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A semi-supervised deep learning approach for vessel trajectory classification based on AIS data

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ABSTRACT

Automatic identification system (AIS) refers to a new type of navigation aid system equipped in maritime vehicles to monitor ship performance. It provides trajectory information of vessels which can be used for the classification task. The classification results facilitate ocean surveillance and conservation, vessel management enhancement, fishery regulation, marine ecological sustainability, and nautical safety protection. Some progresses have been made based on machine learning or deep learning strategies to perform supervised learning by assuming that during the training process, the category labels of historical trajectory data are available. However, in reality, the label information may be difficult or expensive to obtain, resulting in that only a small part of the training data is labeled, and most of the training data is unlabeled. To address this issue, this paper proposes a semi-supervised deep learning approach to integrate the knowledge of unlabeled data for vessel trajectory classification. Here, we call our approach SSL-VTC. Specifically, we first extract vessel trajectories by integrating the kinematic and static information from historical AIS messages. Then, we design convolutional neural networks to extract feature representations from the vessel trajectories. Finally, we develop a semi-supervised learning algorithm based on the variational autoencoder to perform discriminative learning and generative learning simultaneously. In this way, our SSL-VTC framework can fully leverage the labeled data and unlabeled data during the training process. To the best of our knowledge, we are the first to utilize semi-supervised learning for vessel trajectory classification. Experimental results on the public AIS dataset show that our SSL-VTC can effectively extract feature representations from the AIS messages and its performance is significantly better than the traditional supervised learning methods. The approach and findings of this study provide important implications for researchers and stakeholders in the field of ocean management.

1. Introduction

Automatic identification system (AIS) is an automatic vessel self-reporting system used for navigation safety and maritime transportation management (Zhang et al., 2018). The AIS system transmits the vessel status information at a variable refresh rate, such as vessel name, position, speed, course, dimension, and draft, and those pieces of information can be received by other vessels or vessel traffic service (VTS) centers (Harati-Mokhtari et al., 2007). With the widespread use of AIS systems onboard, AIS data has arguably kickstarted the era of digitization in marine governance and port and shipping operation and management (Yang et al., 2019; Cominelli et al., 2020) and has attracted great attention from the academia recently (Le Tixerant et al., 2018; Svanberg et al., 2019; Chen et al., 2020; Liu et al., 2021b; McWhinnie et al., 2021; Meyers et al., 2021; Tan et al., 2021).

Vessel trajectory classification is an important research topic using AIS data by predicting the category of ship trajectories. Ship types are often used as the category labels for the classification task. The common ship types include fishing, cargo, passenger, and tanker. The classification results play a crucial role in ocean surveillance and conservation (Almpanidou et al., 2021), vessel management enhancement (Zhang et al., 2021a), and navigation safety protection (Liu et al., 2021a). For example, by identifying and tracking illegal, unreported, and unregulated (IUU) fishing vessels and overfishing activities, the classification results strengthen the fishery management and the ocean ecosystem conservation (Krüger, 2019; Arasteh et al., 2020; Alves, 2021; Cánovas-Molina et al., 2021; Garcia et al., 2021; Yu and Wang, 2021). In addition, the classification results can also be used to assist navigators or coastal authorities in detecting suspicious or unsafe vessel

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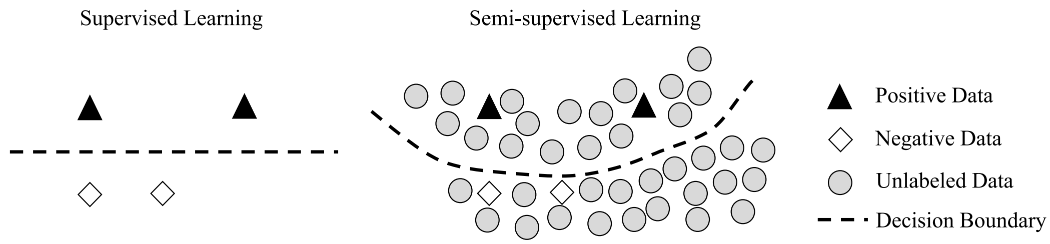


Fig. 1. Illustration of supervised learning and semi-supervised learning. Compared with supervised learning, semi-supervised learning can learn a more accurate decision boundary to achieve better classification performance with the help of the unlabeled data.

behaviors and possible threats by comparing the classified ship types with the ones reported by vessels (Ljunggren, 2018; Nguyen et al., 2018).

To research the problem of vessel trajectory classification, different approaches (Hu et al., 2016; Sheng et al., 2018; Herrero et al., 2019) based on machine learning have been proposed. Due to the great successes of deep learning in many domains (LeCun et al., 2015; Goodfellow et al., 2016), some researchers (Ljunggren, 2018; Mantecón et al., 2019; Arasteh et al., 2020; Kontopoulos et al., 2021) have applied it for vessel trajectory classification, and have achieved higher performance than traditional methods. Despite their progress, they are limited to the following two issues.

Firstly, previous works usually perform the task of vessel trajectory classification with supervised learning by assuming that the label information is available during the training process. However, in reality, it may be expensive or time-consuming to obtain the labeled data (Chapelle et al., 2009; Zhu and Goldberg, 2009; Van Engelen and Hoos, 2020). As a result, during the training process, only a small part of the data is labeled, and most of the data is unlabeled. Unlabeled data usually still contains useful information for classification. Secondly, most previous works only use the kinematic information of AIS messages, such as latitude, longitude, speed over ground, and course over ground, to extract vessel trajectories. Static information is usually overlooked, including the length, width and draft of vessels. In fact, static information can also be used effectively for vessel trajectory classification (Zhong et al., 2019). So far, there are few works which take into account both kinematic and static information to classify vessel trajectories.

To address these problems, this paper proposes an efficient approach for vessel trajectory classification with semi-supervised deep learning. In the following, we call our approach SSL-VTC for brevity. Specifically, we first exploit both kinematic and static information from historical AIS messages to extract vessel trajectories. Inspired by deep learning, we then design convolutional neural networks to learn feature representations from the extracted vessel trajectories. Furthermore, in order to make full use of the AIS data which may be labeled or unlabeled, we resort to semi-supervised learning (Chapelle et al., 2009; Zhu and Goldberg, 2009). It can use both labeled data and unlabeled data to help us learn a better classification model. Unlike semi-supervised learning, traditional supervised learning only uses the labeled data, so its classification performance is limited. The difference between supervised learning and semi-supervised learning is shown in Fig. 1. Here, we develop a semi-supervised learning algorithm based on the variational autoencoder (Kingma and Welling, 2013; Kingma et al., 2014) for the classification task. It can perform discriminative learning and generative learning simultaneously. In this way, our SSL-VTC architecture can effectively take advantage of both labeled data and unlabeled data for vessel trajectory classification. We conduct experiments on the public AIS dataset to demonstrate that based on the variational autoencoder, our semi-supervised deep learning framework can learn feature representations efficiently from the AIS data and outperform traditional supervised learning approaches.

