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Collision Avoidance Situation Matching with Vessel Maneuvering Actions Identification from Vessel Trajectories

Peng Chen[a,b], Guoyou Shi[a,*], Shuang Liu[c], and Miao Gao[a]

[a]Navigation College, Dalian Maritime University, Dalian, 116026, China
[b]Department of Software Engineering, Dalian Neusoft University of Information, Dalian, 116030, China
[c]School of Computer Science and Engineering, Dalian Minzu University, Dalian, 116605, China

Abstract

Vessel trajectories implied in AIS data are crucial to obtain a good understanding of the maritime traffic situation for shipping safety. Starting from raw AIS data, a trajectory database is created for vessels within surveillance area after parsing, noise reduction, and DBSCAN clustering. With *mmsi* as the key index, the trajectory for each vessel is extracted ordering by timestamp. To remove the time interval difference between points in trajectories, interpolation and cleaning are carried out on each vessel trajectory to get trajectories with equal time intervals. Through implied motion pattern computation between adjacent points in each trajectory, maneuvering actions can be identified. Then, sailing segments with continuous same maneuvering actions are merged. With sailing segments partition results, critical points are extracted for already known different collision avoidance situations. Trajectory similarity computation for different vessels are computed with our new multi-scale and multi-resolution trajectory matching method. Experiments for the recognition of collision avoidance situations show that the adoption of the matching algorithm with multi-scale and multi-resolution trajectories for different vessel pairs to complete collision avoidance situations analysis is effective and achieves good performance.

Keywords: collision avoidance; vessel trajectory; maneuvering action; sailing segments; similarity computation

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1. Introduction

As the most important part of transport for international merchandise trade, ocean shipping is becoming more and more popular in international trade because of its cheap cost, according to the Review of Maritime Transport 2017. Therefore, shipping safety is especially important with its increasing development. Over 70% of vessels under shipping duty have installed AIS (Automatic Identification Systems) receivers, which provide a means to track the location of vessels in the most remote areas of the world. Taking full advantage of historical AIS data to avoid collisions in decision-making and provide navigation safety is a main research focus of recent years.

The AIS message consists of a vessel's position, call sign, vessel name, course, speed, and navigation status. With this AIS information, intelligent processing will enable commercial vessels to see each other more clearly in any conditions and improve the helmsman's information about the surrounding environment, providing support for collision avoidance. The AIS tracking system also helps manage maritime traffic and reduce the hazards of marine navigation. The only problem that needs to be solved is that the increasingly overwhelming AIS data within a given area of long interval is already beyond manual operations. Thus, an intelligent processing method automatically is required to process AIS data to capture key points in traffic patterns and discover important patterns or traffic knowledge for collision avoidance decision making.

Many researchers have conducted related research. For example, Chen et al. put forward a classification method from vessel motion patterns in inland waterways based on AIS in [1]. Zheng et al. studied robust MPC-based fault-tolerant control for trajectory tracking of surface vessels in [2]. To solve collision avoidance of underactuated vessels with disturbances, Abdelaal et al. designed a nonlinear model predictive control method for trajectory tracking in [3]. Sun et al.

* Corresponding author.
E-mail address: shiguoyoudmu@163.com

proposed a spatial-temporal motion pattern mining method for vessel recognition in [4]. For marine accidents, Oh et al. put forward a vessel trajectory mechanism in [5]. Li et al. discussed a dimensionality reduction-based multi-step clustering method for robust vessel trajectory analysis in [6]. In [7], Fu et al. used feature learning to find abnormal vessel trajectories. Wang et al. proposed a shape-based analysis method for vessel trajectories in [8]. Qi et al. put forward a vessel trajectory data compression based on course alteration recognition and a trajectory prediction method for vessels based on data mining and machine learning in [9-10]. Ma studied vessel motion pattern recognition based on one-way distance and spectral clustering algorithm in [11]. There is also some research for ship collision avoidance in [12-15], such as chaotic particle swarm optimization, dynamic prediction, AIS data processing, and dynamic support system based on ship maneuverability. These studies only consider vessel trajectory or collision avoidance by AIS data mining. Few of them combine vessel trajectory mining with vessel maneuvering actions to complete collision avoidance, which is the focus of this paper.

