SHIP TRAJECTORY CLUSTERING METHOD BASED ON DEEP NEURAL NETWORKS

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Cluster analysis of ship trajectory data collected by Automatic Identification System (AIS) can provide support for route planning, abnormal trajectory discovery and traffic flow analysis, and has important application value for ensuring navigation safety and improving inbound and outbound efficiency. Traditional clustering algorithms face many problems when dealing with AIS trajectory data, such as trajectory similarity measurement, feature extraction and clustering parameter setting. In this paper, the AIS ship trajectory clustering method based on deep neural network is proposed. Using the feature extraction ability of auto-encoder network, the data feature representation and clustering allocation are realized in low-dimensional feature space, and iteratively optimizes clustering by minimizing Kullback-Leibler (KL) divergence. The experimental results show that the proposed algorithm can effectively cluster ship trajectories and accurately extract the main route of ships in the water area.

Keywords: AIS ship trajectory, Trajectory clustering, Deep clustering, Route extraction

1. Introduction

At present, more than two-thirds of the total international trade and about 90% of China's total imports and expert freight are carried out by sea. The continuous increase in the number of ships on the sea has caused the density of ship traffic in some coastal port waters to continue to increase, and the navigation of ship in the waters is becoming more and more complicated. The Automatic

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Identification System (AIS) is a new type of navigation aid system applied to maritime safety and communication between ship and shore, ship and ship. It can provide navigation information including ship name, position, speed and course, can effectively reduce the risk of water traffic and has been widely used in various types of ships [1-3].

Clustering is an unsupervised data mining method. The original data set is divided into multiple clusters by measuring the similarity between objects. The similarity of objects in clusters is high and the similarity of objects between clusters is low. Trajectory data clustering first obtains the similarity between trajectories by analyzing and comparing the trajectory feature information, and then classifies the trajectories with high similarity into one class.

Through cluster analysis of AIS trajectory data, it can provide effective support for typical route extraction, abnormal trajectory discovery, navigation trajectory prediction, and traffic flow analysis. It has important applications value for solving ship navigation safety issues and improving port entry and exit efficiency [4-7]. However, compared with common pedestrian and car trajectories, in addition to temporal and spatial attributes, AIS trajectory data also includes various attribute information such as ground speed, ground course, heading, navigation status, ship type, etc. The amount of data is large. In addition, there are many feature dimensions, and the direct application of traditional trajectory clustering algorithms does not work well.

The deep neural network technology has been widely used in computer vision, natural language processing and other fields. Its effectiveness has also been proved for trajectory clustering [8, 9]. This paper proposes a ship trajectory clustering method based on deep neural networks, which combines trajectory feature extraction and clustering assignment in a neural network, and iteratively optimizes clustering by minimizing Kullback-Leibler (KL) divergence. This method avoids the problems of feature engineering and parameter setting in the clustering process, can effectively improves the accuracy and computational efficiency of AIS ship trajectory clustering.

2. Related works

Mon et al. [10] used the Douglas-Peucker (DP) trajectory compression algorithm to pre-process the AIS trajectory data, and then based on the Hausdorff distance, designed a similarity measurement function that automatically selects scale parameters. After constructing the similarity matrix, combined with spectral clustering to achieve fast clustering of ship trajectories. Zhao et al. [11] also uses DP trajectory compression algorithm to remove redundant information in trajectory data, then uses Dynamic Time Warping (DTW) distance to measure trajectory similarity, and finally uses DBSCAN algorithm to cluster ship trajectories. Yu et al. [12] uses informatics theory, the AIS trajectory is segmented according to the principle of minimum description length, and then the improved Euclidean distance (involving vertical distance, parallel distance and angular distance) is used to find sub-trajectory segments with similar characteristics, and finally clustering is achieved using the DBSCAN algorithm. Jiang et al. [13] uses ship position steering angle and speed change to segment the ship AIS trajectory, uses discrete Fréchet distance as the trajectory similarity measure, uses DBSCAN algorithm to cluster the trajectory segments, and extracts typical sub-clusters in each cluster. Trajectory, connect the typical sub-trajectories in chronological order to obtain a complete trajectory.

