To cite this article：LI K X, GUO J, LI R C, et al. Ship trajectory anomaly detection method based on encoder-decoder architecture composed of Transformer_LSTM modules [J/OL]. Chinese Journal of Ship Research, 2024, 19(2). http://www.ship-research.com/en/article/doi/10.19693/j.issn.1673-3185.03291 (in both Chinese and English).

DOI: 10.19693/j.issn.1673-3185. 03291

Ship trajectory anomaly detection method based on codec architecture composed of Transformer_LSTM modules

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Abstract: ［**Objective**］To improve the accuracy and efficiency of ship trajectory anomaly detection and solve the problems of traditional anomaly detection methods such as limited feature characterization ability, insufficient compensation accuracy, gradient disappearance and overfitting, an unsupervised ship trajectory anomaly detection method based on the Transformer_LSTM codec module is proposed. [**Method**] Based on the encoder-decoder architecture, the Transformer_LSTM module replaces the traditional neural network to achieve track feature extraction and track reconstruction. By embedding the transformer into the recursive mechanism of LSTM, combined with the cyclic unit and attention mechanism, self-attention and crossattention can be used to calculate the state vector of the cyclic unit and effectively construct the long sequence model. By minimizing the difference between the reconstructed output and original input, the model learns the characteristics and motion mode of the general trajectory, and trajectories with a reconstruction error greater than the abnormal threshold are judged as abnormal trajectories. [**Results**] AIS data collected in January 2021 were adopted in the experiment. The results show that the accuracy, precision and recall rate of the model are significantly improved compared with those of LOF, DBSCAN, VAE, LSTM, etc. The F_1 score is improved by 8.11% compared with that of the VAE-LSTM model. [**Conclusion**] The anomaly detection performance of the proposed method is significantly superior to the traditional algorithm in various indexes, and the model can be effectively and reliably applied to the maritime trajectory anomaly detection of ships.

Keywords: anomaly detection; deep learning; encoder-decoder; transformer; longshort-term memory (LSTM); trajectory reconstruction

CLC number：U665.2

0 Introduction

With the development of technologies such as multi-source sensors and wireless network communication, the mining of massive trajectory big data has become a research hotspot in the construction of new service systems such as smart transportation and smart ocean. Ocean shipping, as a significant part of world trade[1], has seen continuous growth in the scale of ship trajectory data, and presents features such as uncertainty and sparsity, leading to increasingly prominent issues of maritime safety and risks[2]. To avoid potential maritime accidents, ensure the safety of ocean shipping and enhance maritime situational awareness, it is crucial to have real-time ship monitoring with proactive responses to abnormal behaviors and establish an efficient and precise system for ship trajectory anomaly detection [3].

Automatic identification system (AIS) serves as the main data source for ship behavior analysis and supervision of maritime law enforcement. Ship trajectory anomaly detection is a prerequisite for ensuring maritime safety. Therefore, how to mine

Received：2023－03－01 **Accepted**：2023－04－21

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abnormal data patterns from massive trajectory data and build an intelligent and efficient model for ship trajectory anomaly detection becomes the key issue.

Previous research methods for ship trajectory anomaly detection mainly focus on algorithm models based on statistics [4-5], proximity [6-8], time series prediction [9-10] and trajectory reconstruction[11-12]. Statistics-based methods formate statistical models by calculating mean, variance, kurtosis and skewness to obtain the probability distribution of ship trajectories, such as fitting Gaussian distribution [13] . This type of method is suitable for data with simple features and single-type anomalies but cannot adapt to high-dimensional data. Proximity-based methods measure data similarity through distance or density calculations, identifying data outside the similarity threshold as anomalies. Clustering was used to discover abnormal ship trajectories by Xiang [6] and Gao [7] et al. Li et al. [8] identified the aircraft anomaly judgment by constructing anomaly discrimination factors based on the characteristics of the trajectory probability distribution. Ristic et al.[13] employed an adaptive kernel density estimation algorithm to evaluate abnormal ship motion patterns. These above methods require prior knowledge, with threshold selection based on dataset distribution. Also, models are not universal and typically focus only on spatial correlations while overlooking the temporal correlation of the data.

With the advancement of hardware devices, deep learning models represented by recurrent neural network (RNN) [14-15] and long short-term memory (LSTM) [10, 16-17] are widely used in anomaly detection for time series data. These methods based on RNN and its derivatives are effective in handling the relationship of time series data. However, they require labeling massive datasets, leading to large computing resource consumption, serious data feature loss and complex processing. Additionally, as the network layers increase, issues like gradient disappearance or exploding arise. Due to the lack of anomaly labels in real-life datasets, emerging unsupervised deep learning models such as the variational autoencoder (VAE) are often combined with the above time series data processing models to detect abnormal data. Qin et al. [11] used VAE to achieve trajectory reconstruction, and obtained anomaly detection through multi-directional comparison. Li et al. [18] combined RNN with VAE, realizing anomaly detection by calculating the reconstruction error as the basis for judging trajectory anomalies. Yin et al. [19] preprocessed the data through a two-stage sliding window, extracted data features and combined convolutional neural networks with an autoencoder to improve the effect of anomaly detection. Wang et al. [20] combined the generative adversarial network and LSTM to realize the generation, discrimination and reconstruction of trajectory, built an unsupervised anomaly detection model, and avoided problems such as data sensitivity and sample imbalance. The above methods can effectively handle temporal data relationships and mine the deep features of data, but appropriate regularization is required to avoid performance degradation caused by model overfitting. For massive high-dimensional data, the calculation cost of this type of method is high, and the timeliness of the model is limited.