To sum up, our main contributions are three-fold:

- To the best of our knowledge, this paper is the first work to develop a semi-supervised deep learning approach based on the variational autoencoder for vessel trajectory classification using AIS data.
- We utilize, for the first time, both kinematic and static information of the AIS messages to extract vessel trajectories for the classification task, which is more efficient than previous works.
- We conduct extensive experiments on the public AIS dataset to show the effectiveness of our approach and further provide important implications of our study in the field of ocean management.

The rest of this paper is organized as follows. In Section 2, related works are reviewed. In Section 3, this paper proposes the procedure of trajectory extraction. In Section 4, we present our SSL-VTC framework, which includes problem formulation, the semi-supervised learning algorithm, and the network. In Section 5, extensive numerical experiments are conducted. Then, we propose some important implications of our study in Section 6. Finally, conclusions and some future works are shown in Section 7.

2. Related works

In this section, we review previous works of vessel trajectory classification, which are based on machine learning or deep learning methods. In addition, we show two other related problems that also use the AIS data: trajectory clustering and trajectory reconstruction. For a comprehensive understanding of these works, please refer to the survey papers (Tu et al., 2017; Le Tixerant et al., 2018; Svanberg et al., 2019; Yang et al., 2019).

2.1. Vessel trajectory classification

Vessel trajectory classification refers to classifying the trajectories into several categories based on the AIS spatio-temporal data. Considerable attention has been given by researchers to study this problem with machine learning or deep learning methods.

In terms of machine learning methods, different techniques have been used to address the classification problem. For example, Hu et al. (2016) present an approach to detect fishing activities from historical AIS data with conditional random fields. Sheng et al. (2018) use the logistic regression algorithm to build a classifier with trajectory features to classify ship trajectories into fishing and cargo. Herrero et al. (2019) first filter AIS data using the interacting multiple model and then classify ship trajectories with a multiclass binary decision tree. Zhong et al. (2019) utilize a classifier based on random forest to classify ships into fishing, cargo, and tanker.

Motivated by the great success of deep learning, researchers then design different methods based on deep learning for vessel trajectory classification. Jiang et al. (2016) focus on the detection of fishing activities in vessel trajectories using autoencoders. Ljunggren (2018) employ a convolutional neural network to learn vessel-specific features and classify the ship types into fishing, passenger, cargo, and tanker based on AIS kinematic data. Mantecón et al. (2019) propose a deep learning framework with a convolutional neural network for vessel monitoring as a basis for anomaly detection. Chen et al. (2020) present a convolutional neural network-ship movement mode classification algorithm. Arasteh et al. (2020) propose a simple yet effective convolutional neural network for trajectory classification, where the model is trained with a set of invariant spatio-temporal features extracted from the behavioral characteristics of vessel movements. Kontopoulos et al. (2021) transform vessel trajectory patterns into images and employ deep learning algorithms to classify vessel activities. These deep learning methods have achieved higher performance than traditional machine learning methods.

Although the above methods have made progresses on the problem of vessel trajectory classification, they often assume that all data are labeled during the training process. However, in practice, it may be time-consuming or expensive to obtain labeled data, resulting in only a small part of the training data being labeled, and most of the training data being unlabeled. These methods are unable to tackle this challenge. To the best of our knowledge, we are the first to leverage semi-supervised learning for the task of vessel trajectory classification, which can efficiently combine the information of the labeled and unlabeled data. In addition, most previous works only use the kinematic information of the AIS data to extract ship trajectories. Here, we exploit both kinematic and static information to make full use of the AIS data.

2.2. Vessel trajectory clustering and reconstruction

Apart from vessel trajectory classification, two other related problems are also reviewed here: vessel trajectory clustering and vessel trajectory reconstruction. The former splits all trajectories into multiple groups, so that the trajectories of the same group are very similar and the trajectories of different groups are different, while the latter is to preprocess the original AIS messages because the AIS data collected by sensors are often incomplete or noisy. Similar to vessel trajectory classification, researchers are increasingly using machine learning or deep learning methods to analyze the AIS data for vessel trajectory clustering. In addition, the AIS data preprocessing technique in vessel trajectory reconstruction also needs to be considered in vessel trajectory classification.

For vessel trajectory clustering, Dobrkovic et al. (2016) use a genetic algorithm to cluster vessel position based on the AIS data. Yao et al. (2017) propose a moving behavior feature extraction algorithm to extract moving behavior features that capture space and time invariant characteristics of trajectories. Wang et al. (2020) present a ship trajectory motion pattern extraction algorithm using the one-dimensional convolutional auto-encoder without spatio-temporal trajectory measurement methods. For vessel trajectory reconstruction, Zhang et al. (2018) employ a multi-regime vessel trajectory reconstruction model which includes three steps, namely (i) outliers removal, (ii) ship navigation state estimation, and (iii) vessel trajectory fitting. Chen et al. (2020) propose an ensemble ship trajectory reconstruction framework combining a data quality control procedure and a prediction module. Guo et al. (2021) present an improved kinematic interpolation for the AIS trajectory reconstruction.

3. Trajectory extraction

For vessel trajectory classification, we need to extract trajectories from the AIS data, which are further used as the input of our semi-supervised learning algorithm. Therefore, this procedure provides an important basis for our SSL-VTC framework. In this section, we show how to extract trajectories in detail.

In Fig. 2, we show some examples of the original AIS data, in which each row is an AIS message, including maritime mobile service identity number (MMSI), basedatetime, latitude (LAT), longitude (LON), speed over ground (SOG), course over ground (COG), length (LEN), width (WID), and draft (DRA). To extract trajectories from the AIS messages, most previous works mainly use the vessel kinematic information, including LAT, LON, SOG, and COG. As shown in Zhong et al. (2019), the vessel static information, such as LEN, WID, and DRA, is also beneficial to the classification task. Inspired by this, we propose to extract vessel trajectories from the AIS data by combining the kinematic and static information. In the following, we show how to extract vessel trajectories from the AIS data step by step.

- Step 1 (**Trajectory Division**): The MMSI in Fig. 2 is a unique nine-digit number for identifying a vessel. We use it to separate different vessels. For each vessel, we divide all AIS messages by day. Each AIS message contains a timestamp, kinematic information, and static information. If the timestamps of adjacent AIS messages differ by more than two hours, we further divide the obtained daily AIS data into vessel trajectories.
- Step 2 (**Trajectory Filtering**): To ensure that the time length of each trajectory is sufficient, we filter out trajectories with the time length less than six hours. In addition, we remove trajectories that have fewer than 160 AIS messages to make the extracted trajectories have enough information for the classification task.
- Step 3 (**Abnormal Trajectory Removal**): After filtering, we find that the speeds of some trajectories are very low. To ensure that the trajectory can be distinguished in the spatio-temporal domain, we remove the following two types of abnormal trajectories. The first is the trajectory with a maximum SOG of not greater than 1 knot per hour. The second is the trajectory where the number of AIS messages with SOGs greater than 2 knots per hour accounts for no more than 30% of the total number of AIS messages.
- Step 4 (**Normalization and Seven-hot Encoding**): After removing abnormal trajectories, we discard the timestamp attribute and then normalize the seven attributes of kinematic and static information of AIS messages in the trajectory, including LAT, LON, SOG, COG, WID, LEN, and DRA. Next, we consider how to represent these seven attributes so that they can be sent to our deep learning model for classification. If we use their real values directly, it is difficult for neural networks to disentangle the underlying meaning of these numbers. Inspired by Nguyen et al. (2018, 2021), we perform one-hot encoding for each attribute and concatenate the one-hot encoding of these seven attributes together, as shown in Fig. 3. Here, we call this procedure seven-hot encoding. It is noted that one-hot encoding essentially converts the real value of each attribute into a set of binary representations, in which only one bit is 1 and the others are 0. By discretizing the real values of different attributes, seven-hot encoding helps our framework better learn the spatio-temporal information of the trajectories.
- Step 5 (**Trajectory Sampling**): Finally, since the number of AIS messages per trajectory is different, the length of each trajectory is different. We sample the same number of AIS messages from each trajectory to form fixed-length trajectories and send them to our deep learning model for classification.

