Learning for Prediction of Maritime Collision Avoidance Behavior from AIS Network

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***Abstract*—With the rapid increase in global maritime shipping, there is a great demand for the technology of maritime traffic monitoring to detect inappropriate encountering interaction between ships and prevent ship collision accidents. The Automatic Identification System (AIS) network makes it possible to collect a large volume of maritime traffic data and investigate the collision avoidance behavior of real-world ships. Most collision avoidance systems are based on expert systems and simulations based on the International Regulations for Preventing Collisions at Sea (COLREGs). Those regulations outline the general principles underlying collision avoidance; however, they do not provide specific guidance and fail to account for the complexity of many real-world situations. Furthermore, guidance systems coordinating the movement of a ship must have the capacity to predict the movement behavior of all ships involved in potential encounter situations, and do so as early as possible for anti-collision reaction.**

Our objective in this study was to model the collision avoidance behaviors of human operators in order to formulate a set of realistic trajectory predictions for encountering near collision scenarios. By machine learning approach, the proposed framework is able to learn a model of interaction movement behavior from collected AIS historical traffic data involving near collision situations and then generate a set of predicted trajectories while ships encountering. The proposed model eliminates the need for a priori information related to environmental conditions and the rules governing encounter situations. The resulting projections can be used to suggest anti-collision paths for navigators or to guide the selection of collision-free paths for maritime autonomous surface ships.

Keywords*—*AIS network, maritime traffic data, collision avoidance behavior, encounter situation, trajectory prediction

I. Introduction

The development of the Automatic Identification System (AIS) network has opened the way for advances in monitoring technology for maritime traffic analysis, including abnormal activity detection and collision prevention. 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. This facilitates the tracking and monitoring of vessel location and movement. As shown in Figure 1, AIS tracking data can be collected and 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 apply on analysis of ships' movement behavior and the prediction of the possible collision.

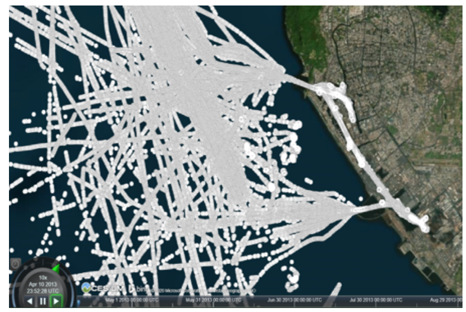


Fig. 1. Screenshot of AIS ship tracking around the port of Kaohsiung, Taiwan.

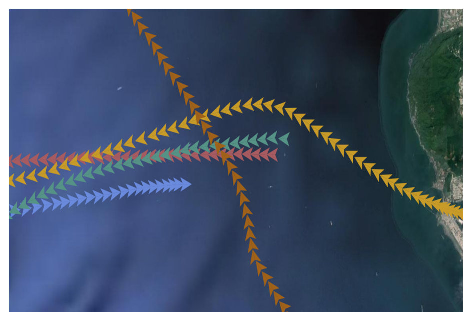


Fig. 2. Real example of multi-ship encountering situation extracted from AIS network

In maritime traffic, the International Regulations for Preventing Collision at Sea (COLREGs) represent standard anti-collision protocols for maritime environments. In an encounter situation, all ships involved are expected to comply with the COLREGs to prevent collision. Thus, previous research into maritime collision avoidance is based on the COLREGs combined with expert opinions and simulated data [4], [9], [10], [6], [8], [1], [5].

However, encountering situations are considerable complexity beyond the scope of regulations in the real world [7]. In contrast to vehicles in road networks, ships at sea are free to move in any direction. The COLREGs define three types of two-vessel encounters and corresponding procedure aimed at preventing collisions. This highly-simplified scheme cannot cover all possible collision situations, such as those involving several ships approaching from different directions at same time (as a real-world example shown in Figure 2). It is obvious that in practice, maritime collision avoidance depends heavily on the experience of navigators.