To reduce the computing cost and improve the timeliness of model training, a Transformer model with powerful feature-extraction capability was proposed. This model allows parallel computing and utilizes attention mechanisms to memorize long sequence information, significantly reducing model training time, and avoiding performance degradation of the LSTM model due to the gradient disappearance in reverse propagation and forget gate information loss. Zhou et al. [21] applied the Transformer model to the prediction of highway traffic flow, optimizing global information exploration through attention mechanisms to mine inter-data correlations. Ouyang et al. [22] combined a temporal convolutional network with a Transformer model to extract features from power grid data and assign weights to achieve fault detection of the power grid. However, this type of method suffers from the weak ability to obtain local information, the issues that the top-level residual module and the normalization module are easy to cause gradient disappearance, and so on.

The above algorithm determines hyper-parameters such as anomaly thresholds by combining calibrated datasets. Thus, the reliability of the model depends on these calibrated datasets. However, geographical regions have an impact on ship behavior. As application scenarios become more complex and data dimensions continue to increase, the existing algorithms have issues such as high computing cost, poor generalization performance, limited feature characterization ability and insufficient compensation accuracy.

Aiming at the above problems, this paper proposes a method for the detection of ship trajectory anomaly based on Transformer_LSTM codec model, which takes the codec as the infrastructure, and replaces the neural network in the code with Transformer_LSTM. Transformer_LSTM embeds the Transformer into the recurrent unit module of LSTM, combines the attention mechanism with the recurrent function, realizes parallel computing while learning multiple context information, captures global spatial correlation and avoids gradient disappearance in reverse propagation. The recurrent function compensates for the Transformer's weaker ability to capture long-time sequences, achieving unified modeling of spatio-temporal information. Experiments will be carried out on real datasets to verify the effectiveness of this method.

1 Design of trajectory anomaly detection algorithm based on Transformer_LSTMcodec model

The purpose of anomaly analysis is to explore the special behavior patterns and maneuvering intentions implied in ship trajectories, enabling the inference from data to behavior, thus identifying differences and providing a reference for analyzing and detecting abnormal ship behaviors. According to the significance of anomaly analysis, abnormal ship behavior is defined in this paper as the particularity of ship behavior reflected by trajectory data (excluding data anomalies produced by non-human factors), such as the particularity of spatial position (navigating in no-sailing area, no-fishing area or deviating from the channel) and the particularity of motion characteristics (abnormal speed and abnormal turns). A model is constructed to fully mine the spatiotemporal characteristics of trajectory data and detect abnormal ship behaviors, to realize ship anomaly detection, and evaluate and warn against dangerous behaviors.

The architecture of the trajectory anomaly detection algorithm based on Transformer_LSTM is shown in Fig. 1 (in the figure, P represents input data points, p output data points and h hidden layer data). In this paper, according to the multi-dimensional feature attributes of AIS data, trajectory data are firstly preprocessed to generate temporal trajectory segments. The main model includes model training and anomaly detection. The training process extracts trajectory features and reconstructs the trajectory based on the encoder-decoder architecture. The Transformer_LSTM module captures the hidden multivariate distribution of input trajectory sequences, extracts multiple feature attributes of the trajectory and constructs them as hidden layer embedding vectors. Subsequently, the Transformer_LSTM module reconstructs the hidden layer data back to output trajectories, with the training objective being to minimize the reconstruction error between input and output vectors. For anomaly detection, an anomaly discrimination coefficient is set to calculate the reconstruction loss of the trajectory data through the model input data and output data. The anomaly score and reconstruction score of the trajectory data are computed according to the operation loss and the anomaly discrimination coefficient of data sets. Trajectories with reconstruction scores greater than anomaly scores are classified as an anomaly (output−1), otherwise they are normal trajectories (output 1).

1.1 Trajectory data preprocessing

The quality of datasets and feature engineering is the foundation of machine learning methods.

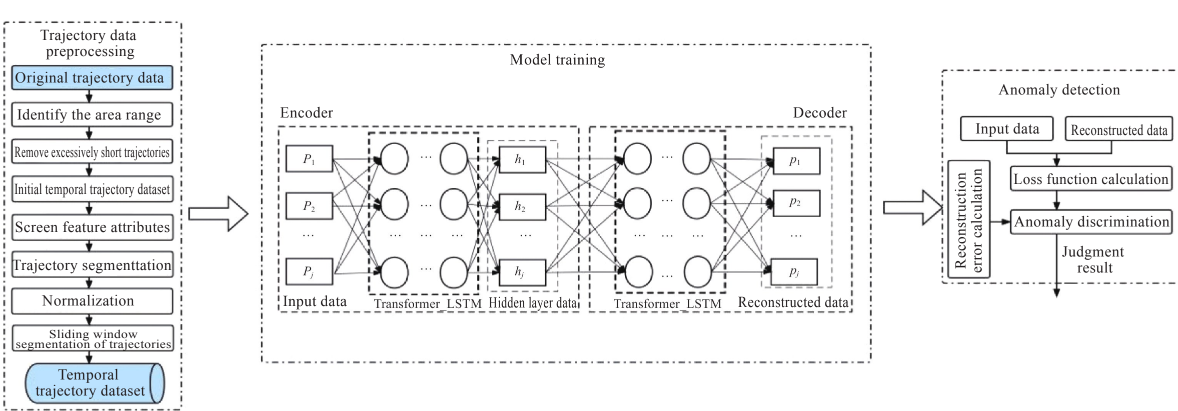


Fig. 1 Architecture of ship anomaly detection based on Transformer_LSTM codec model

Therefore, preprocessing trajectory data is crucial to extract features from raw data to the greatest extent, to improve the modeling performance of datasets. It is very important to build datasets with excellent feature representation.