The above steps are summarized in Fig. 4. Through these procedures, we transform the AIS data into vessel trajectories. Each trajectory is used as the input to our framework for vessel trajectory classification, which contains both kinematic and static information.

4. Proposed framework

In this section, we first show the problem formulation and the overview of the proposed semi-supervised deep learning framework, then explain how our SSL-VTC model is trained, and finally describe network structures, including the encoder, decoder, and classifier, to implement our semi-supervised learning algorithm.

MMSI	BaseDateTime	LAT (degrees)	LON (degrees)	SOG (knots)	COG (degrees)	LEN (meters)	WID (meters)	DRA (meters)
354868000	2019-01-01T00:00:04	27.58599	-96.24882	12	86.9	179	28	10.1
367174890	2019-01-01T00:00:04	27.8443	-92.47822	9.1	-123.8	40	11	5.4
636015993	2019-01-01T00:00:05	24.22163	-81.78727	15.8	74	182	31	9
316001268	2019-01-01T00:00:05	48.8018	-123.33748	19.1	182.2	167	32	5
548799000	2019-01-01T00:00:06	29.20933	-89.27852	9.5	-78.6	174	27	11
354891000	2019-01-01T00:00:06	40.14955	-125.0976	9.8	-53.1	294	32	13.5

Fig. 2. Examples of the original AIS data.

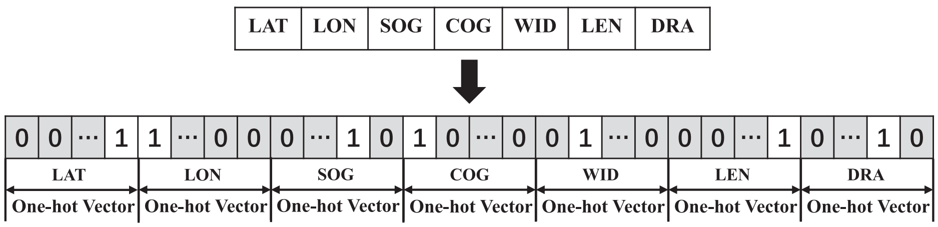


Fig. 3. Seven-hot encoding.

4.1. Problem formulation

Suppose during the training process, we have two datasets: labeled and unlabeled. We use $D_1 = \left\{\left(\mathbf{x}^{(i)}, y^{(i)}\right)\right\}_{i=1}^{n_1}$ to represent the labeled dataset, where $\mathbf{x}^{(i)}$ is the i-th trajectory we extract based on the AIS data using procedures in Section 3, $y^{(i)}$ is the corresponding label, such as fishing, cargo, tanker, and passenger, and n_1 is the size of the dataset D_1. We then use $D_2 = \left\{\left(\mathbf{x}^{(i)}\right)\right\}_{i=n_1+1}^{n_1+n_2}$ to represent the unlabeled dataset, where n_2 is the size of D_2. For brevity, the superscript i is omitted in the following when referring to a single trajectory point. In addition, we assume that each trajectory $\mathbf{x}$ in D_1 and D_2 has a corresponding latent variable $\mathbf{z}$. Our target is to combine the information of the labeled and unlabeled data based on the variational autoencoder to learn a classifier that has good classification performance.

4.2. Overview

We propose the semi-supervised learning framework for vessel trajectory classification, as shown in Fig. 5. Our semi-supervised learning approach is achieved based on the variational autoencoder. It has three modules: encoder, decoder, and classifier. We use the classifier for discriminative learning, and the encoder and decoder for generative learning. The classifier is used to classify trajectories. The encoder is used to extract latent variables from the labeled and unlabeled trajectories. If the input trajectory is labeled, the decoder reconstructs the input trajectory combining the corresponding label embedding and the latent variable learned by the encoder. If the input trajectory is unlabeled, the decoder reconstructs the input trajectory combining the knowledge of the label embedding predicted by the classifier and the latent variable learned by the encoder. The encoder, decoder, and classifier are a unified whole, and are trained together for discriminative learning and generative learning. The training of these three modules affects each other. The good discrimination performance of the classifier promotes the encoder and decoder to achieve good reconstruction results. The good generation performance of the encoder and decoder can in turn promote training the classifier. In this process, the classification ability of the classifier is enhanced by exploiting the knowledge of the labeled and unlabeled data.

It is worth noting that our semi-supervised learning method is significantly different from traditional supervised learning methods. For supervised learning, the data used for training is required to be labeled, which makes the unlabeled data unusable. Our semi-supervised learning can efficiently use both labeled data and unlabeled data. Based on the variational autoencoder, the unlabeled data is exploited in our deep learning model to help with the classification task. In this way, the classification performance of our method is better than that of the traditional supervised learning method.

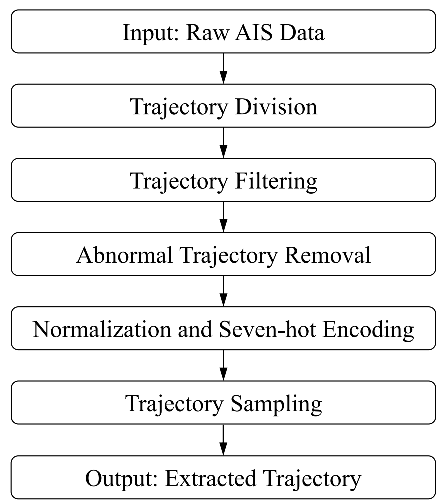


Fig. 4. The procedure of trajectory extraction.