For accurate prediction of anti-collision behavior, it is

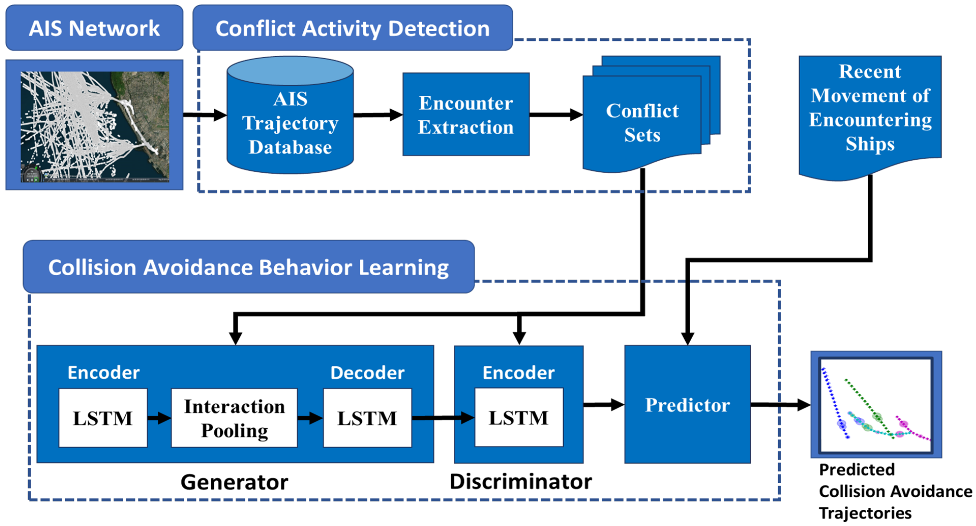


Fig. 3. Overview of detection-and-learning framework

therefore necessary to learn collision avoidance behavior from real ship movement data. In this work, the ship trajectory is generated by AIS network. Such trajectory data records the ships' true movement and implies the maneuvering behavior of navigators hidden in the data, including maneuvering behavior for collision avoidance. Based on collected AIS trajectory data and machine learning technique, our objective in this study was to develop a framework of learning and prediction to establish a model of the collision avoidance behaviors in order to formulate a set of realistic trajectory predictions for encountering near collision scenarios.

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 evaluate its performance using a real-world dataset collected from the AIS network. Finally, we summarize our conclusion and future work in Section V.

II. Framework Overview

As shown in Figure 3, we formulated learning and prediction of collision avoidance behavior by detection-and-prediction framework, using a *conflict activity detection module* and a *collision avoidance behavior learning module*.

1) **Conflict activity detection module.** The conflict activity detection module cleans up the AIS data by organizing the data points into sequential trajectories and clustering the ships to form groups indicating conflict activity. Then, the processed conflict sets serve as input for collision avoidance behavior learning module to enhance training efficiency and effectiveness.
2) **Collision avoidance behavior learning module.** This module is tasked with predicting the trajectories of other ships and generates collision avoiding trajectories as anti-collision recommendations. Note that the proposed scheme does not base the predictions on theoretical rules but rather on the model learned from the conflict activity of historical AIS data, which is largely the product of human decisions in real-world encounters.

III. Detection-and-Learning for Prediction of Collision Avoidance Behavior

In this section, we present detailed procedures for the two main modules of the proposed framework.

A. Conflict Activity Detection

A high-quality training dataset is critical for machine learning. However, according to statistics published by the Maritime and Port Bureau of Taiwan, there are only 20 to 40 collisions worldwide each year. Therefore, a real-world collision dataset would be insufficient for in-depth behavior analysis.

For learning collision avoidance behavior effectively, the task of conflict activity detection module is to create high-quality training dataset from the trajectory data collected by AIS network. The module analyzes historical data related to maritime traffic in order to identify the traffic situations involving conflicts in AIS trajectory data. Traffic conflict is identified as a near collision situation, which refers to ships movement that could lead to a collision if no evasive action is taken. We referred to these situations as conflict activity. A specific set of trajectories associated with conflict activity, referred to as a conflict set, is identified for learning the model of collision avoidance behavior. The encountering ships within conflict situation could result in a collision unless evasive actions were taken. Thus, we can reasonably assume that conflict sets should contain the collision avoidance behavior of ship navigators and could be the high-quality training data for effective learning results.

The method proposed for the detection of these events is based on our previous work [7]. Note that AIS data may include inaccurate GPS measurements and that slow transmission speeds can also make it difficult to determine the time that conflicts occurred. Thus, before identifying the ships involved in a conflict, we segment the AIS records $\{r_1, r_2, ..., r_n\}$ into multiple trajectories $\{T_1, T_2, ...T_n\}$. Each T_i contains numbers of positions $p_i^t = \{x_i^t, y_i^t, c_i^t, s_i^t\}$ respectively , indicating the latitude (x-axis), longitude (y-axis), course, and speed at time

t. The sampling rate of AIS varies according to the speed of the ship; therefore, we interpolated the positions of the ships per minute and recalculated the speed and course as well.

