A Framework for Maritime Anti-Collision Pattern Discovery from AIS Network

Po-Ruey Lei*, Pei-Rong Yu†, and Wen-Chih Peng†
*ROC Naval Academy, Zuoying, Taiwan
†National Chiao Tung University, Hsinchu, Taiwan
barry@cna.edu.tw, pryu.iie07g@nctu.edu.tw, wcpeng@nctu.edu.tw

***Abstract*—The avoidance of collisions between ships in encounter situations is crucial to maritime traffic safety. Most research on maritime collision avoidance has focused on planning a safe path by which to avoid approaching ships in accordance with the requirements laid out in the International Regulations for Preventing Collision at Sea (COLREGs). The resulting solution provides reference for the navigator in planning movements to avoid collisions.**

Nonetheless, specific anti-collision actions are generally based on the experience of the navigator. This study differed from existing works in that we sought to derive collision avoidance behavior from the trajectory data of actual ships. The Automatic Identification System (AIS) network makes it possible to collect an enormous volume of trajectory data and investigate real-world ship behavior.

Unfortunately trajectory data that introduces uncertainty can hinder behavior mining for collision avoidance. Irregular and/or asynchronous location sampling can lead to situations in which the movement of a ship does not necessarily follow a given trajectory, even if its movement behavior is similar to that of other ships. In this study, we developed a framework to decipher the anti-collision behavior of ships in encounter situations from a large database of trajectory data collected by AIS network, and to present this behavior in the form of anti-collision patterns. A prototype of the proposed framework was built to enable pattern analysis and visualization functions, thereby providing a deeper understanding of collision avoidance behavior in maritime traffic. The proposed framework is applicable to the development of pattern-aware collision avoidance systems aimed at improving maritime traffic safety.

Keywords*—*AIS network, ship trajectory data, maritime conflict detection, ship anti-collision pattern

I. Introduction

Collision avoidance is a major concern in maritime traffic safety. Any reduction in the distance between ships increases the likelihood of collision. The standard anti-collision protocol is the International Regulations for Preventing Collision at Sea (COLREGs), published by the International Maritime Organization (IMO). These navigational rules and regulations to prevent collisions must be obeyed by all navigational ships. However, navigators in the real world must deal with situations of considerable complexity beyond the scope of regulations. Unlike cars moving along road networks, there is no maritime road for ships to follow. Thus, the ships can move freely in the open sea. In a free-movement environment, encounter situations can be highly complex. COLREGs establishes "the rules of the road" in a maritime environment; however, they amount to general principles rather than a set of easy-to-follow rules. They do not provide specific guidance.

Thus, most previous research into maritime collision avoidance has focused on planning a safe path for one's own ship while remaining at a safe distance from approaching ships, in accordance with the requirements outlined in COLREGs. Numerous methods have been devised to achieve this, including heuristic search methods [8], [1], [2], evolutionary algorithms [9], [7], [10], and ant colony optimization [11], [3]. The spatial locations of one's own ship and the approaching ships as well as their speed and course of motion is used to generate a collision free path by searching for optimal or near-optimal solutions.

In the past, it was difficult to determine the true trajectory of the ship. Most collision avoidance methods were developed based on COLREGs, expert opinions, and simulated data. Resulting solutions therefore serve only as a reference for navigators to guide them in collision avoidance. Actual anti-collision decision-making is thus primarily dependent on the experience of the navigators. However, there are now numerous location-aware devices and navigation services that can be used to track the movement of ships. In this work, the ship trajectory is generated by using the Automatic Identification System (AIS) network. For collision avoidance and navigational safety control, ships equipped with AIS automatically exchange navigation information, such as their unique identification, position, course, and speed, with nearby ships and terrestrial receivers of AIS networks to facilitate the tracking and monitoring of vessel location and movement. These trajectories are used to record the ships' true movement and reveal the maneuvering behavior of navigators. The availability of AIS trajectory data from AIS network makes it possible to discover hidden behaviors, which serve in the analysis of ships in encounter situations as well as the development of data mining algorithms to discover trajectory patterns for collision avoidance.

Unlike existing solutions, we sought to derive the collision avoidance behavior of navigators through the analysis of massive volumes of ship trajectory data collected by AIS network. Specifically, we discover anti-collision patterns (hereafter referred to as ATC Patterns) which proved effective in previous encounter situations. In the analysis of collision avoidance behavior, these patterns represent actual anti-collision maneuvers implemented successfully by navigators. The effectiveness of the proposed framework was evaluated by putting together a prototype for use in experiments via real-world AIS trajectory data. The anti-collision patterns revealed by the proposed framework provide the foundation for further development of pattern-aware collision avoidance systems.