4.3. Semi-supervised learning algorithm

In the above section, we discuss the problem formulation and the overview of the proposed framework. In this section, we further present how to design a semi-supervised learning architecture to utilize the labeled and unlabeled data for vessel trajectory classification. In the deep learning model, the loss function plays a crucial role in updating the model parameters. Here, we utilize a loss function based on the variational autoencoder to combine the unlabeled data, as follows:

$$L = L_1 + L_2 + \alpha \cdot L_{clf} \tag{1}$$

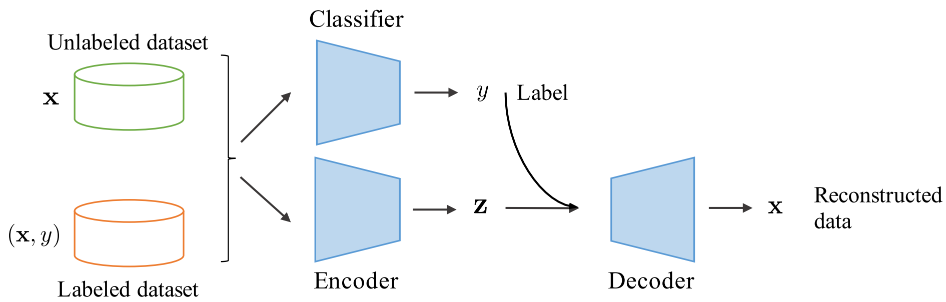


Fig. 5. Our semi-supervised learning framework for vessel trajectory classification. It has three modules: encoder, decoder, and classifier. The encoder and decoder are used for generative learning, and the classifier is used for discriminative learning.

It can be found that L has three parts: L_1, L_2, and L_{clf}. We use L_1 for generative learning with the labeled data, L_2 for generative learning with the unlabeled data, and L_{clf} for discriminative learning to measure the classification performance of our approach. In addition, α is the coefficient to weigh generative learning and discriminative learning. Here, we set

$$\alpha = \beta \cdot \frac{n_2}{n_1} \tag{2}$$

where n_1 is the size of the labeled dataset, n_2 is the size of the unlabeled dataset, and β is a hyperparameter. In the following, we show the probability expressions of L_1, L_2 and L_{clf}.

Maximum likelihood estimation (Myung, 2003) is a common technique in deep learning to design loss functions. It maximizes the likelihood function of observed samples so that the observed samples are the most probable. As shown in Kingma and Welling (2013), Kingma et al. (2014), the log-likelihood of a single labeled sample in the labeled dataset has a variational bound, as follows:

$$\log p(\mathbf{x}, y) \geq \mathbb{E}_{q(\mathbf{z}|\mathbf{x},y)}[\log p(\mathbf{x}|y,\mathbf{z}) + \log p(y) + \log p(\mathbf{z}) - \log q(\mathbf{z}|\mathbf{x}, y)] \tag{3}$$

where $\log p(\mathbf{x}|y,\mathbf{z})$ is used to reconstruct the original input $\mathbf{x}$ with the corresponding label y and the latent variable $\mathbf{z}$, $\log p(y)$ is used to measure the label distribution, and $\log p(\mathbf{z}) - \log q(\mathbf{z}|\mathbf{x}, y)$ is used to learn the latent variable $\mathbf{z}$ from $\mathbf{x}$ and the corresponding label y, and make the latent variable $\mathbf{z}$ follow a certain distribution, such as Gaussian distribution. By using the latent variable $\mathbf{z}$, this variational bound can effectively perform generative learning with the labeled data.

Since the input data is high-dimensional, it is difficult to directly optimize the likelihood function for deep learning. Here, we use the variational bound as our objective function. In addition, in deep learning, the loss function is in the minimization form. We define the negative of the variational bound as $\mathcal{L}(\mathbf{x}, y)$:

$$\mathcal{L}(\mathbf{x}, y) = -\mathbb{E}_{q(\mathbf{z}|\mathbf{x},y)}[\log p(\mathbf{x}|y,\mathbf{z}) + \log p(y) + \log p(\mathbf{z}) - \log q(\mathbf{z}|\mathbf{x}, y)] \tag{4}$$

Then, we define the sum of the variational bound of all the samples in the labeled dataset as L_1:

$$L_1 = \sum_{(\mathbf{x},y)\in D_1} \mathcal{L}(\mathbf{x}, y) \tag{5}$$

In fact, we need to give the specific forms of the probability expressions in L_1 to use L_1. In Section 4.4, we will introduce the structures of the encoder and decoder to effectively characterize L_1 for generative learning.

Similarly, we show how to perform generative learning using the unlabeled data. The log likelihood of a single unlabeled sample in D_2, $\log p(\mathbf{x})$, also has a variational bound (Kingma et al., 2014):

$$\log p(\mathbf{x}) \geq \mathbb{E}_{q(y,\mathbf{z}|\mathbf{x})}[\log p(\mathbf{x}|y,\mathbf{z}) + \log p(y) + \log p(\mathbf{z}) - \log q(y,\mathbf{z}|\mathbf{x})] \tag{6}$$

$$= \sum_{y} q(y|\mathbf{x})(-\mathcal{L}(\mathbf{x}, y)) + \mathcal{H}(q(y|\mathbf{x})) \tag{7}$$

We define the negative of the lower bound as $\mathcal{U}(\mathbf{x})$:

$$\mathcal{U}(\mathbf{x}) = -\sum_{y} q(y|\mathbf{x})(-\mathcal{L}(\mathbf{x}, y)) + \mathcal{H}(q(y|\mathbf{x})) \tag{8}$$

The calculation of $\mathcal{U}$ is partly the same as $\mathcal{L}$. In addition, we also need to calculate $q(y|\mathbf{x})$, which is implemented by the classifier, and the corresponding entropy $\mathcal{H}$ (Cover and Thomas, 2006). Then, we define L_2 as the sum of all $\mathcal{U}$ on the unlabeled dataset:

$$L_2 = \sum_{\mathbf{x}\in D_2} \mathcal{U}(\mathbf{x}) \tag{9}$$

In this way, we use L_2 for generative learning on the unlabeled dataset. Similar to L_1, it can also be implemented with the encoder and decoder. In addition, the classifier also contributes to L_2.

Next, we use L_{clf} for discriminative learning by measuring the performance of the classifier on the labeled dataset with the cross-entropy loss:

$$L_{clf} = \mathbb{E}_{\mathbf{x}\in D_1}[-\log q(y|\mathbf{x})] \tag{10}$$

To summarize, we use L_1, L_2 and L_{clf} to perform generative learning and discriminative learning simultaneously. By using unlabeled data for generative learning, discriminative learning is promoted to improve classification performance.

4.4. Network

To implement our algorithm for generative learning and discriminative learning, we design three modules: the classifier, the encoder, and the decoder, which are used to learn $q(y|\mathbf{x})$, $q(\mathbf{z}|\mathbf{x}, y)$, and $p(\mathbf{x}|y, \mathbf{z})$, respectively. The network architectures of these three modules are all based on the convolutional neural network (CNN) (LeCun et al., 1989, 1998, 2015), which is an artificial neural network using convolution kernels to extract features from the input data. There are two main reasons for this setting: (1) The extracted trajectory data in this paper is two-dimensional, and CNN can effectively extract feature representations from the two-dimensional data. (2) Compared with other feedforward neural networks, CNN requires fewer parameters, making it an attractive substructure for deep learning (Li et al., 2019). In the following, we describe the CNN structures of the classifier, the encoder, and the decoder in detail.