The original AIS ship data are a series of points collected, including multidimensional numerical and non-numerical features, which are ship call sign, ship name, trajectory point longitude and latitude, speed, course and heading. In the preprocessing of trajectory data, firstly the data space range is limited according to the research area, and the important information loss data caused by data transmission and signal loss is removed. Trajectory segments are constructed according to the ship call sign and arranged in chronological order. The initial temporal trajectory dataset is shown in Eq. (1).

$$\begin{cases} T = \{T_I, T_2, ..., T_n\} \\ T_i = [p_{i1}, p_{i2}, ..., p_{in}] \\ p_{ij} = [Y_{ij}, X_{ij}, S_{ij}, C_{ij}, S''_{ij}, C''_{ij}, t_{ij}] \end{cases} \tag{1}$$

where T represents the ship trajectory dataset; T_i represents the i-th trajectory segment, that is, the trajectory data of the i-th ship; p_{ij} is arranged in chronological order and represents the S''_{ij} trajectory point in the i-th trajectory segment; Y_{ij}, X_{ij}, S_{ij}, C_{ij}, S''_{ij}, C''_{ij} and t_{ij} are the attribute information contained in the ($t_{it} = r_{it} - r_{it-1}$)-th trajectory point in the ($t_{it} = r_{it} - r_{it-1}$) -th trajectory segment, respectively represent longitude (°), latitude (°), speed (kn), heading angle (°), calculated speed (kn), calculated rotation angle (°) and report time interval (s).

The report time represents the time difference between adjacent points, which can be calculated as shown in Eq. (2). The calculated speed can also be regarded as the average speed, which can be computed based on the distance and time difference between adjacent points, as shown in Eq. (3).

$$t_{it} = r_{it} - r_{it-1} \tag{2}$$

$$S''_{it} = \frac{D(p_{i(t-1)}, p_{it})}{t_{it}/3\,600 \times 1.852} \tag{3}$$

where t_{it} represents the time stamp of the t-th point in the i-th trajectory segment; $D(p_{i(t-1)}, p_{it})$ represents the distance between adjacent points, calculated by haversine formula in km; S''_{it} represents the average calculated speed between adjacent points in kn (1 kn = 1.852 km/h).

Trajectories with reporting time intervals greater than 30 min are segmented from the initial temporal trajectory dataset. Since the sampling frequency of sensors is not uniform, the processed time series trajectory data set is resampled at 3-min intervals. After resampling, to address the issue of differences in dimensions among various characteristic attributes of trajectory data, numerical and dimensionless processing is performed. Firstly, through standardization, the convergence speed and accuracy of the model are improved, and the influence of dimensions is eliminated at the same time; the standardized data are further normalized. The calculation formula is as follows.

$$\begin{cases} c''_k = \dfrac{c_k - c_{k\_\text{mean}}}{c_{k\_\text{std}}} \\ C_k = \dfrac{c''_k - c''_{k_\text{max}}}{c''_{k_\text{max}} - c''_{k_\text{min}}} \end{cases} \tag{4}$$

where c''_k represents the processed value after standardizing the C_k-th dimensional feature attribute; c_k represents the original value of the k-th dimensional feature attribute; c_{k_mean} represents the mean value of the C_{k_std}-th dimensional feature attribute; c_{k_std} represents the variance of the C_k-th dimensional feature attribute; C_k represents the value of the $C_{k\_\max}$-th dimensional feature attribute after standardization and maximum-minimum normalization; $c''_{k\_\max}$ denotes the maximum value after standardizing the $c''_{k\_\min}$-th dimensional feature attribute; $c''_{k\_\min}$ represents the minimum value after standardizing the $\boldsymbol{W}$-th dimensional feature attribute.

1.2 Transformer_LSTM codec trajectory anomaly detection algorithm

To address the difficulties in extracting trajectory features, overfitting and poor detection accuracy faced by traditional anomaly detection models, this paper designs a trajectory reconstruction error-based Transformer_LSTM autoencoder anomaly detection algorithm based on the architectures of Transformer, LSTM and VAE codec. Among them, the codec modules of VAE are implemented by Transformer_LSTM combined module. The model takes the feature vectors with series ship trajectories of fixed-length time as input. The encoder extracts the features of the input trajectory data and encodes them into latent variables, while the decoder reconstructs the original input trajectory by reconstructing the latent variables. The reconstruction error of trajectories serves as the basis for anomaly detection. Trajectories with reconstruction errors greater than the anomaly threshold are classified as anomalous trajectories, otherwise they are classified as normal ones.

1.2.1 Transformer base model

The Transformer [23] model was initially used for machine translation tasks. It demonstrates powerful feature extraction capabilities and allows parallel computing, gradually extending to other scenarios involving sequential data processing. Transformer uses stacked encoders and decoders to explore deep features in time series data. The attention mechanism and feedforward neural network layers in the encoder and decoder are connected by residual connections, and then layer standardization operations are carried out to make the model gradient multiplied in the reverse propagation process to avoid gradient disappearance. The position mask is constructed so that when aligning the fill input sequence, the fill position is avoided from distracting the model's attention. The sequence mask is used in the self-attention mechanism of the decoder to construct an upper triangular matrix during decoding to avoid the interference of future information on the model accuracy. The multi-head attention architecture is illustrated in Fig. 2. The essence of Transformer's multi-head attention mechanism lies in concatenating multiple independent attention mechanisms, and each group is initialized independently to avoid random parameter effects, enhancing the expression ability of the model and efficiently realize parallelization. The attention mechanism of the Transformer can judge the correlation between different regions by calculating the scores of the current region and all other regions, to better extract the global information from the data, uncover internal sequence relationships and realize the self-association between source and target sequences.