Li et al. [14] proposed an AIS trajectory clustering method based on density peaks, using Symmetric Segment Path Distance (SSPD) to measure the similarity between two trajectories to extract real and natural classic trajectories from large-scale trajectories. Yao et al. [9] proposes an AIS trajectory clustering method based on Deep Representation Learning (DRL) for mining similar trajectory clusters that appear in different regions and time periods. First, a sliding window is used to extract ship motion features, and then Long Short-Term Memory (LSTM) is used. The neural network builds a sequence-to-sequence autoencoder to learn the depth representation of the ship trajectory with a fixed length, and finally uses the K-means clustering method to cluster the depth representation of the ship trajectory, and the effect is better.

In addition, in the research on the trajectory clustering of targets such as vehicles and airplanes, Liang et al. [15] proposed a trajectory clustering method for aerial targets. This method first fits the target trajectory and replaces the trajectory with the fitting parameters. Then use the k-means algorithm to cluster the feature points based on the Euclidean distance, which effectively reduces the number of clustering trajectory points. Lu et al. [16] improved the DBSCAN algorithm according to the geometric characteristics of vehicle trajectory data and the requirements of trajectory clustering, transformed trajectory data from low-dimensional space to high-dimensional Hilbert space for distance measurement, and proposed K-DBSCAN algorithm based on kernel distance to reduce the number of parameters of clustering algorithm.

In summary, most trajectory clustering methods are limited to the original data space. In the face of massive and high-dimensional AIS trajectory data, due to the difficulties in trajectory similarity measurement, feature extraction and clustering parameter setting, the clustering accuracy and efficiency are very low. Even the DBSCAN algorithm, which is the most widely used in trajectory clustering, can find clusters of arbitrary shapes and is not sensitive to noise, but it still needs to manually select trajectory features, preset radius and the minimum number of points to be included. When the trajectory data density is uneven, the clustering effect is difficult to meet the needs of practical application.

3. Implementation of ship trajectory clustering

3.1. Clustering principle

The AIS trajectory clustering based on deep neural network mainly uses the idea of Deep Embedded Clustering (DEC) algorithm [8], using auto-encoder network to map the original high-dimensional data to the low-dimensional feature space, and embed the reduced trajectory features The points are clustered to obtain the initial cluster center, and the soft allocation probability of each feature embedded point assigned to the initial cluster point is calculated as the original target distribution. Then, construct the auxiliary target allocation, use KL divergence to calculate the distance between the original target distribution and the target distribution, and iteratively train the network while updating the optimized network parameters and clustering parameters. When the clustering distribution between successive iterations changes less than the predefined when the threshold is set, the clustering process stops, and the final clustering result is obtained.

Considering the advantages of DEC clustering algorithm in processing high-dimensional data, we apply it to AIS trajectory data and propose deep neural network-based AIS trajectory clustering. The principle is shown in Fig.1. The upper part of the figure is auto-encoder network, and the lower part is deep clustering network.

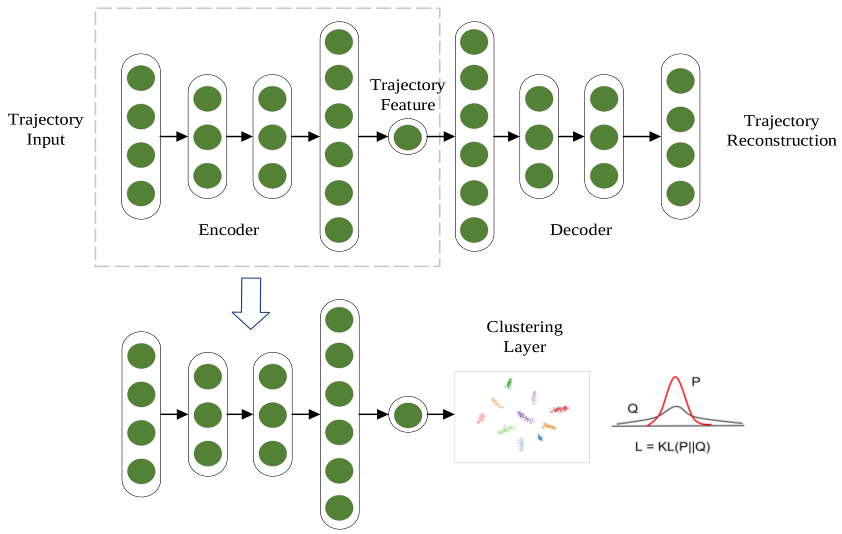

Fig.1. Principle diagram of ship trajectory clustering based on deep neural networks

3.2. Clustering realization

The AIS trajectory clustering based on deep neural network process mainly includes four parts: AIS trajectory data preprocessing, trajectory feature extraction, initialize the clustering center, and construct a deep clustering network to perform feature-based trajectory clustering.