The classifier module is used to learn $q(y|\mathbf{x})$ to classify vessel trajectories. Its input is the processed trajectory in the seven-hot form, and the output is the probability of each ship type. We firstly feed the trajectory into five convolutional layers. The number of input channels of each layer is 1, 5, 5, 5, and 5, and the corresponding kernel size of each layer is 10, 10, 10, 5, and 3, respectively. Each convolutional layer is followed by a ReLU function. Then, the output of those convolutional layers is flattened into a feature vector with size 250 and sent into a fully connected layer. Finally, we design a softmax layer after the fully connected layer to generate the probability of each class.

Algorithm 1 Training Process of Our Semi-supervised Learning Algorithm for Vessel Trajectory Classification (SSL-VTC).

Input: E: The number of epochs.
Initialize the parameters of the classifier, encoder, and decoder.
for $i = 1$ **to** E **do**
  Draw a mini-batch from the labeled dataset D_1.
  Calculate the loss function L_1 using Eq. (5).
  Calculate the loss function L_{clf} using Eq. (10).
  Draw a mini-batch from the unlabeled dataset D_2.
  Calculate the loss function L_2 using Eq. (9).
  Calculate the overall loss function L using Eq. (1).
  Perform gradient descent to update the parameters of the classifier, encoder, and decoder.
end for

The encoder module is used to learn $q(\mathbf{z}|\mathbf{x}, y)$, i.e., capture the latent variable $\mathbf{z}$ for each trajectory $\mathbf{x}$. If the input trajectory $\mathbf{x}$ is labeled, we send it to the encoder together with the corresponding label y to enhance the expression ability of $\mathbf{z}$. If the input trajectory $\mathbf{x}$ is unlabeled, we pair it with every possible label and send them to the encoder. Note that the input label is in the one-hot format. For the input trajectory, we feed it into five convolutional layers, which have the same configuration as the convolutional block in the above classifier. Then, we flatten the features produced from the convolutional layers into a feature vector with a size of 250. For the input label, we send it into a fully connected layer to generate a feature vector with 50 nodes. Then, we concatenate these two vectors and send them into two fully connected layers to obtain variables $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$. By using the reparameterization technique (Kingma and Welling, 2013; Doersch, 2016; Blei et al., 2017) with $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$, we can obtain the latent variable $\mathbf{z}$.

The decoder module is used to learn $p(\mathbf{x}|y, \mathbf{z})$, i.e., generate the trajectory $\mathbf{x}$ with the latent variable $\mathbf{z}$. Similar to the encoder, the label information is also used to improve the generation performance of the decoder. Firstly, we concatenate the latent variable $\mathbf{z}$ and the label y in one-hot form. Then, we send them into two fully connected layers to generate a feature vector with size 250. After reshaping, we feed it into five deconvolutional layers to generate the original trajectory. The number of output channels in each layer is 5, 5, 5, 5, and 1, and the corresponding kernel size in each layer is 3, 5, 10, 10, and 10, respectively. Each of the first four deconvolutional layers is followed by a ReLU function, and the last deconvolutional layer is followed by a sigmoid function.

In this way, we show how to use the classifier, encoder, and decoder to implement our whole architecture for semi-supervised learning. The algorithm of our approach is shown in Algorithm 1. Based on the variational autoencoder, our semi-supervised learning algorithm can fully leverage the labeled and unlabeled data to perform discriminative learning and generative learning simultaneously. The classification performance of the proposed framework will be verified in the next section.

5. Experiments

In this section, we first illustrate the public AIS dataset used in this study and the experimental setting, and then display and analyze the extensive experimental results to show that our SSL-VTC approach can learn good feature representations from trajectories of different ship categories for classification.

5.1. Dataset

The original AIS dataset used in this study is provided by the U.S. Coast Guard Navigation Center (available at https://marinecadastre.gov/ais/), covering the coastal waters of Canada, the United States, and Mexico. We analyze the data from January to June in 2019. Inspired by previous works (Krüger, 2019; Wang et al., 2019; Zhang et al., 2019; Li et al., 2020; Nguyen et al., 2021), we split all the original AIS data into three parts: training set, validation set, and test set, corresponding to the data collected from January to April, May and June, respectively. The reason behind these settings is that the historical AIS data is used as the training set to train our model, which can help us perform the predictive classification task based on the current or future data. The validation set is used to select the suitable model trained on the training set, while the test set is used to evaluate the performance of the final model trained on the training set. By using the validation set, the evaluation results are ensured to be unbiased (Tennenholtz et al., 2018). Finally, the sizes of the training set, validation set and test set are 168.3 GB, 52.6 GB, and 56.0 GB, respectively. We classify trajectories into four categories, including fishing, passenger, cargo, and tanker. The dataset is processed as shown in Section 3. The regions covered by the AIS dataset and processed AIS trajectories are shown in Fig. 6. The number of trajectories in each category is displayed in Table 1. It can be observed that the number of cargo vessels is the most, the number of fishing vessels is the least, and the number of tankers is slightly greater than the number of passenger vessels.

Table 1
The numbers of trajectories of different categories of the processed dataset.

Vessel Type	Fishing	Passenger	Cargo	Tanker
Training Set	1436	13678	37842	17335
Validation Set	479	4349	11808	5291
Test Set	786	5030	12263	5223

5.2. Experimental setting

In each experiment, we use the training set to train our framework, and use the validation set to select the best model and report its accuracy on the test set as the final result. The model is trained using the Adam optimizer (Kingma and Ba, 2014). In addition, we set the learning rate, batch size, and number of epochs to 0.0001, 100, and 50, respectively. We perform a series of experiments with PyTorch (Paszke et al., 2019) on an NVIDIA TITAN V GPU card.

5.3. Experimental results

In this section, we first show that our framework learns feature representations effectively for vessel trajectory classification, then show the necessity of combining static information, next show that our method can efficiently leverage the knowledge of the unlabeled data in different semi-supervised settings, and then investigate the influence of hyperparameter β in our semi-supervised learning algorithm, and finally study the scenario where static information may be missing.

5.3.1. Validation of the proposed neural network and seven-hot encoding

In order to show the effectiveness of the convolutional neural network and seven-hot encoding, we compare our classifier with other machine learning and deep learning methods, including support vector machine (SVM) (Cortes and Vapnik, 1995), decision tree (DT) (Wu et al., 2008), K-nearest network (KNN) (Altman, 1992), multilayer perceptron (Haykin, 1994), convolutional neural network (LeCun et al., 1989, 1998, 2015) which directly use the real values of kinematic and static information, and multilayer perceptron using the seven-hot method. Note that SVM, DT, and KNN are all traditional machine learning methods that can perform the classification task. Besides, the multilayer perceptron is also a deep learning-based approach that consists of several fully connected layers. Unlike the convolutional neural network, the multilayer perceptron has no convolutional layers. The classification accuracies of different methods are shown in Table 2.