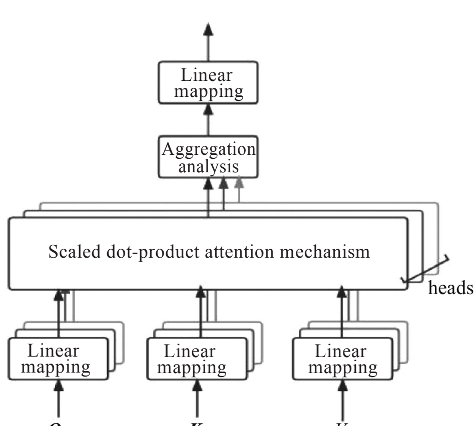


Fig. 2 Multi-head attention mechanism architecture

Formulas for calculating the attention mechanism of the Transformer are shown in Eqs. (5)−(7).

$$M(\boldsymbol{Q},\boldsymbol{K},V) = J(h_i,\dots,h_h)\boldsymbol{W} \tag{5}$$

$$h_i = A(\boldsymbol{Q}\boldsymbol{W}_i^{Q},\boldsymbol{K}\boldsymbol{W}_i^{K},V\boldsymbol{W}_i^{v}) \tag{6}$$

$$A(\boldsymbol{Q},\boldsymbol{K},V) = \mathrm{softmax}\left(\frac{\boldsymbol{Q}\boldsymbol{K}^{\mathrm{T}}}{\sqrt{d_K}}\right)V \tag{7}$$

where $\boldsymbol{M}(\boldsymbol{Q}, \boldsymbol{K}, \boldsymbol{V})$ represents the output sequence of multi-head attention, which is a parallel output of concatenated attentions; d_K represents the dimension of $\boldsymbol{K}$, the scaling factor is $\sqrt{d_K}$; $\boldsymbol{W}$, $\boldsymbol{W}_i^Q$, $\boldsymbol{W}_i^K$, and $\boldsymbol{W}_i^v$ represent vector matrices for linear transformations; $\boldsymbol{Q}$ represents the query calculation vector; $\boldsymbol{K}$ represents the vector being queried; $\boldsymbol{V}$ represents the actual features; $A(\boldsymbol{Q}, \boldsymbol{K}, \boldsymbol{V})$ represents attention weight, outputting vector sequences through scaled dot-product.

1.2.2 LSTM base model

LSTM is a sequence data processing model that introduces "gates" based on RNN to address the gradient disappearance and gradient explosion problems encountered during long sequence training in RNN models. The LSTM model achieves selective information passage through gate mechanisms. The network structure of an LSTM unit is shown in Fig. 3, where the forget gate selectively inputs information; the input gate updates with new information and the output gate provides output based on judgment conditions. Inputs are c_{t-1}, h_{t-1} and x_t. Outputs are c_t, h_t and y_t after passing through the LSTM unit. c_t, h_t, y_t, c_{t-1} and c_t represent global information carriers from the previous and current rounds; h_{t-1} and h_t represent the neuron state of the previous round and the current round respectively.

The gate mechanism calculation formulas are as follows.

$$z_f = \mathrm{sigmoid}(\boldsymbol{w}_f\cdot[h_{t-1},x_t]+b_f) \tag{8}$$

$$\begin{cases} z_i = \mathrm{sigmoid}(\boldsymbol{w}_i\cdot[h_{t-1},x_t]+b_i) \\ z = \tanh(\boldsymbol{w}\cdot[h_{t-1},x_t]+b) \end{cases} \tag{9}$$

$$c_t = z_f\cdot c_{t-1} + z_i\cdot z \tag{10}$$

$$\begin{cases} z_0 = \mathrm{sigmoid}(\boldsymbol{w}_0\cdot[h_{t-1},x_t]+b_0) \\ h_t = z_0\cdot\tanh(c_t) \end{cases} \tag{11}$$

where z_i represents the updated value of LSTM; z represents the new candidate value vector; c_{t-1} and c_t represent global information carriers from the previous and current rounds respectively; h_{t-1} and h_t represent neuron state quantities from the previous and current rounds respectively; $\boldsymbol{w}$ and b are weight

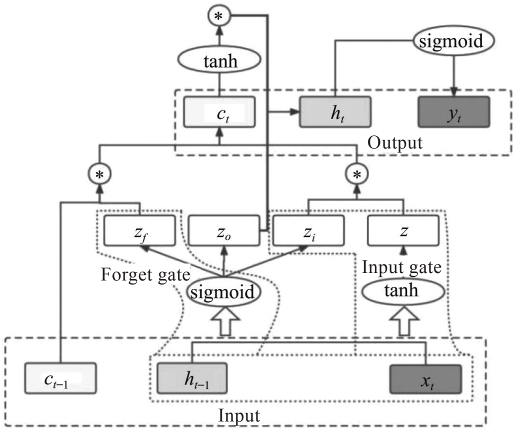


Fig. 3 LSTM unit network structure

matrices and bias terms for the output gate, input gate, and forget gate respectively.

1.2.3 Transformer_LSTM codec model

Based on the encoder-decoder architecture of the VAE model, this paper replaces the BP neural network layer in the VAE model with the Transformer_LSTM module. The model architecture, as shown in Fig. 4, fully utilizes trajectory temporal information and avoids gradient disappearance during feature extraction. The essence of the encoder-decoder architecture is to train a generative model by assuming that input data follows a certain prior probability distribution, transforming input data into latent space and reconstructing data from the latent space. If the model has a better ability to reduce the error between the reconstructed data and the initial input data, the model performance will be better. The application of the codec architecture in ship trajectory anomaly detection is based on the theoretical foundation that anomalous data loses a large amount of information during spatial transformation and feature mapping. Therefore, data with high reconstruction errors can be identified as anomalies. The encoder-decoder trajectory generation model is trained using a Transformer_LSTM encoder to model ship trajectory data and obtain latent variables. Another Transformer_LSTM acts as the decoder to reconstruct the latent variables. The model is trained in an unsupervised manner, where the training data may include a small amount of anomaly data, meeting the case of uneven distribution between positive and negative samples in actual ship trajectory data. During encoding and decoding of the original input data to implement feature mapping and spatial transformation, the model outputs the mean and variance of the samples, calculating the average value as the reconstruction probability threshold. Based on this, trajectory data with low reconstruction probabilities