The remainder of the paper is organized as follows. The proposed framework is generally introduced in Section II. Section III technically details the main modules of the proposed framework. In Section IV, we perform an empirical performance evaluation on real data set collected from AIS network. Finally, we summarize our conclusion and future work in Section V.

II. Framework Overview

AIS network collects ships' movements, including its movements for collision avoidance. Thus, the proposed framework is developed to discover the anti-collision patterns (abbreviated as ATC patterns) hidden in the historical AIS trajectory data. Figure 1 presents an overview of our proposed framework, which comprises four components: conflict trajectory clustering, situation-aware classification, maneuvering action extraction, and anti-collision pattern mining.

Prior to clustering, the ship trajectory data is extracted from AIS network, i.e., AIS trajectory database. An AIS trajectory is an ordered sequence of spatial-temporal points. Each point is indicated by latitude and longitude coordinates and a timestamp. First, *conflict trajectory clustering* is performed to identify a group of trajectories associated with situations of conflict, referred to as a cluster of conflict trajectories (CCTs). Second, the discovered CCTs are distinguished into different encounter situation classes by *situation-aware classification*. Based on a specific situation-aware class of CCTs, *maneuvering action extraction* recognizes anti-collision actions for each trajectory of CCTs. At the final stage, anti-collision patterns for each specific encounter situation are generated by *anti-collision pattern mining*.

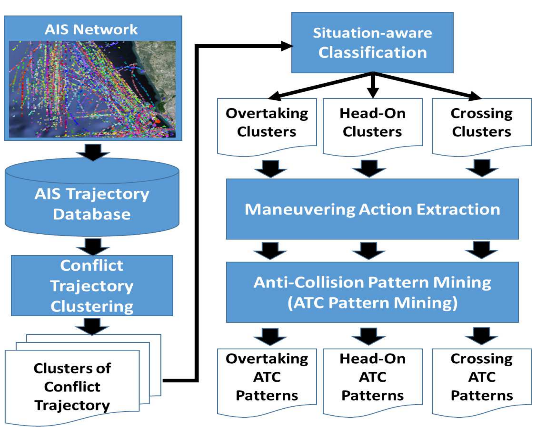

Fig. 1. Framework of anti-collision pattern discovery

III. Anti-Collision Pattern Discovery

In this section, we present the details of the four main modules of the proposed framework, including conflict trajectory clustering, situation-aware classification, maneuvering action extraction, and anti-collision pattern mining.

A. Conflict Trajectory Clustering

The *Conflict Trajectory Clustering* module is used to identify a group of trajectories associated with situations of conflict, referred to as a cluster of conflict trajectories (CCTs). This type of situation could result in a collision unless evasive action were taken. The method proposed for the detection of these events is based on our previous work [4]. A cluster of encounters (CoE) is extracted via soft clustering. The distances between trajectories in a CoE are close to each other.

Given an observation timestamp t_i and a collected AIS trajectory database D_A, we can extract a snapshot of the data $D_A(t_i) = \{s_1^{t_i}, s_2^{t_i}, s_3^{t_i}, ..., s_n^{t_i}\}$, where $s_n^{t_i} = (x_n^{t_i}, y_n^{t_i}, v_n^{t_i}, c_n^{t_i})$. $(x_n^{t_i}, y_n^{t_i})$ represents the geo-position of $s_n^{t_i}$, and $v_n^{t_i}$ and $c_n^{t_i}$ indicate the speed and course. The clusters of encounters (CoEs) are extracted from each $D_A(t_i)$ via soft clustering. The distances between trajectories in a CoE are close to each other. With the user-defined circle of observation d_o, the cluster of encounters $CoE_k(t_i) = \{s_{k.1}^{t_i}, s_{k.2}^{t_i}, s_{k.3}^{t_i}, ..., s_{k.m}^{t_i}\}$ is discovered and the distance between any two members $s_{k.x}^{t_i}$ and $s_{k.y}^{t_i}$ are satisfied with condition $dist(s_{k.x}^{t_i}, s_{k.y}^{t_i}) \leq d_o$. The ships' trajectories that are far away from each other are not the information we concerned about. Then, based on the extracted CoEs, the distance at closest point of approach (DCPA) and the time to collision avoidance (TCA) are adopted to measure the maritime conflict behavior of CoEs. Given a pair of ships s_1 and s_2 at observation time t_i, we can derive their mobility information as $s_1^{t_i} = (x_1^{t_i}, y_1^{t_i}, v_1^{t_i}, c_1^{t_i})$ and $s_2^{t_i} = (x_2^{t_i}, y_2^{t_i}, v_2^{t_i}, c_2^{t_i})$. Then, by employing kinematics, DCPA and TCA can be derived as $DCPA(s_1, s_2) = \min Dist_{s_1,s_2}(t)$ and $TCA(s_1, s_2) = \arg\min Dist_{s_1,s_2}(t)$.

