS data segments with the length of $Data\_Size$. According to the sequence of the AIS data, the training dataset and test dataset of the detection model are chosen from multiple pieces of data. For any AIS data segment, if all AIS data are normal data, the data segment is considered normal and marked as 1; if the data segment contains one or more artificially marked abnormal AIS data, it is considered abnormal and marked 0.

Based on the artificially labeled AIS dataset, we compare the proposed TLTAD with the following detection models: abnormal AIS data screening (AAISS) model [4], VAE model, LSTM anomaly detection model [28], isolated forest (iForest), Support Vector Machine (SVM) and Decision Tree (DT). Among them, LSTM, DT and SVM are three commonly used supervised classification algorithms, and isolated forest is an unsupervised anomaly detection method suitable for continuous data, which is widely used in anomaly detection. We select false negative rate (FNR) (5), false positive rate (FPR) (6), accuracy rate (7), recall rate (16), precision (17), and F1-score (18) are used as comparison indexes given by

$$Recall = \frac{TP}{TP + FN}, \tag{16}$$

$$Precision = \frac{TP}{TP + FP}, \tag{17}$$

$$F1 - score = \frac{2 \times Precision \times Recall}{Precision + Recall}. \tag{18}$$

To verify the model convergence of the proposed TLTAD scheme, we give the model training time based on the following three different model transfer situations, namely the transfer between different regions in the same sea area, the transfer between different sea areas, and the transfer between different regions and different sea areas.

B. Experiment Results

1) Anomaly Detection Accuracy: Figure 4 uses FPR and FNR as indicators to show the change of abnormal trajectory detection accuracy as $Data\_Size$ increases in the three cases of abnormal position, abnormal speed and abnormal heading. As shown in Fig. 4, we found that as $Data\_Size$ increases, the FPR and FNR of the proposed TLTAD experienced fluctuations and eventually stabilized. Obviously, for each value of $Data\_Size$, in any type of exception, the FPR is at most 4%, and the FNR is 5%. The experimental results shown in Fig. 4 show that the detection accuracy is affected by $Data\_Size$. This is because the characteristics of the ship's acceleration, deceleration, left and right turns, and straight sail cannot be accurately described with a small $Data\_Size$. In addition, the correlation between adjacent AIS messages is complicated. As a result, abnormal AIS data might be misjudged by the detection model, thus increasing FPR.

The comparison of the trajectory anomaly detection accuracy between the proposed TLTAD and the baseline strategy

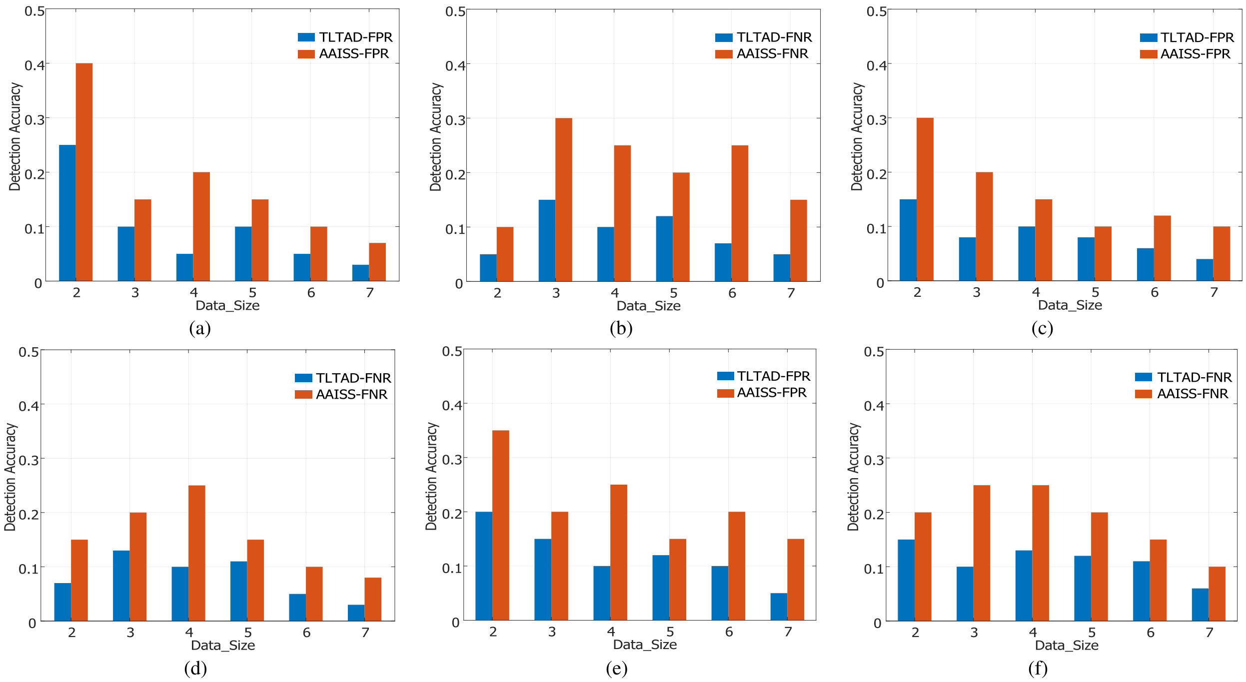


Fig. 4. Trajectory anomaly detection accuracy in (a) FPR and (b) FNR for the position abnormality, (c) FPR and (d) FNR for the speed abnormality, and (e) FPR and (f) FNR for the course abnormality with the variation of $Data\_Size$.