The definition of a conflict activity is based on the distance between two trajectories. We stipulated that a conflict activity occurs when the distances between the positions in trajectories $\{T_1, T_2, ...T_n\}$ are less than a user-defined critical distance d_c (Eq.1). The positions of the two ships (ship A and ship B) when the conflict begins (the starting point in Eq. 2) are respectively denoted as $P_A^{t_{start}}$ and $P_B^{t_{start}}$. The distance at closest point of approach (CPA) is used to determine whether the two ships are approaching each other (i.e., a potential collision). The position of each ship at time t is determined by adding the effects of its current course to its start position (Eq. 3).

$$dist(T_A, T_B) < d_c \tag{1}$$

$$p_A^{t_{start}} = (x_A^{t_{start}}, y_A^{t_{start}}, c_A^{t_{start}}, s_A^{t_{start}}) \tag{2}$$

$$P_A(t) = p_A^{t_{start}} + t(cos(c_A^{t_{start}}), sin(c_A^{t_{start}})) \tag{3}$$

The time corresponding to the CPA is denoted as t_{CPA}. We substitute t_{CPA} into the distance formula to determine the distance between the ships at the CPA, as follows:

$$DCPA_{P_A,P_B} = |P_A(t_{CPA}) - P_B(t_{CPA})| \tag{4}$$

The two trajectories are deemed to be close to each other if $t_{CPA} > 0$ and $d_{CPA} < 1nm$. If $t_{CPA} \leq 0$, then the ships have already passed the CPA. If $d_{CPA} \geq 1nm$, then we check whether the following three points along the course are remain at a safe distance. If so, then this point is adopted as the end of the conflict.

B. Collision Avoidance Behavior Learning

Our objective in this work is to model the collision avoidance behaviors of human navigators from real-world data and then to formulate a set of realistic trajectory predictions for anticipated encounter situations. More specifically, we sought to learn a behavioral model related to ship-to-ship interactions in near-collision situations and then predict the future trajectory of all ships with possible collision avoidance behavior. To achive our aim, the collision avoidance behavior learning module is developed as a Generative Adversarial Networks (GAN) with long short-term memory (LSTM) based encoder-decoder architecture, which is an extension of the Social GAN (SGAN) proposed by [3]. Taking into account the human-human interactions, SGAN is proposed for predicting trajectories of pedestrians in a crowd.

The module design is illustrated in Figure 3, which is designed as a GAN model and composed of LSTM based generator and discriminator. A GAN trains two competing neural networks simultaneously [2]. Generator G learns the data distribution with a priori input latent variable z to represent noise, resulting in $G(z)$. The other network is discriminator D, the inputs of which are randomly sampled from AIS data S_i^t and the generated data $\hat{S}_i^t$. The discriminator classifies the inputs as ground truth data (labeled 1) or data generated using $G(z)$ (labeled 0). The objective function of the training procedure is a two-player min-max game. In this paper our aim was to generalize the dynamic decision behavior of the human navigator in a potential conflict activity. The generative model learns the data distribution for a range of circumstances in order to predict the decisions of a human navigator. The generator consists of two LSTM layers for encoding and decoding, and the discriminator contains an LSTM for classification.

Specifically, the generator adopts an interaction pooling layer to capture the anti-collision interaction within a conflict activity. In this work, the interaction pooling layer not only captures the position changes of ships in a neighborhood (as does the social pooling layer of the SGAN), but also takes the consideration of speed changes between ships to improve the effectiveness of trajectory modeling and prediction.

IV. Experiments

To verify the proposed detection-and-learning framework (***D&L***), we extracted a dataset from AIS data pertaining to the region surrounding the Port of Kaohsiung for the period between March and September 2013. This included 21,202,212 records related to 5,202 individual ships. After conflict activity detection module processed, there are 11,493 conflict sets are detected. We assigned 80% of the dataset to training, and the remaining 20% for validation and testing. Due to their enormous inertia, ships must initiate turns early to avoid collisions. We therefore adopted the first five points as the observation length (input) (i.e., within the first five minutes of conflict trajectories) and the remaining points as the prediction length (output).

A. Metric for comparison

Average displacement error (ADE) and final displacement error (FDE) are taken as metrics for performance comparison.