The rest of this paper is organized as follows. The overview of the proposed framework is first given in Section 2. Related AIS data processing and trajectories processing with multi-scale and multi-resolution are also discussed here. Maneuvering actions identification and sailing segments processing are presented in Section 3. Then, the collision avoidance matching scheme based on the proposed framework is listed in Section 4. Experimental results from real AIS data of the proposed algorithm are discussed in Section 5. The conclusions are given in Section 6.

2. Our Collision Avoidance Situation Matching Framework

2.1. Overview of the Proposed Framework

The collision avoidance situation recognition process is divided into three logically connected phases. The first phase is AIS data processing. The second phase is maneuvering actions identification. The third phase is collision avoidance matching based on multi-scale and multi-resolution trajectory matching. The whole framework is shown in Figure 1.

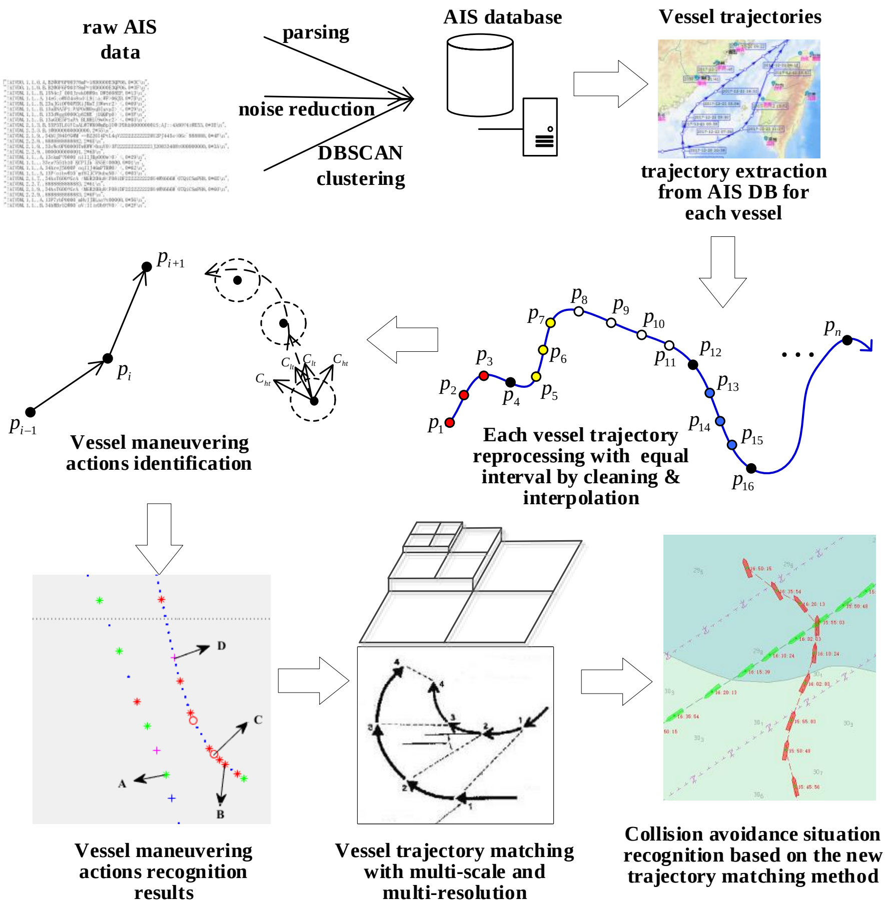


Figure 1. Overview of the proposed framework

2.2. AIS Data Processing

AIS data updates with a frequency of every 2 to 12 seconds while the vessel is underway and every 3 minutes while the vessel is anchored. After parsing, basic AIS data containing information such as vessel identity, position, speed, and course for vessels is stored in the database. However, there may be some errors or points missing in the original dataset. Thus, noise reduction such as error data removal is adopted first. Then, interpolations are adopted to get trajectory points with the same time interval. One improved DBSCAN algorithm called PI-DBSCAN is also called to remove redundancy in a huge volume of original AIS data. This PI-DBSCAN algorithm is an incremental DBSCAN algorithm based on one partition index in [16].

With ECDIS (Electronic Chart Display and Information System) as a visualization tool, the pre-processed trajectory of one vessel from December 31, 2018 to January 1, 2019 is shown in Figure 2.