3.2.1. Data preprocessing

The original AIS data usually has abnormal trajectory points, time disorder, missing data, etc. In addition, in order to improve the training speed of deep neural networks, it is necessary to convert ship trajectories of different lengths to fixed lengths and normalize them.

(1) Trajectory extraction: The trajectory points with the same Maritime Mobile Service Identify (MMSI) number of the ship in the AIS is taken as a trajectory. For the case of multiple round trips within the same ship area, it is divided into multiple trajectories according to the heading information. The *i*-th trajectory is expressed as follows:

$$T_i = (p_{i1}, p_{i2}, p_{i3}, \cdots, p_{in}) \tag{1}$$

Where $i = 1,2,\cdots,n$, n represents the number of trajectory points included in the trajectory, trajectory point $p_i = (t, lon, lat, sog, head)$, t represents the time when the trajectory point was collected, lon represents longitude, lat represents latitude, sog represents the speed over the ground, and $head$ represents the heading of the ship.

(2) Deletion of abnormal points: delete abnormal points belonging to the trajectory, such as negative speed, deviation from all trajectory points and other abnormal points. In addition, for trajectories that contain less than half of the average number of trajectories, the entire trajectory is deleted, and it does not participate in the later trajectory clustering.

(3) Data interpolation: Linear interpolation is performed for the vacancies of trajectory points that will appear after the abnormal points are deleted, and for the missing intermediate values of the original AIS data. To this end, first calculate the time interval between the two trajectory points that need to be interpolated to get the number of trajectory points that need to be inserted,

$$N = \frac{p_b^t - p_a^t}{t_{sample}} \tag{2}$$

Where $p_b^t - p_a^t$ represents the time interval between P_b and P_a, $t_{\mathrm{sample}} = p_i^t - p_{i+1}^t$ is the sampling frequency of the trajectory. After obtaining the number of inserted trajectory points *N*, it is necessary to interpolate the trajectory's latitude and longitude, the ground speed and the heading direction, so as to obtain the missing ship trajectory data in this time period.

$$x_i = x_a + \frac{n\,|\,(x_b - x_a)\,|}{N}, \ n = 1,\cdots,N \tag{3}$$

Where $n = 1,2,\cdots,N$, x can respectively represent *lat, lon, sog* and *head* information in the trajectory.

(4) Data padding: As the sampling rate of AIS data changes with the ship's speed, the length of each trajectory is not exactly the same. In order to meet the input requirements of the auto-encoder, it needs to be completed to a fixed length. The method takes the longest trajectory length in the trajectory data set as the standard, and uses the end copy filling mechanism, that is, only the time attribute of the filled trajectory point changes, and other attributes remain unchanged.

(5) Data normalization: In order to accelerate the training speed of the network and improve the calculation efficiency, Normalize the interpolated AIS data, and map each attribute component in the trajectory point to the range of [0,1]. The normalization expression is as follows,

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{4}$$

Where x' is the attribute value after normalization, x is the attribute value before normalization, $x_{\max}$ is the maximum value among the attribute values, and $x_{\min}$ is the minimum value among the attribute values.

3.2.2. Feature extraction

Before trajectory clustering, the auto-encoder network needs to be pre-processing to extract trajectory features. The auto-encoder network consists of an encoder and a decoder and is a completely symmetrical neural network. The encoder mainly completes the task of encoding the input trajectory data and mapping the high-dimensional trajectory data features to the low-dimensional trajectory data features. The decoder is the opposite of the encoder, which can recover the original input data from the low-dimensional trajectory data features. The network structure of the auto-encoder is shown in the upper part of Fig.1.

Assuming that the *i*-th trajectory in the original AIS trajectory data is T_i, after data pre-processing, the formed trajectory data is,

$$Trj_i = (p_{i1}, p_{i2}, \cdots, p_{im}) \tag{5}$$

where *m* represents the number of trajectory points contained in the trajectory.