We can use the calculation of TCA to evaluate the occurrence of the conflict movement behavior. If the value of TCA is equal to or greater than zero, then DCPA is happening or going to occur in the future. Thus, a CoE is able to be determined as cluster of conflict (CoC). Finally, the accumulated set of CoCs is a set of maritime trajectories with conflict situations, called a cluster of conflict trajectory (CCT), represented as $CCT_k = \{d_{cpa}^k, t_{start}^k, t_{tca}^k, t_{end}^k, CT_m^k\}$, where $t_{start}^k < t_{tca}^k < t_{end}^k$. CT_m^k is a set of subtrajectory belongs to CCT_k, which includes m subtrajectories. The location sequence of each subtrajectory starts from time t_{start}^k to t_{end}^k. In each CCT_k, the distance at closest point of approach d_{cpa}^k is identified at time t_{tca}^k.

B. Situation-aware Classification

In accordance with COLREGs, the discovered CCTs are classified by *Situation-aware Classification* module into three encounter situations: crossing, head-on, and overtaking, as shown in Fig. 2. COLREGs also suggests maneuvers to avoid a collision. Although navigators base anti-collision actions on the specific context and their previous experience, they also draw on the principles outlined in COLREGs, particularly in a potential collision situation. Thus, different CCTs associated with a given encounter situation present similar anti-collision behaviors. Therefore CCTs are classified into specific classes of situation-aware CCT. Thus, when ships encounter each other and the distance between them is shrinking, the user ship will characterize the encounter situation based on the bearing of the approaching ship (target ship). In the example presented in

Fig.3, the user ship and the target ship are on a bearing of 010-112.5 degrees, which means that the operator is encountering a potential "crossing" collision.

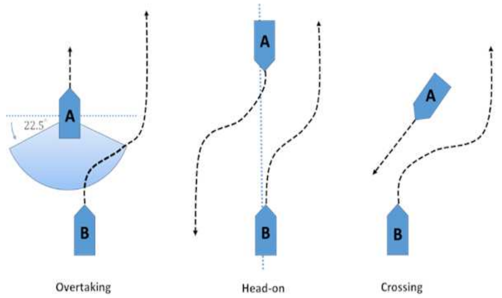

Fig. 2. Potential collision situations described in COLREGs

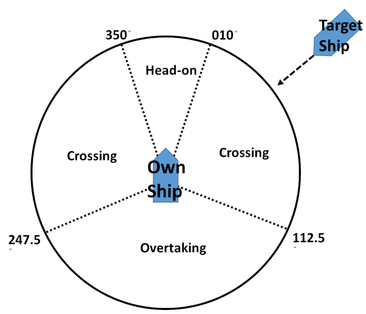

Fig. 3. Characterization of encounter situation

C. Maneuvering Action Extraction

The module of *Maneuvering Action Extraction* is responsible for identifying behavior of ship maneuvering to prevent a potential collision from CCTs, a set of spatial-temporal sequential points associated with anti-collision movements. In practice a ship could avoid collision by taking action in altering course or changing speed in encounter situations. However, studies of real-world data [12] have shown that ships tend to change their course only to avoid a collision.

Nonetheless, the extraction of anti-collision actions is not a trivial problem due to the fact that trajectory data brings with it a degree of uncertainty. Location information tends to be unreliable, due to inaccuracies in GPS measurements or incomplete data caused by radio signal attenuation or loss.

We developed an extraction scheme based on linear regression to overcome the problem of uncertainty in identifying features of anti-collision actions. We first transform raw AIS trajectory data into a sequence of course changes. This sequence can be regarded as a signal. Linear regression is used to smooth out short-term noise and highlight longer-term mobility trends to provide a smooth window size W_s. The zero-mean-signal is then used to extract potential anti-collision actions. Finally, a sliding filter for action correlation is defined as a mask of length F_s using all '1's with the aim of eliminating abrupt fluctuations and generating a sequence of anti-collision actions. A subsequence with length F_s is denoted as $sub(F_s)$. Any action in a $sub(F_s)$ can be identified as an anti-collision action. $Size(sub(F_s)) = F_s$, where $Size(sub(F_s))$ returns the number of absolute values greater than 0 in $Size(sub(F_s))$. After the process of *Maneuvering Action Extraction*, each AIS trajectory in CCTs can be transformed into a sequence of anti-collision actions $\{A^1_{type}, A^2_{type}, A^3_{type}, ..., A^{t_i}_{type}\}$.