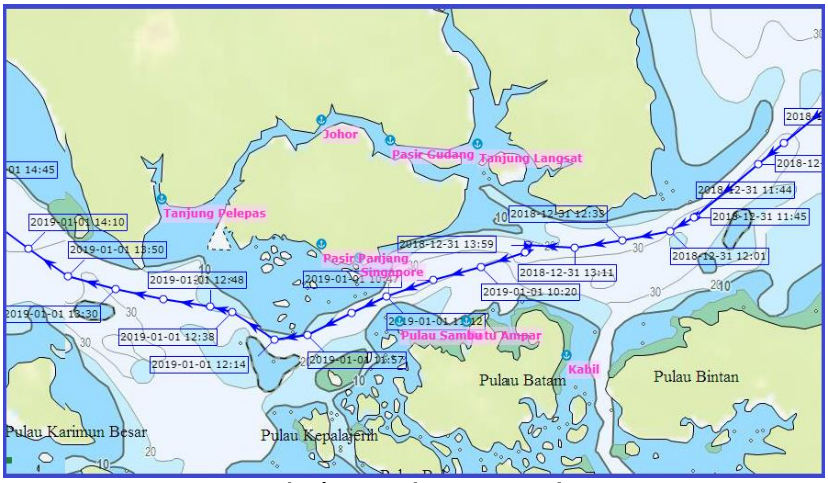


Figure 2. An example of one vessel trajectory visualization in ECDIS

2.3. Multi-Scale and Multi-Resolution Trajectory Processing

Drawing on the idea of wavelet decomposition, each trajectory is divided into multiple regions. The illustration for trajectory partition referenced by wavelet decomposition is shown in Figure 3. As shown in Figure 3, the whole trajectory is divided into four parts, T_1, T_2, T_3, and T_4. Taking T_1 as an example, it is also divided into four parts, T_{11}, T_{12}, T_{13}, and T_{14}. Then, T_{11} is further divided into four parts, T_{111}, T_{112}, T_{113}, and T_{114}. All these partitions can be done by different sampling intervals. For example, the sampling interval for scale-1 T_1, scale-2 T_{11}, and scale-3 T_{111} is 4 seconds, 2 seconds, and 1 second respectively.

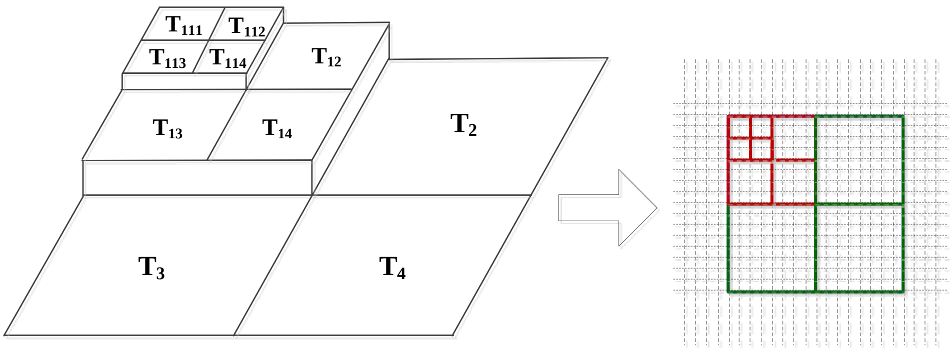


Figure 3. Illustration for trajectory partition idea reference by wavelet decomposition

Figure 4 is the trajectory partition result of three scales. All trajectories consist of longitude, latitude, and timestamp. One trajectory may imply a complex navigation path and behavior pattern. The trajectory is partitioned into multi-scale and multi-resolution representations. Multi-scale and multi-resolution trajectories not only help discover motion patterns, but also help provide collision avoidance support in trajectory matching. Based on the analysis of local features in each partition, the motion pattern in trajectory segments is found. Based on the combined features of different partitions, the global motion pattern can also be obtained. Comparing the trajectory similarity in different resolutions leads to comparable results of behavior pattern in fine scale and in coarse scale to find similar meeting situations for vessels.