The preprocessed trajectory Trj_i is input to the auto-encoder network for training. After multiple loop iterations of the network training are completed, that is, the input and output are infinitely close, and the network has completed the process from input to feature extraction to reconstruction. At this time, the output of the encoder Trj_i is the feature of the trajectory after dimension reduction. The encoder at this time can be regarded as a neural network that maps the high-dimensional data space to the low-dimensional data space, which can be expressed by the following formula:

$$f(Trj_i,\theta)=z_i \tag{6}$$

Where f is the nonlinear mapping function, θ is the learnable nonlinear mapping parameter in the neural network, Trj_i is the preprocessed trajectory data, and z_i is the corresponding feature of the trajectory Trj_i in the low-dimensional feature space. That is the trajectory feature that we will cluster later.

3.2.3. Initialize cluster centers

Assuming that the trajectory data set is the trajectory data set $(Trj_1, Trj_2, \cdots)$ after the feature extraction from the auto-encoder, the resulting low-dimensional feature space set is $Z=(z_1, z_2, \cdots)$. In order to obtain the initialized cluster centers, the k-means algorithm based on Euclidean distance is used to cluster the trajectory feature set Z. Suppose the number of clusters after clustering is K, and the center of each cluster is μ_j, $1 \le j \le K$.

3.2.4. Trajectory clustering

This part of the content is to build a deep clustering network and perform feature-based trajectory clustering. The clustering process consists of three parts: initial soft allocation, construction of auxiliary target allocation, and construction of loss function to train the clustering network.

(1) Initial test of soft distribution: After the autoencoder training is completed, the encoder part is taken out, and a clustering layer is added behind the encoder to construct a deep clustering network. Its structure is shown in the lower part of Figure 1. In the clustering layer, the similarity between trajectories needs to be measured. To this end, based on $t-SNE$ the algorithmic idea, that is: similar data in the high-dimensional data space is also similar in the middle of the low-dimensional features, and the t distribution is used to measure the similarity between the data in the low-dimensional feature space Z and the cluster center μ_j, $1 \le j \le K$, which is called Soft distribution probability, which is expressed by the following formula,

$$q_{ij}=\frac{\left(1+\left\|z_i-\mu_j\right\|^2/\alpha\right)^{-\frac{\alpha+1}{2}}}{\sum_j\left(1+\left\|z_i-\mu_j\right\|^2/\alpha\right)^{-\frac{\alpha+1}{2}}} \tag{7}$$

Where $f(Trj_i,\theta)=z_i$ represents the value of the original trajectory Trj_i after feature extraction from the encoder, and α is the degree of freedom of the $Student-t$ distribution, which is usually set to 1. q_{ij} indicates the probability value of assigning the trajectory to the cluster center μ_j.

(2) Construction of auxiliary target distribution: Since it is necessary to measure whether the clustering distribution is reasonable, a target distribution is also needed. However, since unsupervised learning is used, there is no probability distribution in the high-dimensional data space. Therefore, an auxiliary target distribution needs to be established. It should have the following characteristics: 1) Strengthen the probability distribution, 2) Highlight points with high confidence, and assign higher weights to them, 3) Can normalize the probability distribution to prevent some clusters from being too large and distorting the hidden feature space. The distribution of auxiliary targets constructed p_{ij} is expressed by the following formula:

$$p_{ij} = \frac{q_{ij}^2 / f_j}{\sum_{j'} q_{ij'}^2 / f_j} \tag{8}$$

Where q_{ij} represents the probability value of assigning the trajectory Trj_i to the cluster center μ_j, and $f_j = \sum_i q_{ij}$ represents the probability of soft clustering.

(3) Construct a loss function to train the clustering network: In order to make the soft allocation probability q_{ij} of the clustering layer close to the auxiliary target distribution p_{ij}, the relative entropy KL divergence is used to measure the difference between the two distributions, which is used as the loss of the deep clustering network Function, can be expressed as:

$$L = KL(P\|Q) = \sum_i \sum_j p_{ij} \log \frac{p_{ij}}{q_{ij}} \tag{9}$$

In the training process, in order to simultaneously learn the nonlinear mapping parameters θ (pre-training in section 3.2.2) and the clustering center μ_j (k-mean is the initial clustering center), the gradient descent algorithm is used to obtain the loss function L relative to the gradient of each feature embedded point z_i and cluster center μ_j is shown in the following formula,

$$\begin{cases} \dfrac{\partial L}{\partial z_i} = \dfrac{\alpha+1}{\alpha} \sum_j \left(1 + \dfrac{\|z_i - \mu_j\|^2}{\alpha}\right)^{-1} \times (p_{ij} - q_{ij})(z_i - \mu_j) \\ \dfrac{\partial L}{\partial \mu_j} = -\dfrac{\alpha+1}{\alpha} \sum_i \left(1 + \dfrac{\|z_i - \mu_j\|^2}{\alpha}\right)^{-1} \times (p_{ij} - q_{ij})(z_i - \mu_j) \end{cases} \tag{10}$$