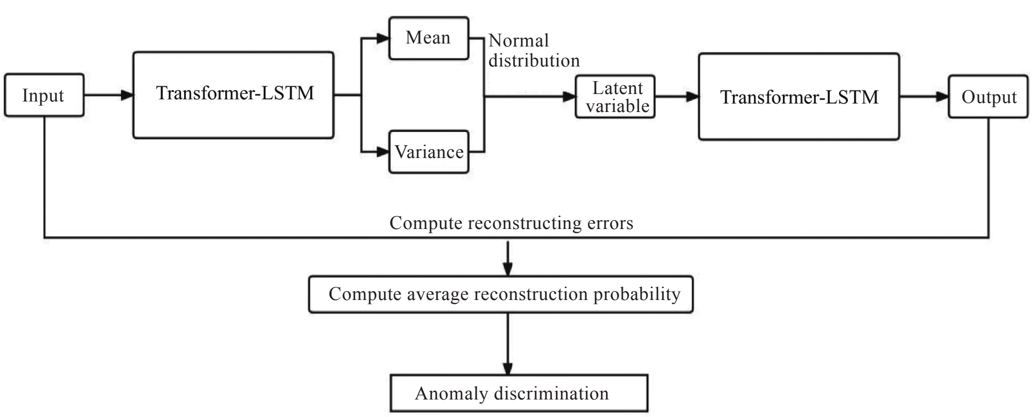
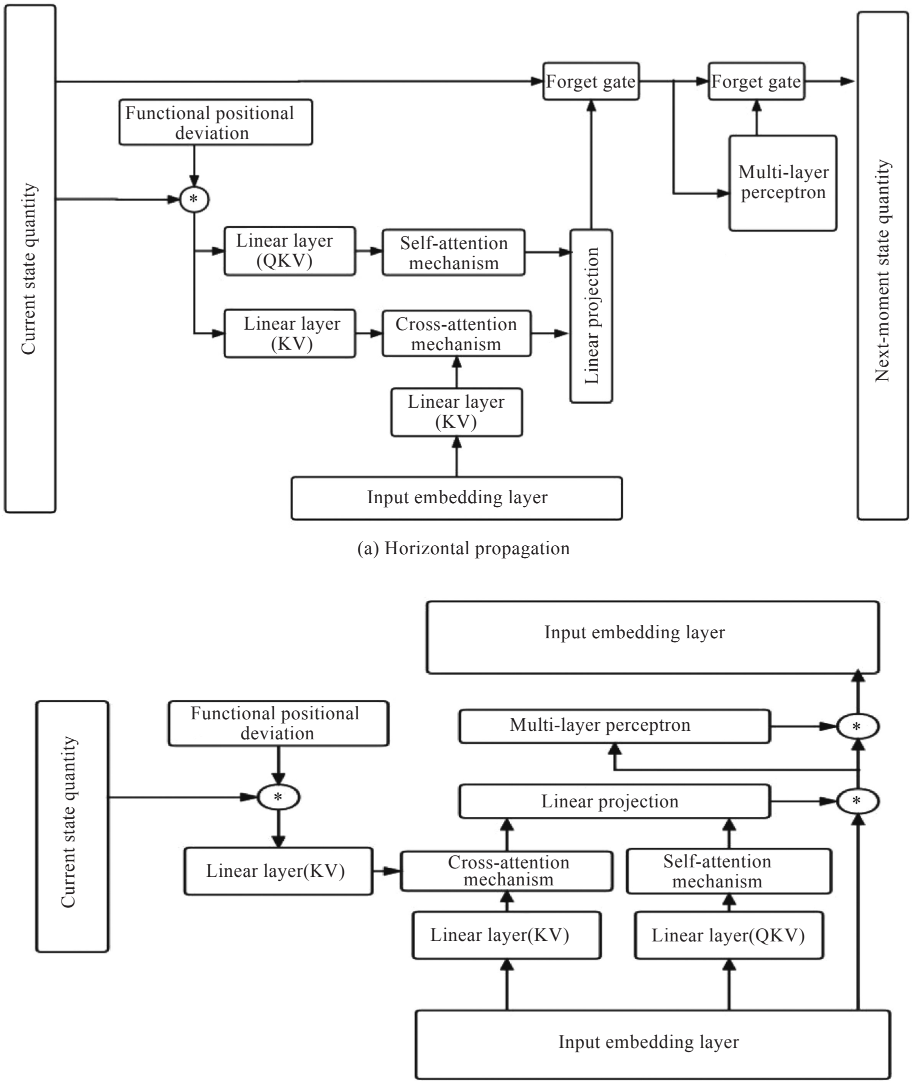


Fig. 4 Transformer_LSTM encoder-decoder model

are classified as anomalous trajectories.

The structure of the Transformer_LSTM module, as shown in Fig. 5, is essentially a cyclically callable Transformer layer. The Transformer_LSTM module takes the LSTM recurrent unit as the basic structure and is embedded with the Transformer module. It integrates the parallel processing mechanism and attention mechanism of the Transformer and the advantages of the LSTM recurrent unit, makes full use of the recurrent structure to capture long-term information, and then significantly reduces the operation cost and complexity of the model. The module uses the self-attention mechanism and cross-attention mechanism to perform encoding and decoding operations at the same layer simultaneously. It obtains output embedding vectors vertically and state quantities for the next time step horizontally so that the module can be simply stacked horizontally or vertically without introducing additional parameters. Each layer of state variables will be processed by the same multi-layer



(a) Horizontal propagation

(b) Vertical propagation

Fig. 5 Transformer_LSTM module structure

perceptron network before output. To prevent the state vectors from tending to be consistent and indistinguishable in iterative training, functional positional biases are added to the state vectors before computing keys ($\boldsymbol{K}$), values ($\boldsymbol{V}$), and queries ($\boldsymbol{Q}$). Functional positional biases are based on the queries issued by the input sequence.

2 Experiments and analysis

2.1 Dataset

To evaluate the anomaly detection performance of the trajectory anomaly detection algorithm, this paper uses the AIS dataset published by the US Coast Guard to screen the AIS data in the Gulf of Mexico region during January 1−10, 2021 for experimental research. The raw data include 21 137, 485 trajectory records, involving 5 633 ships. The recorded trajectory points of each ship range from 1 to 13 057 with an average of 3 752 trajectory points per ship. After data processing, there are 18 447, 341 trajectory data points available, involving 5 226 ships. Each record includes the ship's maritime mobile service identity (MMSI), latitude and longitude, speed, course, heading and other characteristic attributes.