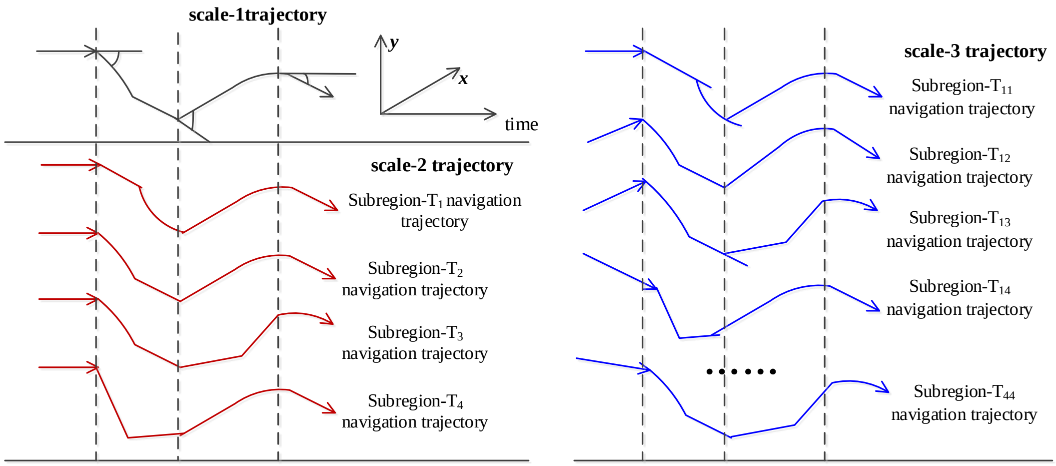


Figure 4. Multi-scale and multi-resolution trajectory partition in three scales

3. Vessel Maneuvering Actions Identification

3.1. Sailing Segment Classification

There are two categories for actual vessel maneuvering patterns under various navigational environments, that is, course keeping and emergency manoeuvres. Here, vessel maneuvering actions are classified by course keeping and course turning. Course changing is further classified as small course turning or sharp course turning. Sixteen vessel maneuvering actions are defined here, including speed keeping, deceleration, acceleration, weak yaw of left rudder, weak yaw of left rudder with acceleration, weak yaw of left rudder with deceleration, weak yaw of right rudder, weak yaw of right rudder with acceleration, weak yaw of right rudder with deceleration, strong yaw of left rudder, strong yaw of left rudder with acceleration, strong yaw of left rudder with deceleration, strong yaw of right rudder, strong yaw of right rudder with acceleration, strong yaw of right rudder with deceleration, and stopping.

Based on the classification of vessel maneuvering actions, the AIS trajectory for vessels is categorized into different sailing segments. Each sailing segment corresponds to one or two maneuvering actions. Considering kinematics constraints, the AIS trajectory is classified as normal sailing segment, acceleration sailing segment, deceleration sailing segment, stopping sailing segment, weak yaw sailing segment, weak yaw sailing segment with acceleration, weak yaw sailing segment with deceleration, strong yaw sailing segment, strong yaw sailing segment with acceleration, and strong yaw sailing segment with deceleration.

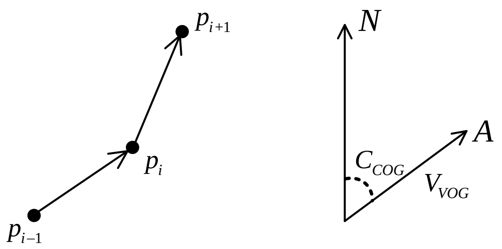
3.2. Maneuvering Actions Identification

The vessel maneuvering action reflects the motion process of the vessel. Every three points in the trajectory imply one motion process. That is, every three trajectory points imply one vessel maneuvering action event. The vessel maneuvering action can be obtained based on three trajectory points of sampling data at a uniform time interval. Figure 5(a) shows the identification illustration for vessel maneuvering actions.

In the field of nautical science, the velocity vector can be represented with speed over ground (*SOG*) and course over ground (*COG*). That is, $\vec{v} = (V_{VOG}, C_{COG})$, which is a sub-image (b) of Figure 5.