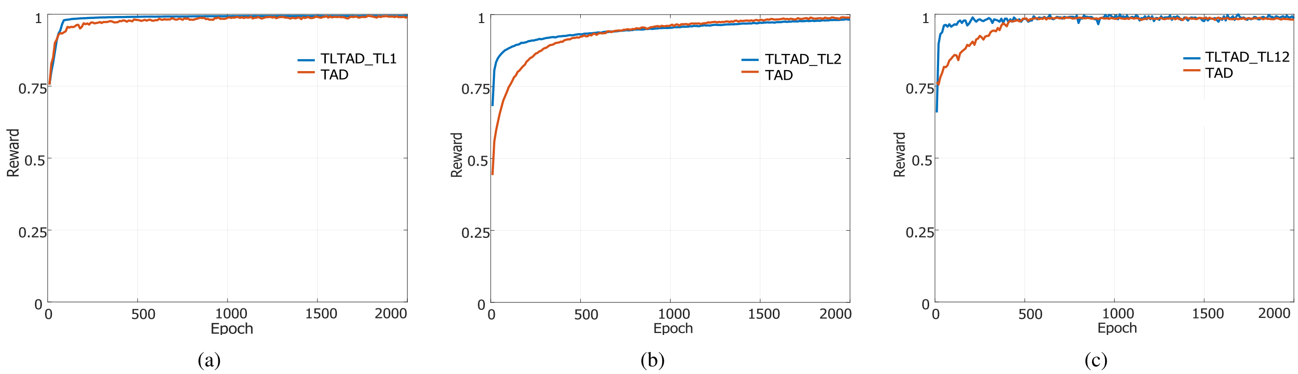


Fig. 5. The convergence of the proposed TLTAD using the model transfer (a) between different regions of an sea area, (b) between different sea areas, and (c) between different regions of different sea areas.

TABLE I

TRAJECTORY ANOMALY DETECTION ACCURACY COMPARISON BETWEEN THE PROPOSED TLTAD AND BASELINES

Model	Accuracy	Precision	Recall	F1-score
DT	78.2%	81.7%	75.1%	78.2%
iForest	85.7%	90.3%	79.4%	84.5%
SVM	83.4%	84.5%	81.3%	82.9%
LSTM	88.5%	91.2%	86.4%	88.7%
VAE	90.3%	88.7%	88.1%	88.4%
AAISS	91.5%	92.4%	91.3%	91.8%
TLTAD	96.1%	95.5%	94.6%	95%

is shown in Table I. By observing Table I, we can get that the recall rates of VAE, DT, SVM, and iForest are relatively low. This is because the trajectory is time series data, the abnormal trajectory and its neighboring trajectories will have obvious differences in the motion characteristics, but if only the information of the current point is used and the motion characteristics of the ship before and after the trajectory section are ignored, this will inevitably limit the model's performance so that the recall rate of the model is low. In addition, the LSTM anomaly detection model combined with the DBSCAN clustering algorithm and the VAE based on the BP neural network are relatively close in accuracy, recall and F1 value. Obviously, the TLTAD outperform all baseline methods in every comparison indicator. This is because TLTAD not only finds the potential connection between each dimension of the trajectory feature, but also finds the spatial connection between the normal trajectories.

2) *Model Convergence:* The convergence of TLTAD is shown in Fig. 5. For simplicity, we use TLTAD_TLi to represent the proposed trajectory anomaly detection strategy, in which the i type of transfer learning and those without transfer learning are represented by TAD. Observed from

Fig. 5, we find that the convergence speed of each TLTAD_TLi is faster than that of TAD, and TLTAD_TLi will get as many rewards as TAD when the strategy converges. Note that the detection accuracy is used as a reward for the DRL-based anomaly detection strategy. Therefore, the results given in Fig. 5 show that the application of transfer learning can not only reduce the model training time, but also maintain high anomaly detection accuracy.

VI. Conclusion

The abnormal ship trajectories may cause shipwrecks, resulting in huge economic losses and casualties. In this paper, we propose a transfer learning based trajectory anomaly detection strategy for IoT-MTS, named TLTAD. In TLTAD, a variational autoencoder is used to discover the potential connections between each dimension of the ship's trajectory, while a graph variational autoencoder is utilized to explore the spatial similarity between the trajectories. On this basis, the deep reinforcement learning algorithm is designed to construct the abnormal trajectory detection model. Then, the transfer learning is applied to reduce model training time, and an efficient dataset transformation mechanism is developed to improve the model transfer. Experimental results show that the proposed TLTAD can provide accurate abnormal trajectory detection for IoT-MTS and significantly reduce model training time.

Although the proposed strategy can effectively improve the accuracy of abnormal trajectory detection, the deep learning algorithm TD3 used in the strategy may not be able to effectively combine the reconstruction probability generated by VAE and GVAE like the attention mechanism. That is, the weight assigned to the reconstruction probability generated by the VAE may be too large, so that the spatial similarity between the trajectories may be ignored. Therefore, our future research direction includes trajectory anomaly detection based on the multi-head attention mechanism.

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