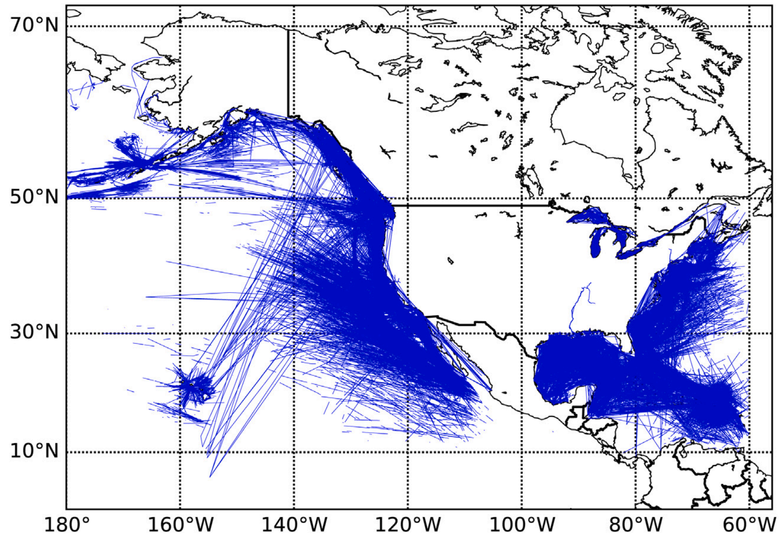


Fig. 6. The region covered by the used AIS dataset, in which the blue lines represent the processed AIS trajectories.

Table 2
Performance comparison of our approach with different methods.

Method	Accuracy(%)
Support Vector Machine	78.50
Decision Tree	77.62
K-Nearest Network	81.25
Multilayer Perceptron	81.80
Convolutional Neural Network	85.08
Multilayer Perceptron with Seven-hot	89.61
Convolutional Neural Network with Seven-hot (SSL-VTC)	**92.22**

From Table 2, we make the following observations: (1) Our proposed convolutional neural network with seven-hot encoding achieves the highest accuracy. (2) In the scenario with or without seven-hot encoding, the convolutional neural network performs better than the multi-layer perceptron, which shows that the convolutional neural network has a stronger discrimination ability by learning better feature representations from the AIS trajectory data. (3) Compared with deep learning methods without seven-hot technique, the accuracy of the seven-hot technique is higher, which demonstrates the benefits of seven-hot encoding by enabling our architecture to better capture the spatio-temporal information of trajectories. (4) The accuracies of the traditional machine learning methods (SVM, DT, KNN) are significantly lower than those of deep learning methods, which verifies the superiority of deep learning. To summarize, by comparison with other methods, we not only show the benefit of seven-hot encoding, but also present that the feature representation using our convolutional neural network has sufficient discriminant ability.

5.3.2. Ablation study of the static information

To illustrate the necessity and importance of combining the static information for vessel trajectory classification, we compare our classifier with the classifier that does not combine the length information (WO-LEN), the classifier that does not combine the width information (WO-WID), the classifier that does not combine the draft information (WO-DRA), and the classifier that does not combine the information of length, width, and draft (WO-LWD). For a fair comparison, we make different methods have the same network structure. The accuracy of different methods is shown in Table 3.

It can be found that the accuracy of the method without static information is lower than that of our method with static information. The WO-LWD method has the lowest accuracy, indicating that combining

Table 3
Ablation study of the static information.

Method	Accuracy(%)
Without Length, Width, Draft (WO-LWD)	71.43
Without Length (WO-LEN)	80.54
Without Width (WO-WID)	88.48
Without Draft (WO-DRA)	87.96
Full (SSL-VTC)	**92.22**

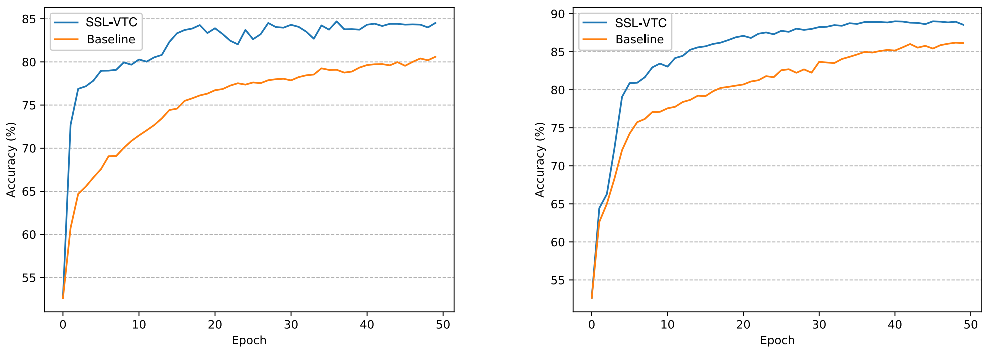
Table 4
Performance comparison between our method and the baseline method in different semi-supervised learning setting.

Percentage of labeled data	5%	20%	40%	60%
Baseline (WO-LWD)	56.36	65.02	67.15	69.88
Baseline	72.60	80.59	86.13	89.35
SSL-VTC (WO-LWD)	59.74	66.83	68.08	70.25
SSL-VTC	**77.93**	**84.51**	**88.96**	**90.01**

the information of length, width, and draft significantly improves the classification performance. In addition, by comparing the performance of the WO-LEN, WO-WID, and WO-DRA methods, we find that WO-LEN has the lowest accuracy and WO-WID has the highest accuracy, which indicates that different static information contributes differently to the classification performance. The length information has the greatest contribution, which implies that the length information may be more distinguishable than the width and draft (Zhong et al., 2019).

5.3.3. Performance of our semi-supervised deep learning approach

In the above, we discuss the effectiveness of our network and the necessity of incorporating static information, which lay the foundation for our whole semi-supervised learning architecture. In the following, we conduct a series of semi-supervised learning experiments to verify that our framework can effectively combine the information of the unlabeled data for vessel trajectory classification. We set 5%, 20%, 40%, and 60% of the training set as the labeled dataset and the corresponding remaining training data as the unlabeled dataset. In each semi-supervised learning setting, we compare the performance of our method with the baseline method which only uses the labeled data. In addition, we also show the performance of these two methods without combining static information of length, width, and draft (WO-LWD). The experimental results are shown in Table 4.



(a) 20% of training data is labeled. (b) 40% of training data is labeled.

Fig. 7. Trends of test accuracies of our SSL-VTC method and the baseline method.

It can be observed that: (1) For each percentage of labeled data, the classification accuracy using our semi-supervised learning method is higher than that using the baseline method, which shows the effectiveness of our semi-supervised learning framework based on the variational autoencoder. (2) With the increase in the percentage of unlabeled data, the accuracies of our method and baseline method decrease, but the gap between them increases. This indicates that the scarcer the labeled data, the more effective our semi-supervised learning method improves the classification performance by exploiting the unlabeled data, which is consistent with other works about semi-supervised learning (Berthelot et al., 2019; Ma et al., 2020). (3) Regardless of our method or the baseline method, the accuracy without combining the static information is lower than that with combining the static information, which further demonstrates that combining the static information is beneficial to improving the classification performance.