Suppose the time interval between p_i and p_{i+1} and between p_{i-1} and p_i is Δt. $\overrightarrow{v_i^{in}}$ is the velocity vector of the trajectory $p_{i-1}p_i$. $\overrightarrow{v_i^{out}}$ is the velocity vector of trajectory $p_i p_{i+1}$. Then, $\overrightarrow{v_i^{in}}$ and $\overrightarrow{v_i^{out}}$ can be computed as Equation (1).

$$\overrightarrow{v_i^{in}} = \frac{\overline{p_{i-1}p_i}}{\Delta t}, \quad \overrightarrow{v_i^{out}} = \frac{\overline{p_i p_{i+1}}}{\Delta t} \tag{1}$$



(a) Motion pattern between points in trajectory (b) Decomposition of speed vector in nautical science
Figure 5. Illustration for vessel maneuvering actions identification

The rate of vessel speed change and rate of vessel course change can be denoted as RV, RC . To compare maneuvering patterns between p_i and its adjacent up and down sailing segments, *RC* and *RV* are defined as Equation (2). With some thresholds of course change and speed change, the sailing segment of sharp turn or acceleration rapidly or deceleration rapidly can be obtained for further processing.

$$RV = \frac{\Delta v}{\Delta t} = \frac{V_{SOG}^{i,out} - V_{SOG}^{i,in}}{\Delta t}, \quad RC = \frac{\Delta C_{COG}}{\Delta t} = \frac{C_{COG}^{i,out} - C_{COG}^{i,in}}{\Delta t} \tag{2}$$

3.3. Sailing Segments Merging

To construct multi-scale and multi-resolution trajectories, a merging operation is adopted at a coarse scale. That is, a merging operation is adopted for sailing segments with continuous same maneuvering actions. As shown in Figure 6, three red points p_1, p_2, and p_3 belong to the weak yaw of left rudder and then are merged as one point in the trajectory. Similarly, three yellow points, four white points, and three blue points are merged as well. It is not restricted to combine three or four points because the same maneuvering actions are more important than the point selection of different scales.

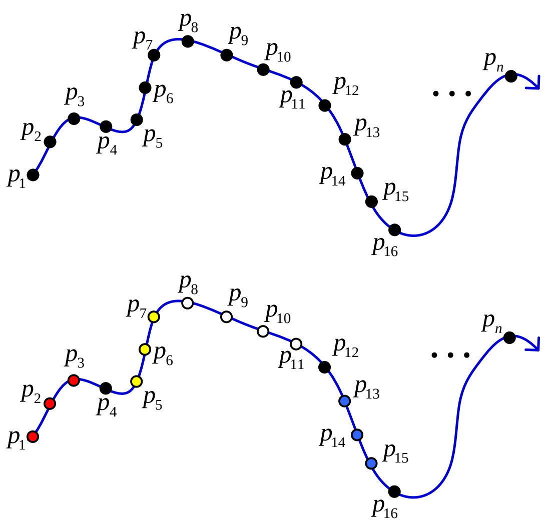


Figure 6. Merging operation for continuous same maneuvering actions

4. Collision Avoidance Matching

4.1. Meeting Situations Classification

According to the provisions of the International Regulations for Preventing Collisions at Sea (COLREGS), there are three meeting situations related to collision avoidance. The overtaking situation is based on Rule 13. In sight of one another, the vessel overtaking any other should keep out of way of the way of the vessel being overtaken. The head-on situation is based on Rule 14. In sight of one another, two power-driven vessels have the same responsibility to avoid each other; each shall alter her course to starboard so that each shall pass on the port side of the other. The crossing situation is based on Rule 15. In sight of one another, the vessel that has the other on her own starboard side shall keep out of the way. According to the rules, when vessels are not in sight of one another in or near an area of restricted visibility, if a close-quarters situation is developing and/or risk of collision exists, each of them has a responsibility to avoid the others and take action to alter her course.

4.2. Matching based on LCSS Similarity Computation

Without loss of generality, a vessel trajectory is an aggregation of its broadcasting AIS information, which is represented as $TV_{mmsi}=\{p_1,p_2,\cdots,p_n\}$ with *mmsi* as its unique ID. Here, each trajectory point p_i is defined as $p_i=\{\varphi_i,\lambda_i,t_i,SOG_i,COG_i\}$. Each trajectory point records the vessel identity, position, speed, and course for the vessel. This is the representation of a trajectory with no compression. After compression, the new trajectory for the same vessel is denoted as $Q_{mmsi}=\{p_{k_1},p_{k_2},\cdots,p_{k_m}\},\ m\le n$, and the index set is $I=\{k_1,k_2,\cdots,k_m\},\ k\in\{1,\cdots,n\}$.