The first formula above is to optimize the parameters θ of the neural network, and the second formula is to optimize the cluster centers μ_j . In order to ensure that the algorithm converges, and the cluster assignment result is reasonable, when the cluster assignment change between successive iterations is less than a predefined threshold, the clustering process stops and the final clustering result is obtained.

4. Experimental results

4.1. Implementation details

We implemented our trajectory clustering method using PyTorch framework. The depth of the auto-encoder network is 9 layers in Figure 1, the input data feature dimension is 568 dimensions (twice the AIS trajectory length), the second and third layers are both 300, the fourth layer is 1000, the 5th layer is 8(extracted trajectory feature length), the 6th layer is 1000, the 7th and 8th layers It is 300, and the 9th layer is the data feature dimension of 682 dimensions. All neural networks are in the form of fully connected, the middle layer uses the ReLU function as the activation function, and the mean square error (MSE) as the loss function. When the cluster assignment change between successive iterations is less than a predefined threshold 0.01, the clustering process stops and the final clustering result is obtained. The parameter settings of deep clustering network are shown in Table 1.

Table 1

Parameter setting of deep clustering network

Network parameters	Setting
number of neurons	682
activation function	ReLU
initial cluster number	15
loss function of auto-encoder network	MSE
loss function of deep clustering network	KL divergence
threshold for clustering iteration termination	1e-4
network training optimizer	SGD
learning rate	1e-3

4.2. Datasets

The experimental data are from the website https://marinecadastre.gov/ais/ , we downloaded AIS trajectory data from March 1, 2019 to March 31, 2019, ranging from 70°52'E-69°91'E, 47°27’N-481°65’N, including 150526 AIS ship trajectory data, involving 144 vessels. After data preprocessing of the original AIS trajectory, including trajectory extraction, outlier deletion, data interpolation and data completion, 946 AIS trajectory data are obtained, and each trajectory contains 362 trajectory points, as shown in Fig.2.

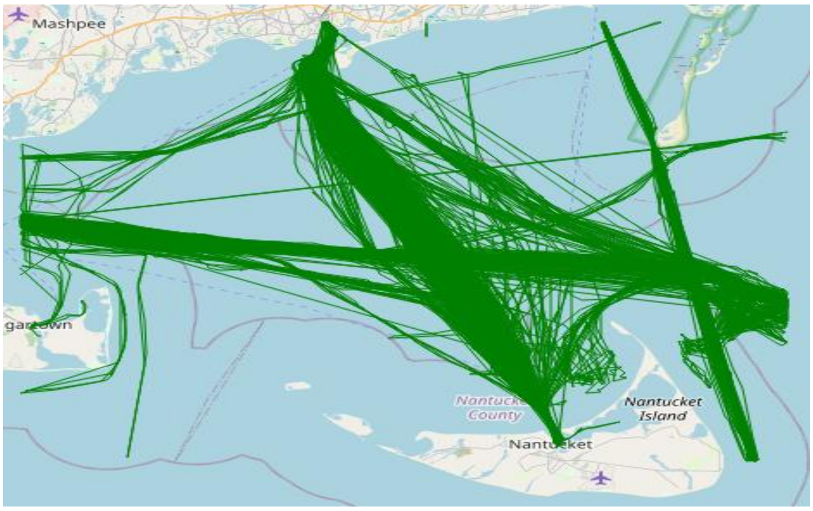

Fig.2. AIS ship trajectory

4.3. Results and analysis

In order to measure the effectiveness of the AIS ship trajectory clustering method based on depth neural network proposed in this paper, we cluster the AIS trajectory data to obtain the typical ship routes in the water area, and view the clustering effect through map visualization.

In addition, the experiment compares it with the trajectory density clustering based on DP trajectory compression, DTW distance and DBSCAN algorithm proposed in reference [11], the clustering algorithm proposed by them has good performance, but many parameters need to be preset.