We next show trends of test accuracies of our method and the baseline method during the training process in two scenarios: 20% of the training data is labeled and 40% of the training data is labeled. The results are displayed in Fig. 7. We can observe that in these two scenarios, the test accuracy of our method increases faster than the test accuracy of the baseline method, which shows that our method can significantly improve the classification performance by effectively using the unlabeled data. By comparing the performance when 20% of the training data is labeled with the performance when 40% of the training data is labeled, we again find that when the proportion of labeled data becomes lower, our method has more obvious advantages than the baseline method.

Then, in the scenarios where 20% of the training data is labeled and 40% of the training data is labeled, we display the confusion matrices of our method and the baseline method respectively, as shown in Figs. 8 and 9. We can see that when 20% of the training data is labeled, the classification accuracy of each class using our method is higher than that of the corresponding class using the baseline method. When 40% of the training data is labeled, the classification accuracy of fishing using our method is lower than that using the baseline method, but the overall classification accuracy of our method is still higher than that of the baseline method. This demonstrates that our approach can effectively capture clues of most classes for vessel trajectory classification, but the baseline method cannot. In addition, we can further find that the classification accuracy of different categories is different, which shows that in our deep learning model, different categories have different discrimination abilities. It is worth noting that with the help of deep learning, we do not need to manually set parameters for different categories, but let our model automatically update the corresponding parameters for each category.

Table 5
The values of β for different percentage of labeled data.

Percentage of labeled data	5%	20%	40%	60%
β	10	10	100	1000

Table 6
Influence of β in our semi-supervised learning algorithm when only 40% of training data is labeled.

β	1	10	100	1000
Accuracy	75.02	84.44	**88.96**	88.94

5.3.4. *Influence of β in our semi-supervised learning algorithm*

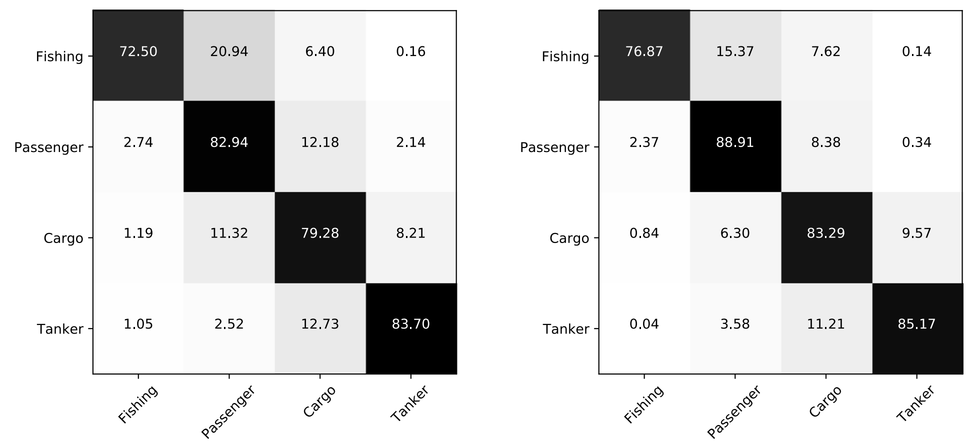
In Section 5.3.3, we show the performance of our approach when the percentage of the labeled data is set to 5%, 20%, 40%, and 60%. It is worth noting that to implement the semi-supervised algorithm, we first need to determine the value of α, as mentioned in Eq. (2) in Section 4.3. α equals $\beta \cdot \frac{n_2}{n_1}$, where n_1 is the size of the labeled dataset, n_2 is the size of the unlabeled dataset, and β is a hyperparameter. As we already know the percentage of the labeled data, that is, the ratio of n_2 to n_1, determining the value of α is equivalent to determining the value of β. Here, we use grid search (LaValle et al., 2004; Syarif et al., 2016) to determine β for each percentage of the labeled data, as shown in Table 5. It can be found that different semi-supervised settings have different appropriate values of β.

To explain this phenomenon, we investigate the impact of β in our semi-supervised learning algorithm for vessel trajectory classification when 40% of the training data is labeled. We set the value of β to 1, 10, 100, and 1000, and make other settings the same as in Section 5.3.3. The experimental results are shown in Table 6.

It can be seen that the classification accuracy increases rapidly as β increases from 1 to 100. However, when β increases from 100 to 1000, the classification accuracy does not change significantly, indicating that the value 100 of β is appropriate for vessel trajectory classification when only 40% of training data is labeled. These observations explain that for a certain percentage of labeled data, we need to select an appropriate value for β to achieve good classification performance. They are also what we are trying to do by using grid search to select β.

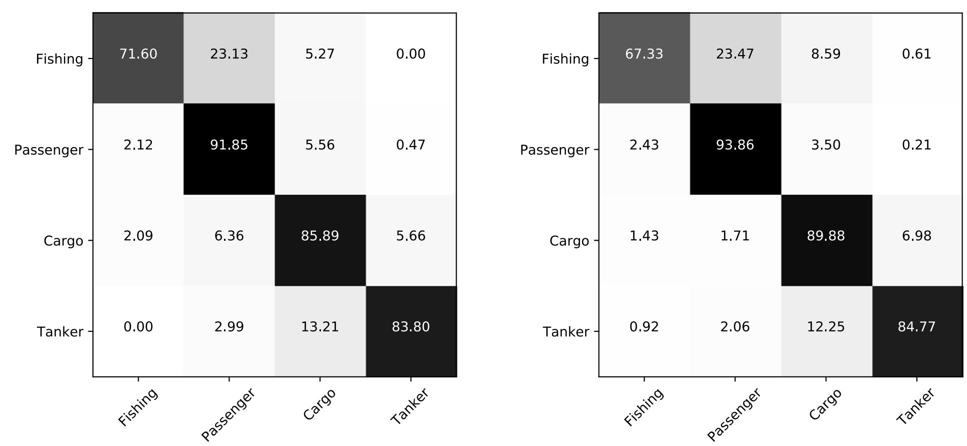
5.3.5. *Performance with missing static information*

In the above, we study the label missing of the training data. At the same time, we also show that the static information is useful for vessel trajectory classification. However, from the original AIS messages, we find that the vessel static information is not always available. This phenomenon is called data missing, which often exists in raw data (Scheffer, 2002; Enders, 2010; Little and Rubin, 2019). Motivated by this, in this section, we study the scenario in which the



(a) Baseline (b) SSL-VTC

Fig. 8. The confusion matrices of the baseline method and our SSL-VTC method when only 20% of the training data is labeled.



(a) Baseline (b) SSL-VTC

Fig. 9. The confusion matrices of the baseline method and our SSL-VTC method when only 40% of the training data is labeled.

static information is missing when only 20% of the training data is labeled. We assume that only a small part of the static information is available, and the remaining information is unknowable. We consider two methods for dealing with the missing static information: one is to directly set the static information to zero for the trajectory that cannot access the static information, which is a common way to handle data missing. Another method is to fill the unknown static information with the mean of the available static information. This method leverages the knowledge of the available static information. We set the static information of 5%, 20%, and 60% of the training data to be available. In each setting, we compare the performance of our method and the baseline method. The experimental results are shown in Table 7.