For any two points $p_1(\varphi_1,\lambda_1,t_1,SOG_1,COG_1)$ and $p_2(\varphi_2,\lambda_2,t_2,SOG_2,COG_2)$ in the trajectories, its sphere distance is computed with Equation (3).

$$x=(R\cos(\frac{\lambda_1+\lambda_2}{2}\frac{\pi}{180}))(\frac{\pi}{180}(\varphi_1-\varphi_2)),\ y=R(\lambda_1-\lambda_2)\frac{\pi}{180},\ d(p_1,p_2)=\sqrt{x^2+y^2} \tag{3}$$

For a point *q*, its similarity with a trajectory $T_a=\{a_1,a_2,\cdots,a_n\}$ is defined as Equation (4).

$$D(q,T_a)=\min_{p'\in T_a} d(q,p') \tag{4}$$

For trajectory $T_a=\{a_1,a_2,\cdots,a_n\}$ and $T_b=\{b_1,b_2,\cdots,b_m\}$, $Head(T)$ and $Rest(T)$ are defined as Equation (5).

$$Head(T_a)=\{a_1\},\ Head(T_b)=\{b_1\};\ Rest(T_a)=\{a_2,\cdots,a_n\},\ Rest(T_b)=\{b_2,\cdots,b_m\} \tag{5}$$

For collision avoidance situation mapping, critical points or sharp turn sailing segments are very important. Therefore, the shape of the trajectory is key for the matching result. LCSS (Longest Common Subsequence) is adopted here to complete collision avoidance situation mapping. $LCSS(T_a,T_b)$ is defined as Equation (6). In Equation (6), ε is the distance threshold and δ is an integer.

$$LCSS(T_a,T_b)=\begin{cases}0, \quad \text{if } n=0 \text{ or } m=0\\ 1+LCSS(Rest(T_a),Rest(T_b)), \quad \text{if } d(Head(T_a),Head(T_b))\le\varepsilon \,\&\&\, |n-m|<\delta\\ \max(LCSS(Rest(T_a),T_b),LCSS(T_a,Rest(T_b))), \quad \text{otherwise}\end{cases} \tag{6}$$

5. Experimental Results and Analysis

Taking Qiongzhou straits as an example, 785 vessels' AIS data are collected from July 20, 2018 to August 20, 2018. Based on the pre-processing of data mentioned above, vessel maneuvering actions such as speed keeping, deceleration, acceleration, weak yaw of left rudder, weak yaw of left rudder with acceleration, weak yaw of left rudder with deceleration, weak yaw of right rudder, weak yaw of right rudder with acceleration, weak yaw of right rudder with deceleration, strong yaw of left rudder, strong yaw of left rudder with acceleration, strong yaw of left rudder with deceleration, strong yaw of right rudder, strong yaw of right rudder with acceleration, and strong yaw of right rudder with deceleration are identified.

The sampling time intervals for scale-1, scale-2, and scale-3 are set as 60 seconds, 30 seconds, and 10 seconds respectively. The thresholds for course change ratio, sailing start speed, and acceleration are set as $RC_{weak}=2$, $RC_{sharp}=10$, $VT_{zero}=0.4$, $RV_{acceleration}=1.2$ to get the vessel trajectory with maneuvering actions. Two trajectories for two vessels are shown in Figure 7. By analyzing trajectories, major changes for the vessel movement can be detected and critical points can be marked such as a stop, smooth turn, sharp turn, or slow motion. In Figure 7, the blue dot corresponds to the speed keeping sailing segment, the blue + corresponds to the deceleration sailing segment, the magenta + corresponds to the acceleration sailing segment, the red asterisk corresponds to the stopping sailing segment, the green asterisk corresponds to the weak yaw sailing segment, the red circle corresponds to the strong yaw of rudders sailing segment, and the green circle corresponds to the other sailing segment.