4.3.1 Clustering based on depth neural network

According to the visualization results of the original AIS ship data in Fig.2, we set the number of initial clusters $k = 8$. In order to obtain the typical ship routes in the water area, we analyzed and visualized the clustering results, and extracted a total of 8 typical routes, as shown in Fig.3. As it can be seen from Fig. 3 below, our clustering algorithm proposed in this paper can effectively cluster AIS trajectories, and the extracted typical route information is obvious, which can accurately distinguish different routes.

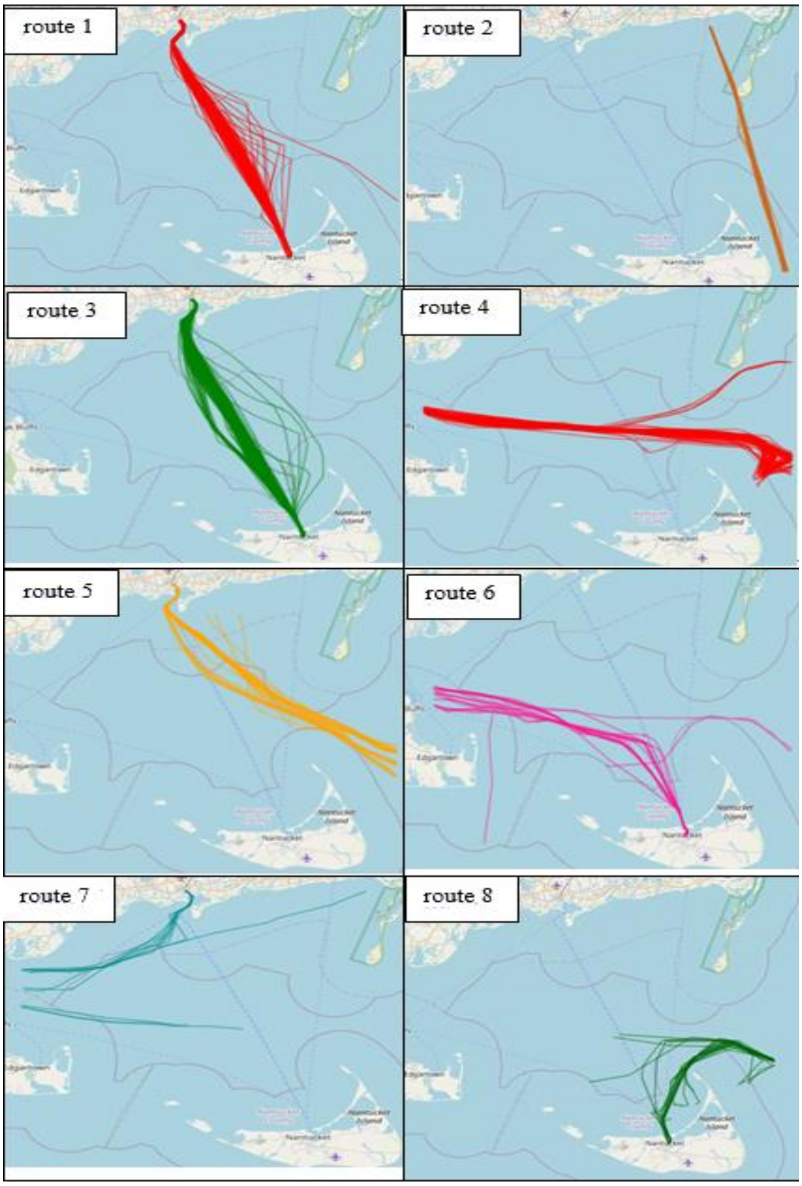

Fig.3. Clustering based on depth neural network

4.3.2 Clustering based on trajectory density

Clustering based on trajectory density uses DP algorithm to compression AIS trajectory at first, then uses DTW distance to measure trajectory similarity, and finally uses DBSCAN algorithm to cluster ship trajectories. In order to compare the clustering effect, we setup compression value *DP*=0.005, neighborhood radius *Eps*=0.5 and minimum density *MinPts*=10, to obtain 10 clusters as in the previous experiment. The clustering results are shown in

Fig.4， and different color trajectories represent different classes, that are typical routes.