D. Anti-Collision Pattern Mining

At the final stage, *anti-collision pattern mining* module generates anti-collision patterns for each specific encounter situation. Our results confirmed that CCTs present similar anti-collision behaviors in similar encounter situations. However, conventional sequential pattern mining is not applicable to raw AIS trajectory data. Any irregularities or asynchronous sampling events would prevent the ship movement from duplicating a given trajectory, even if the movement behavior of the ship is similar to that of other ships. After the process of *Maneuvering Action Extraction*, each AIS trajectory data is transformed into a sequence of specific anti-collision actions. Thus, the problem of discovering similar trajectories can be processed as a problem of conventional sequential pattern mining. Action feature extraction is used to transform each location-based trajectory into an action-based trajectory, i.e., a symbolic sequence. This opens the door to using conventional sequential patterns for anti-collision pattern mining. For a given MinSup, we adopted the Prefixspan algorithm [6] to discover anti-collision patterns. Note that this leads to the generation of a large number of sequential patterns, some of which are contained in other super patterns. We adopted the method used to deal with the longest common subsequence problem to prune out patterns that are fell into a subset of other patterns in order to ensure that every anti-collision pattern is mutually exclusive.

IV. Experiments

The experiments in this study are designed for three objectives. First, we present and statistically analyze the discovered results on a real AIS trajectory dataset. Second, sensitivity analysis on parameters is investigated to show the impact of parameters on the discovery of anti-collision pattern.

The AIS trajectories are obtained from the data received by AIS network. AIS data records the ships' movement data, including unique identification, location, course, speed, and timestamps. The trajectory data is able to extracted by a temporal ordered sequence of AIS points. We selected a dataset covering a period of six months, which included 170,770 trajectories and 7,176,401 spatial-temporal points in an open-sea area of 100km*100km. As we mentioned before, the raw AIS trajectory data is irregular and asynchronous. The pre-process for data interpolation is required for experiments. Furthermore, the experiments are conducted based on a prototype provided by our previous demo work [5]. The prototype is improved for our experimental analysis and visualization.

A. Discovered result analysis

In this section, we demonstrate the effectiveness of our proposed framework by case analysis. According to the best experimental results on our dataset, the parameters for distance $d_o = 5$km for conflict trajectory clustering. The window size W_s is assigned using length of 5 for linear regression smoothing and the sliding filter for action correlation is a mask with length $F_s = 3$.

Following conflict trajectory clustering, CCTs were detected. The CCTs were then classified into three groups using the encounter situation classification module: Overtaking, Head-on, and Crossing. The result of statistic analysis is shown in Fig.4. The crossing situation is the majority of encounter situation in our dataset. Then, the anti-collision patterns are discovered for each situation as shown in Fig. 5. Although the number of CCTs varies greatly in different encounter situation (as shown in Fig.4), the number of anti-collision patterns is similar.

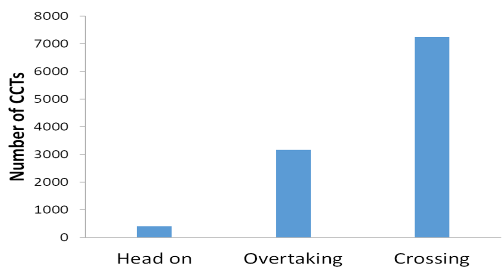

Fig. 4. Discovered situation-aware clusters

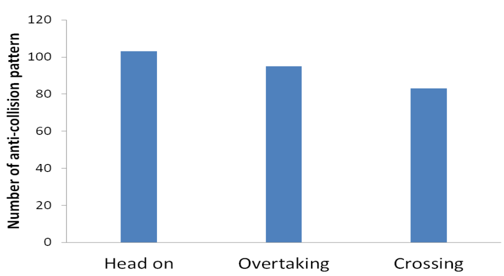

Fig. 5. Discovered anti-collision patterns

B. Sensitivity Analysis

In this section, we evaluate the impact of MinSup for anti-collision pattern mining. Figure 6 shows the experimental results with MinSup varied. Apparently, the number of patterns decreases as the value of MinSup grows. This is a clear indication that the number of discovery patterns and pattern length are both strongly affected by MinSup. This implies that the system determines the frequency with which a pattern appears. Based on our experiment results, when setting up MinSup, it is important to consider the distribution of the data.