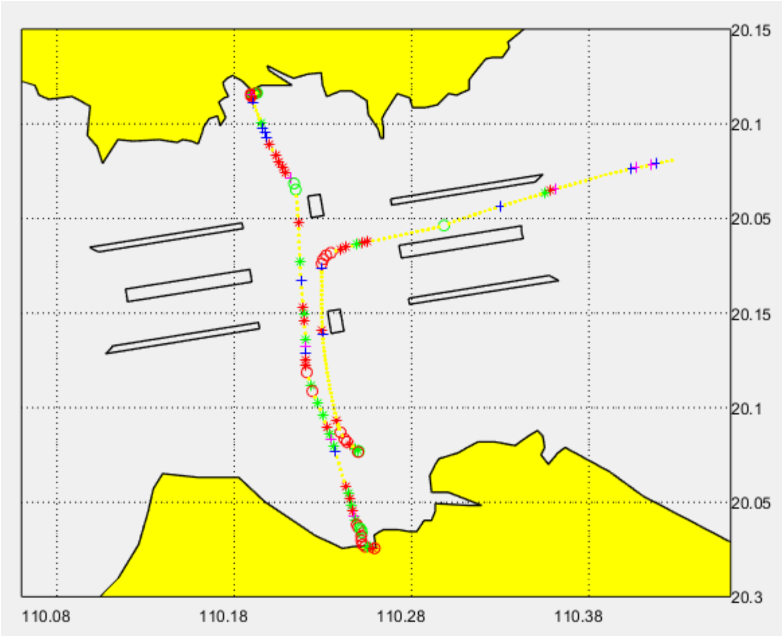


Figure 7. Identification results for vessel maneuvering actions

Figure 8 shows the trajectory similarity computation results based on LCSS matching method for one trajectory. These trajectories have similar turns and similar shapes. Here, the threshold for distance is 10 nautical miles.

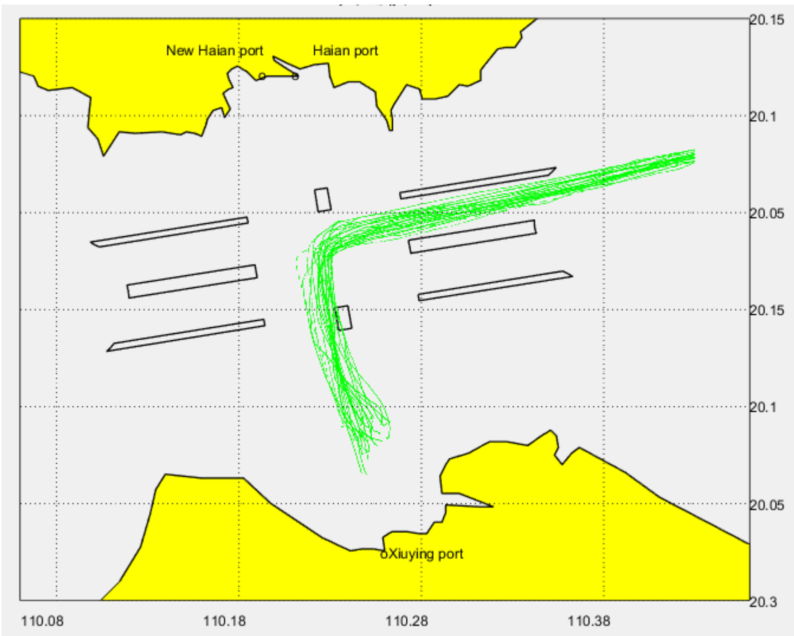
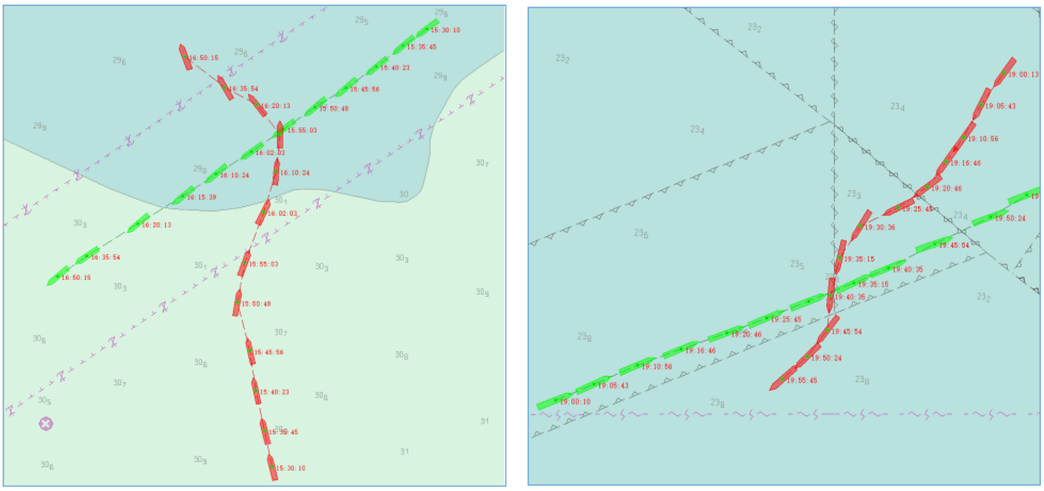