From Table 7, we make the following observations: (1) For each proportion of available static information, the classification accuracy using our method with mean operation is higher than that with zero operation, which shows the effectiveness of our proposed mean operation. (2) For our approach, the accuracy with the zero operation or the mean operation increases as the proportion of available static information increases, while the accuracy gap between these two operations decreases. This can be explained by the fact that when the missing static information decreases, the existing static information may already be sufficient for vessel trajectory classification, and the missing static information plays a lesser role. Therefore, regardless of which operation is used, the accuracy gap between these approaches decreases with the increase in available static information. (3) The trend of the baseline method is consistent with that of our method. But for a certain setting, the accuracy of the baseline method is lower than that of our method, which further verifies our observations above and the superiority of our framework.

Table 7
The performance comparison with different percentages of available static information.

Percentage of available static information	5%		20%		60%	
Operation	Zero	Mean	Zero	Mean	Zero	Mean
Baseline	66.02	68.63	68.64	70.12	80.04	80.76
SSL-VTC	**67.39**	**70.37**	**76.08**	**77.68**	**81.59**	**82.66**

6. Implications

The approach and findings of this study provide important implications for researchers and stakeholders in the maritime field. For researchers, our work shows the following two highlights: (1) The approach in this study mainly consists of two parts: vessel trajectory extraction and semi-supervised learning algorithm, which can empower relevant research directions using the AIS data, such as trajectory prediction and analysis, anomaly detection, and collision avoidance. Besides, it is noteworthy that this study is the first to consider the combination of static and kinematic information for vessel trajectory extraction. In our study, the classification accuracy considering both static and kinematic information is 29.1% higher than that considering only kinematic information. This illustrates the significance of vessel static information for trajectory classification, and further inspires researchers to apply the static information to other AIS trajectory analysis studies. (2) The classification results of ship types in this paper can provide support for studies related to vessel identification. Some previous works reveal that the analysis using the AIS data can be enhanced by considering ship types, such as (a) evaluating the coastal emission policies for vessel evasion behaviors (Tan et al., 2021), (b) tracing illegal oil discharges from vessels (Liu et al., 2021b), and (c) identifying whether to use clean energy or green technology (Bai et al., 2021). By using the classification results of our approach, this study can provide reference and assistance for the above studies.

For stakeholders in the maritime industry, this study provides the following four management implications: (1) This work contributes to the management of fishing activities and the conservation of marine ecosystems. Illegal, unreported and unregulated (IUU) fishing is one of the most serious threats to the sustainability of fisheries worldwide, and the stability and balance of marine ecosystems (Arasteh et al., 2020; Cánovas-Molina et al., 2021). Maritime regulatory authorities and researchers have devoted increasing efforts to regulating fishing activities, and fisheries management is one of the latest research hotspots (Jiang et al., 2016; Krüger, 2019; Garcia et al., 2021; Neto et al., 2021; Sultan, 2021; Yu and Wang, 2021). By identifying the fishing vessels using our trajectory classification framework, this work can contribute to monitoring illegal fishing activities to protect the ecosystem (Kularatne, 2020; Warren and Steenbergen, 2021). Moreover, by extracting, analyzing and mapping the footprint of fishing vessels (i.e., fishing area and intensity), this study can provide guidance and suggestions for policy-makers in fishery management. (2) Apart from identifying fishing vessels, this work can also assist in the identification and management of other ship types. By identifying tankers, it is possible to estimate the environmental risk of oil spill accidents and drift grounding accidents for oil tankers (Yang et al., 2019; Barreto et al., 2021; Liu et al., 2021b; Zhang et al., 2021b). By identifying cargo ships, this work can be applied to track cargo flows and provide a reference for port trade analysis (Jia et al., 2019; Xu et al., 2021). By identifying passenger ships, this work is capable of offering information for maritime search and rescue operations. (3) This study helps to identify abnormal ship behaviors and detect dangerous navigation areas to safeguard shipping safety. For example, if a vessel declares itself as type "A" but performs a maneuver of type "B", it is likely that it may be carrying out illegal activities, which is also known as the false ship effect (Ljunggren, 2018; Nguyen et al., 2018). In our architecture, ship types are identified by vessel trajectories, which enables our framework to be utilized as an important tool to detect illegal, suspicious or unsafe behaviors of vessels. Furthermore, it can be used to alert the surrounding area of anomalous vessels to emphasize the navigation safety of neighboring vessels. (4) This study can provide predictive guidance to shipping regulators on maritime surveillance. In this paper, our model is trained using five months of historical AIS data and tested on the sixth month of AIS data, which is essentially a predictive classification task. By using our framework to make predictions for future AIS data, our work can assist in the predictive analysis of future ocean and coastal developments, thus providing predictive planning and management guidance (Herrero et al., 2019; Yang et al., 2019; McWhinnie et al., 2021; Meyers et al., 2021).

7. Conclusions

In this paper, we propose SSL-VTC, a semi-supervised deep learning approach for vessel trajectory classification based on AIS historical data for the first time. Specifically, we extract vessel trajectories by leveraging the kinematic and static information of AIS messages, and feed them into our convolutional neural network to obtain feature representations. Then, we use these feature representations for semi-supervised learning based on the variational autoencoder to perform discriminative learning and generative learning simultaneously, which enables our architecture to make full use of the unlabeled data for vessel trajectory classification. In the extensive experiments, based on the public AIS dataset, we first verify the effectiveness of the proposed neural network and seven-hot encoding by comparing with other machine learning and deep learning methods. Then, through the ablation study of static information, we illustrate the necessity and significance of combining the AIS data static information. Next, we verify the superiority and robustness of the proposed semi-supervised approach for vessel trajectory classification by varying the proportion of the labeled data, and perform sensitivity analysis on the hyperparameter β to investigate its impact on vessel trajectory classification. In addition, we also consider the missing static information in the raw dataset and propose zero operation and mean operation to further verify the superiority of our approach. Finally, this study provides important managerial implications for researchers and stakeholders in the maritime field.

In future research, the following directions will be considered. Firstly, in addition to the AIS system, synthetic aperture radar (SAR) is also a widely used message transmission system for marine supervision and fishery management (Hou et al., 2020; Barreto et al., 2021; Liu et al., 2021b). SAR has the capability of all-time imaging in all-weather conditions. It will be a promising and attractive research direction to better carry out vessel trajectory classification tasks by combining the advantages of the AIS data and the SAR data. Secondly, we investigate the scenario of missing static information in the actual AIS dataset and propose two operations to address this problem in this paper. We can design more machine learning or deep learning techniques to address the static information missing issue to further improve the performance of our proposed approach. Thirdly, in the actual navigation environment, vessel trajectories are affected not only by their own factors (e.g., speed, course) recorded in the AIS data, but also by external factors (e.g., wind, current) (Yang et al., 2020). Inspired by this, we can comprehensively analyze the AIS data and the meteorological and hydrological data to investigate the interaction between internal and external factors, and provide managerial insights for vessel trajectory analysis and safe navigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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