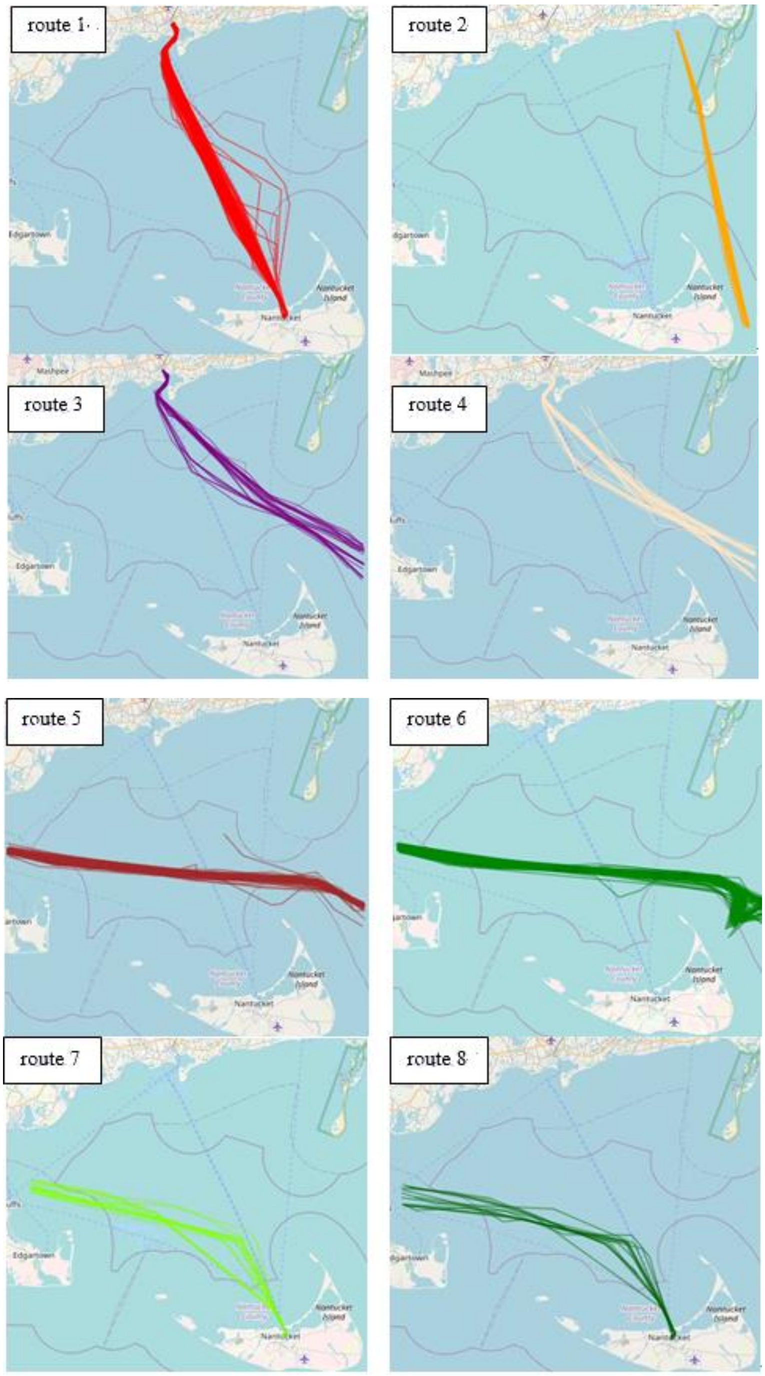

Fig.4. Clustering based on trajectory density

As it can be seen from Fig.4, the clustering algorithm based on trajectory density has good performance. However, due to the *DP* trajectory compression value, radius *Eps* and density *MinPts* threshold set during clustering, the algorithm will automatically delete some trajectories. As a result, some typical routes are ignored, such as route 7 and route 8 in Fig.3, cause the trajectory in the route is too short; it is considered as noise in the clustering process.

5. Conclusions

Ship trajectory clustering is widely used in marine traffic pattern recognition, target anomaly detection, traffic flow analysis and other fields. In this paper, we proposed an AIS ship trajectory clustering based on deep neural network, the experimental results show that the approach is simple and effective, solves the problems of trajectory similarity measurement, feature extraction and clustering parameter setting in the existing trajectory clustering methods, and can accurately extract the typical routes. In our future works, we will focus on optimizing the number of layers and neurons of auto-encoder network and using linear interpolation or padding mask to replace the current end copy filling mechanism in the data preprocessing stage.

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