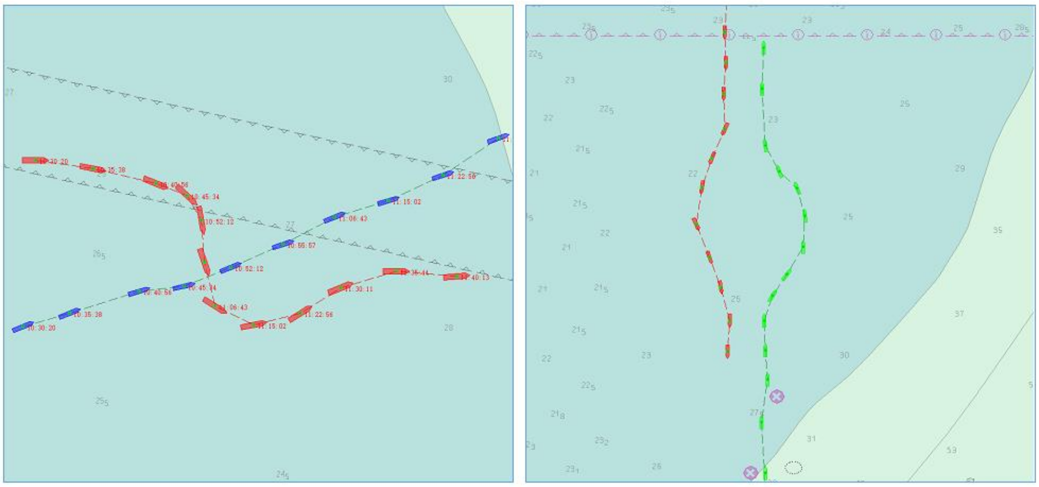
Figure 8. Trajectory similarity computation results

Based on some already known trajectory pairs concerning crossing situations, head-on situations, and overtaking situations, the LCSS matching method mentioned above is called to find similar collision avoidance situations. Figure 9 and Figure 10 show the matching result. Figure 9(a) is a crossing situation with a right angle, and Figure 9(b) is a crossing situation with a small angle. Figure 10(a) is a crossing situation with a large angle, and Figure 10(b) is a head-on situation for two vessels.



(a) Crossing situation with a right angle (b) Crossing situation with a small angle

Figure 9. Two crossing situations matching results



(a) Crossing situation with a large angle (b) Head-on situation

Figure 10. Crossing situation with a large angle and head-on situation matching results

6. Conclusions

With the large, high speed development of marine trade and people's increasing demand for marine resources, vessel collision accidents will lead to a huge loss of life and property. Avoiding collisions is an important part of safe and efficient navigation. The majority of the collision accidents are caused by operator carelessness, negligence, and violation of rules. Therefore, reducing human error is the key to reducing ship collisions. Based on parsing and raw AIS data, one AIS database is created for vessels after parsing, noise reduction, and DBSCAN clustering. To get a trajectory with the same time interval, interpolation and cleaning are also adopted for each vessel trajectory. By computing maneuvering actions between adjacent points in each trajectory, sailing segments are marked with different maneuvering actions. Then, critical points are extracted for already known different collision avoidance situations by key identified maneuvering actions. Finally, collision avoidance situations results can be recognized by LCSS trajectory similarity computation. Our new multi-scale and multi-resolution trajectory matching method is effective and validated by real AIS application experimental results. Deep learning for huge volumes of AIS history data will be introduced in our future research.

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Peng Chen received his B.S. degree in computer science from Liaoning Shihua University in 2000 and his M.S. degree in computer science from Liaoning Shihua University in 2003. Currently, he is a professor at Dalian Neusoft University of Information.

Guoyou Shi is a professor at Dalian Maritime University.

Shuang Liu received her B.Sc. and M.Sc. degrees in computer science from Liaoning Shihua University in 2000 and 2003, respectively, and her Ph.D. in traffic information engineering and control from Dalian Maritime University. Currently, she is an associate professor at Dalian Minzu University.

Miao Gao is a Ph.D. candidate at Dalian Maritime University.