2.2 Experimental settings

1) Experimental environment.

This paper uses the deep learning framework TensorFlow to implement the Transformer_LSTM codec model, completing model training on the NVIDIA GeForce RTX3090 Ti GPU. The programming language is Python, with the Jupyterlab development environment and Windows 10 operating system. The experimental environment configuration is as follows: CPU is Intel (R) i9-12900K@3.19 GHz with 32 GB memory.

2) Evaluation indexes.

Anomaly detection is essentially a binary classification problem. The results are evaluated according to the actual label and predicted label of the trajectory data. The ultimate goal of anomaly detection is to improve the detection accuracy of minority-class anomaly data. To more accurately evaluate algorithm efficiency and accuracy, the experiment uses accuracy (A_{cc}), precision (P), recall (R), F_1 score and false positive rate (F_{PR}) as evaluation indicators to evaluate the anomaly detection performance of the algorithm model. The calculation formula of the evaluation indexes is as follows.

$$A_{cc}=\frac{T_N+T_P}{T_N+T_P+F_N+F_P} \tag{12}$$

$$P=\frac{T_P}{T_P+F_P} \tag{13}$$

$$R=\frac{T_P}{T_P+F_N} \tag{14}$$

$$F_1=\frac{2\times P\times R}{P+R} \tag{15}$$

$$F_{PR}=\frac{F_P}{T_N+F_P} \tag{16}$$

where T_P represents that both the actual and detected samples are normal; T_N represents that both the actual and detected samples are abnormal; F_P represents the abnormal sample that is not correctly detected; F_N represents a normal sample that is misdetected as an abnormal sample; A_{cc} represents the proportion that the model checks correctly; P represents the detection accuracy of the model for positive samples; R is used to evaluate the proportion of positive samples that the model evaluates correctly; F_1 is used to evaluate the overall detection accuracy of the model to avoid excessive or small P and R values under the condition of extreme unevenness of positive and negative samples, resulting in loss of reference value; F_{PR} represents the proportion of negative samples that were misjudged.

2.3 Comparative analysis of the model's results

In this experiment, representative methods based on statistics, proximity, time series prediction and trajectory reconstruction were selected as the experimental control group to compare with the Transformer_LSTM model in this paper.

1) Local outlier factor (LOF): A density-based unsupervised anomaly detection method that discriminates whether a point is anomalous based on its local reachable density.

2) Density-based clustering algorithm (DBSCAN): A density-based clustering algorithm, which divides different clusters by calculating the distance between points and the center point of the cluster.

3) Isolation forest: Comprising numerous binary trees, it isolates anomalies by recursively segmenting and calculating path lengths, known for its low computational complexity and memory consumption. It is widely used in anomaly detection of continuous data. However, its convergence speed and accuracy are affected by cutting points, and different binary trees may have varying discrimination accuracy.

4) Variational auto-encoder (VAE): A generative model that builds a model that generates target data from hidden variables through distribution transformation.

5) Variational auto-encoder-long-short-term memory (VAE-LSTM): Replace the neural network layer in the variational self-encoder with the LSTM residual network. LSTM solves the problem of gradient disappearance or explosion in the layer by building a sequence table, improving model robustness with an encoding-decoding architecture.

After data processing, the experimental dataset in this paper has a total of 18 447 341 trajectory data available, including 5 226 ships. The ships are randomly divided into the training set and test set in a 4:1 ratio. 4 181 ship trajectory training samples and 1 045 test samples are obtained. The model is tuned through experiments to verify the performance of the model, and then the performance comparison based on the commonly used anomaly detection algorithms introduced above is carried out as the experimental control group. The specific steps of the experiment are as follows.

1) Processing of data normalization and setting of input length. To avoid dimensional interference between different attributes of the data, it is necessary to normalize the data to unify the dimensions. The input length of trajectory sequence data is related to the extraction efficiency of time sequence information. If the length is too short, it is not conducive to the extraction of time sequence information and the capture of time sequence relationships. If the length is too long, it may cause redundancy. To ensure model accuracy, referencing relevant research parameter setting experiences, input lengths were chosen as 8, 10, 12, 14, 16, 18,

20, 24 and 26 for training the model. The line chart of input model length and model accuracy is shown in Fig. 6. To avoid the influence of multiple evaluation indicators on the visualization, the F_1 score and F_{PR} were selected as the visualization objects, aiming for a higher F_1 score and a lower F_{PR}. As shown in the figure, with the continuous increase in input sequence length, the F_1 score fluctuates and rises, while the F_{PR} fluctuates and decreases. When the length of the input sequence is 24, both reach a relatively balanced state. Therefore, the model performs the best when the length of the input sequence is 24.

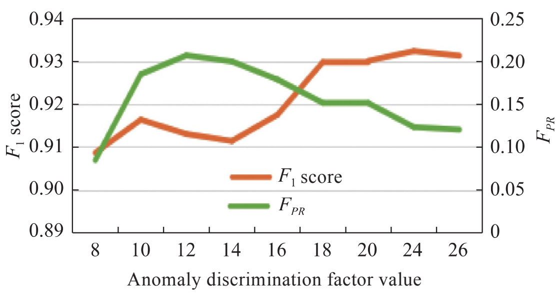


Fig. 6 Input model length and model accuracy line graph

2) Network configuration of Transformer_LSTM and settings of anomaly discriminant factor. During the experiment, since the input dataset has been normalized, the batch value should not be too small. The rough adjustment values are 128, 256 and 512 respectively, but the accuracy of the test model has no significant change. Considering the operating efficiency and generalization ability, and referring to relevant research, a batch size value of 256 was chosen empirically. Since the essence of this model is a regression problem, the L_2 loss function was selected for model training, with the Adam optimizer chosen. The iterative training determines the learning rate to be 0.009. The abnormal discrimination coefficient of trajectory data is assumed to be the proportion of abnormal data in the original trajectory data, and its value is directly related to the output result of model anomaly detection. The line diagram of the abnormal discrimination factor value and model accuracy is shown in Fig. 7. Through the changing trend of F_1 score and F_{PR}, the abnormal discrimination factor value is 0.095.