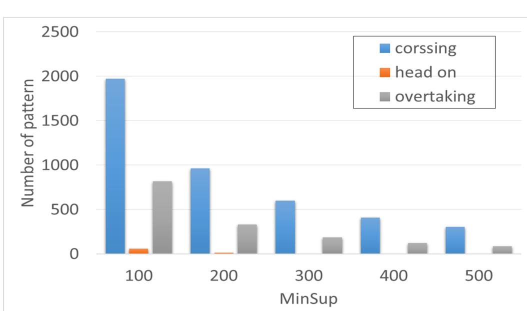

Fig. 6. Effect of MinSup on number of patterns

V. Conclusion and Future Work

This paper addresses that AIS network provides a rich data of ships' movement behavior and presents a novel framework for the characterization of the collision avoidance behavior of ships from historical AIS trajectory data for presentation as anti-collision patterns. The proposed framework of anti-collision pattern discovery includes a conflict trajectory clustering for CCTs detection, a situation-aware classifier, a maneuvering action extractor for the identification of anti-collision maneuvers, and an anti-collision pattern miner to identify the action-based sequences most frequently implemented to avoid collisions. A prototype of proposed system, namely maritime anti-collision pattern miner, was built and evaluated using real-world data. The anti-collision patterns identified from AIS trajectory data provides valuable insight into the collision avoidance behavior of navigators. The proposed framework is applicable to the development of pattern-aware collision avoidance systems aimed at improving maritime traffic safety in the future.

Acknowledgment

Po-Ruey Lei was supported in part by the Ministry of Science and Technology of Taiwan, Project No. MOST-108-2221-E-012-003.

References

[1] M. Blaich, M. Rosenfelder, M. Schuster, O. Bittel, and J. Reuter. Extended grid based collision avoidance considering colregs for vessels. *IFAC Proceedings Volumes*, 45(27):416–421, 2012.

[2] S. Hornauer, A. Hahn, M. Blaich, and J. Reuter. Trajectory planning with negotiation for maritime collision avoidance. *TransNav: International Journal on Marine Navigation and Safety of Sea Transportation*, 9(3):335–341, 2015.

[3] A. Lazarowska. Ship's trajectory planning for collision avoidance at sea based on ant colony optimisation. *The Journal of Navigation*, 68(2):291–307, 2015.

[4] P.-R. Lei, T.-H. Tsai, Y.-T. Wen, and W.-C. Peng. Conflictfinder: mining maritime traffic conflict from massive ship trajectories. In *2017 18th IEEE International Conference on Mobile Data Management (MDM)*, pages 356–357. IEEE, 2017.

[5] P.-R. Lei, L.-P. Xiao, Y.-T. Wen, and W.-C. Peng. Capatternminer: Mining ship collision avoidance behavior from ais trajectory data. In *Proceedings of the 27th ACM International Conference on Information and Knowledge Management*, pages 1875–1878. ACM, 2018.

[6] J. Pei, J. Han, B. Mortazavi-asl, H. Pinto, Q. Chen, U. Dayal, and M. chun Hsu. Prefixspan: Mining sequential patterns efficiently by prefix-projected pattern growth. pages 215–224, 2001.

[7] T. Praczyk. Neural anti-collision system for autonomous surface vehicle. *Neurocomputing*, 149:559–572, 2015.

[8] R. Szlapczynski. A new method of ship routing on raster grids, with turn penalties and collision avoidance. *The Journal of Navigation*, 59(1):27–42, 2005.

[9] R. Szlapczynski and J. Szlapczynska. On evolutionary computing in multi-ship trajectory planning. *Applied Intelligence*, 37(2):155–174, 2012.

[10] M.-C. Tsou. Multi-target collision avoidance route planning under an ecdis framework. *Ocean Engineering*, 121:268–278, 2016.

[11] M.-C. Tsou and C.-K. Hsueh. The study of ship collision avoidance route planning by ant colony algorithm. *Journal of Marine Science and Technology*, 18(5):746–756, 2010.

[12] J. Zhang, D. Zhang, X. Yan, S. Haugen, and C. G. Soares. A distributed anti-collision decision support formulation in multi-ship encounter situations under colregs. *Ocean Engineering*, 105:336–348, 2015.