3) Experiment for comparison of model performance. Under the same data conditions, the model in this paper is compared with the common methods of anomaly detection. The indicators of anomaly detection performance for various algorithms are shown in Table 1 and Fig. 8.

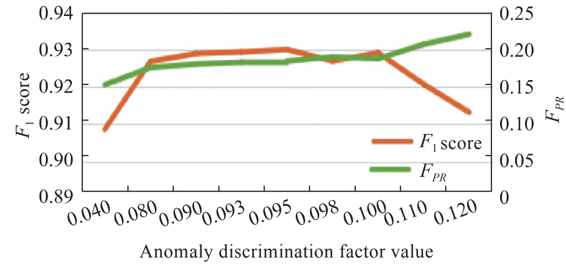


Fig.7 Line diagram of the relationship between anomaly discriminant factor and model accuracy

Ship trajectories are typical time series data, and some anomalies cannot be judged based on single-point information only, so contextual information is needed for identification and determination. LOF, DBSCAN and iForest models can only use single-point information, and cannot capture the temporal relationship of trajectory points and the association of context feature attributes. Hence, the accuracy, recall, and F_1 scores of the models are relatively low. Since anomalous trajectory points are a small proportion of the overall trajectory dataset, the precision of these models is relatively high but with a low reference value. VAE model and LSTM model utilize the trajectory reconstruction and

Table 1 Comparison of abnormal detection results of multiple models

Model	Accuracy rate	Precision rate	Recal rate	F_1 score	False positive rate
LOF	0.5134	0.8845	0.3617	0.5134	0.3171
DBSCAN	0.5983	0.8887	0.4510	0.5983	0.3760
IForest	0.6504	0.9302	0.5000	0.6504	0.2727
VAE	0.7453	0.8786	0.6471	0.7453	0.2392
LSTM	0.7517	0.8809	0.6555	0.7517	0.2352
VAE_LSTM	0.8884	0.9481	0.8070	0.8719	0.1667
Transformer_LSTM codec	0.9318	0.9347	0.9720	0.9530	0.1429

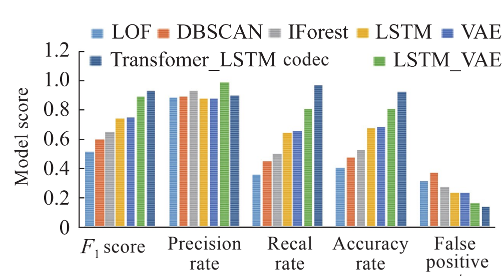


Fig. 8 Comparison of abnormal detection results of multiple models

trajectory prediction respectively, and realize the judgment of trajectory anomaly by calculating the reconstruction loss and prediction loss. VAE maps data features from high-dimensional and dimensional spaces through the codec structure to obtain the hidden relationship of data features. LSTM model can capture the correlation of trajectory data in the time series. Both VAE and LSTM models have similar accuracy, precision, and recall indexes, which are significantly higher compared to traditional models like LOF, DBSCAN, and iForest. The VAE−LSTM model, which combines VAE and LSTM, outperforms both VAE and LSTM individually, with a precision rate of up to 88.84% and an increase in F_1 score of about 12% compared to VAE and LSTM. The Transformer_LSTM codec model improves the LSTM module based on the VAE−LSTM model. The model has the highest accuracy, recall and F_1 score indicators. Compared with the VAE−LSTM model, the F_1 score is increased by about 8.11%, indicating that the Transformer_LSTM codec model can fully integrate the advantages of a single model, which significantly improves the stability and anomaly detection performance of the model network.

3 Conclusions

In recent years, researchers have extensively explored trajectory anomaly detection, but most of the studies focus on the behavior analysis of land vehicles and pedestrians. However, common anomaly detection methods suffer from subjectivity in data modeling, sensitivity to data samples, and susceptibility to overfitting leading to poor universality. To improve the ability of maritime ship anomaly detection, trajectory anomaly detection based on Transformer_LSTM codec is proposed in this paper. The detection model realizes the mapping of the original high-dimensional data to the low-dimensional space through the encoder − decoder architecture and uses the Transformer_LSTM module to replace the traditional codec's BP neural network. It leverages the temporal feature extraction ability of LSTM and the global relationship construction ability of Transformer, better capturing the spatio-temporal feature relationship of trajectory data, and realizing the discrimination between normal and abnormal data through trajectory reconstruction. Experimental results show that compared with the traditional LOF algorithm, DBSCAN algorithm, iForest algorithm and more advanced LSTM, VAE and VAE-LSTM algorithm, the accuracy, recall and F_1 score of the trajectory anomaly detection algorithm proposed in this paper are improved. It shows that the anomaly detection algorithm based on Transformer_LSTM has good detection performance, effectively addressing the ship's unsupervised anomaly detection with good scalability and adaptability. It can provide data support for ship-heading state monitoring, safety assessment and accident analysis. Due to the network complexity of deep learning, the detection time is relatively long. In the future, further research is needed on how to reduce the computational complexity of the model and realize the online abnormal state detection of ships. At the same time, the visualization technology of deep learning network models can further explore the causes of abnormal behavior and the influence of environmental factors to improve the interpretation ability of anomaly detection algorithms.

References

[1] GUO D D, YIN Y, XIAO F B. Overview of route optimization methods data for intelligent ships [J]. Chinese Journal of Ship Research, 2023, 18 (4): 151−161 (in Chinese).

[2] GUAN K W, YAN J. Dilemma of global maritime security governance and its mitigation [J]. Global Review, 2022, 14 (3): 115−133, 161 (in Chinese).

[3] YAN X P, WANG S W, MA F. Review and prospect for intelligent cargo ships [J]. Chinese Journal of Ship Research, 2021, 16 (1): 1−6 (in Chinese).

[4] PALLOTTA G, VESPE M, BRYAN K. Vessel pattern knowledge discovery from AIS data: a framework for anomaly detection and route prediction [J]. Entropy, 2013, 15 (6): 2218−2245.

[5] ZHAO R, YAN R Q, WANG J J, et al. Learning to monitor machine health with convolutional Bi-directional LSTM networks [J]. Sensors, 2017, 17 (2): 273.

[6] XIANG C. Integrated detection of ship abnormal behavior based on isolated forest algorithm [D]. Dalian: Dalian Maritime University, 2020 (in Chinese).

[7] GAO X. Research on trajectory anomaly detection method based on Kalman filter prediction [J]. Ship Science and Technology, 2022, 44 (14): 73−76 (in Chinese).

[8] LI N, SUN B X, FAN R, et al. Research on real-time detection of abnormal trajectory in terminal area based on multidimensional features [J]. Journal of Safety and Environment, 2022, 22 (1): 242−249 (in Chinese).

[9] NOURETDINOV I, GAMMERMAN J, FONTANA M, et al. Multi-level conformal clustering: a distribution-free technique for clustering and anomaly detection[J]. Neurocomputing, 2020, 397 : 279−291.

[10] YANG F, HE Z W, HE F. Detection method of abnor-

mal ship behavior based on LSTM neural network [J]. Journal of Wuhan University of Technology (Transportation Science & Engineering), 2019, 43 (5): 886−892 (in Chinese).
[11] QIN W T, LAO S Y, TANG J, et al. Hurricane trajectory outlier detection method based on variational autoencode [J]. Journal of System Simulation, 2021, 33 (9): 2191−2201 (in Chinese).
[12] RONG H, TEIXEIRA A P, SOARES C G. Data mining approach to shipping route characterization and anomaly detection based on AIS data [J]. Ocean Engineering, 2020, 198: 106936.
[13] RISTIC B, LA SCALA B, MORELANDE M, et al. Statistical analysis of motion patterns in AIS data: anomaly detection and motion prediction [C] // 11th International Conference on Information Fusion. Cologne: IEEE, 2008: 1−7.
[14] ZENG X X. Traffic anomaly detection method based on improved RNN and density clustering [D]. Beijing: Beijing University of Posts and Telecommunications, 2019 (in Chinese).
[15] HE X F, XING W. Research on network abnormal traffic detection based on improved RNN [J]. Wireless Internet Technology, 2021, 18 (22): 21−23, 53 (in Chinese).
[16] HAN Z R, HUANG T L, REN W J, et al. Trajectory outlier detection algorithm based on Bi-LSTM model [J]. Journal of Radars, 2019, 8 (1): 36−43 (in Chinese).
[17] DU Y R, MA Y H, WU J B, et al. Recognition of vehicle abnormal driving behaviors based on LSTM-att [J]. Computer Systems & Applications, 2022, 31 (5): 165−173 (in Chinese).
[18] LI C N, FENG G W, LIU R Y, et al. Traffic trajectory anomaly detection method based on reconstruction error [J]. Computer Science, 2002, 49 (2): 149−155 (in Chinese).
[19] YIN C Y, ZHANG S, WANG J, et al. Anomaly detection based on convolutional recurrent autoencoder for IoT time series [J]. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 2022, 52(1): 112−122.
[20] WANG F Q, GAO L, XU T X, et al. UAV flight data anomaly detection algorithm based on LSTM-GAN [J]. Journal of Chinese Inertial Technology, 2022, 30 (2): 264−271 (in Chinese).
[21] ZHOU C H, LIN P Q. Traffic flow prediction method based on multi-channel Transformer [J]. Application Research of Computer, 2023, 40 (2): 435−439 (in Chinese).
[22] OUYANG Y, WAN D, GAO R, et al. Research on single-phase fault line selection in distribution network based on TCN-Transformer self-attention [J]. Microelectronics & Computer, 2022, 39 (9): 89−97 (in Chinese).
[23] VASWANI A, SHAZEER N, PARMAR N, et al. Attention is all you need [C] // Proceedings of the 31st International Conference on Neural Information Processing Systems. Long Beach: Curran Associates Inc., 2017: 6000−6010.

基于 Transformer_LSTM 编解码器模型的船舶轨迹异常检测方法

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摘　要：［目的］为提升船舶轨迹异常检测的精度和效率，解决传统异常检测方法存在的特征表征能力有限、补偿精度不足、容易出现梯度消失、过拟合等问题，提出一种基于 Transformer_LSTM 编解码器模型的无监督船舶轨迹异常检测方法。［方法］该方法基于编码器解码器架构，由 Transformer_LSTM 模块替代传统神经网络实现轨迹特征提取和轨迹重构；将 Transformer 嵌入 LSTM 的递归机制，结合循环单元和注意力机制，利用自注意力和交叉注意力实现对循环单元状态向量的计算，实现对长序列模型的有效构建；通过最小化重构输出和原始输入之间的差异，使模型学习一般轨迹的特征和运动模式，将重构误差大于异常阈值的轨迹判定为异常轨迹。［结果］采用 2021 年 1 月的船舶 AIS 数据进行实验，结果表明，模型在准确率、精确率以及召回率上相较于 LOF，DBSCAN，VAE，LSTM 等经典模型有着明显提升；F_1 分数相较于 VAE_LSTM 模型提升约 8.11%。［结论］该方法的异常检测性能在各项指标上显著优于传统算法，可有效、可靠地运用于海上船舶轨迹异常检测。
关键词：异常检测；深度学习；编码器解码器；Transformer；长短期记忆；轨迹重建