1) *Average Displacement Error* (ADE) is the average root mean square error (RMSE) between ground truth coordinates and predicted coordinates over all prediction steps.
2) *Final Displacement Error* (FDE) is the root mean square error (RMSE) between ground truth coordinates and predicted coordinates in the final prediction T'.

B. Performance comparison

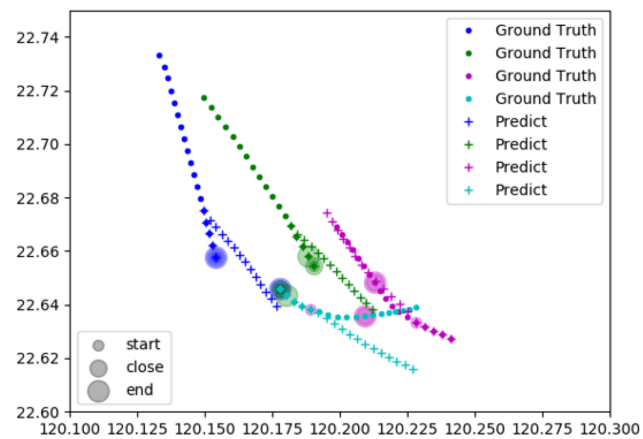
We evaluated the performance of the proposed framework in three conflict situations: head-on, crossing, and overtaking. defined by COLREGs. In addition to these two-ship scenarios defined by the COLREGs, we considered the case of multiple ships. The conflict situation of multiple ships is evaluated for effectiveness. We compared the performance of the proposed framework with that of three baseline methods, ***Linear***, ***LSTM***, and ***SGAN***.

Figure 4 presents a comparison of ADE and FDE results, as indicated in kilometer. The methods based on GAN were capable of learning models of greater complexity and therefore outperformed linear regression and traditional LSTM. Nonetheless, the proposed framework ***D&L*** which concatenated the velocity did perform better than ***SGAN***.

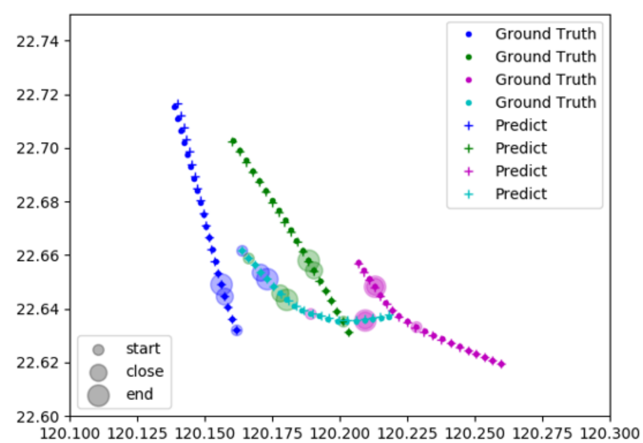
For the sake of illustration, a demonstration comparison of multi-ship conflict situation is presented in Figure 5. Compared with the prediction result of SGAN shown in Figure 5(a), the proposed ***D&L*** takes the continuous velocity of the ships under consideration, its trajectory prediction (presented in Figure 5(b)) is closer to the paths maneuvered by the human navigator.

Metric	Dataset	Linear	LSTM	SGAN	D&L
ADE	Head on	11.75	8.04	0.39	**0.36**
	Crossing	9.98	5.39	0.47	**0.42**
	Overtaking	11.15	4.54	0.67	**0.65**
	Multi-ship	9.1	4.1	0.07	**0.06**
Average		10.49	5.52	0.4	**0.38**
FED	Head on	9.85	7.82	0.87	**0.77**
	Crossing	10.26	5.38	0.95	**0.9**
	Overtaking	11.16	4.52	1.33	1.35
	Multi-ship	8.26	4.09	0.12	**0.11**
Average		9.88	5.45	0.82	**0.78**

Fig. 4. Evaluation results of proposed and baseline methods



(a) SGAN prediction result.



(b) D&L prediction result.

Fig. 5. Demonstration comparison of multi-ship conflict situation.

V. Conclusion and Future Work

In this paper, we propose a machine-learning framework called detection-and-learning, which is based on LSTM-based GAN model. The proposed framework learns collision avoidance behavior from trajectory data collected by the AIS network. This framework can be applied to formulate a set of realistic trajectory predictions with anti-collision behavior in potential collision situations. The proposed framework also makes it possible to model complex encounter situations, such as those involving multiple ships converging from multiple directions. For the future work, the resulting projections can be used to suggest paths for human navigators to improve the safety of maritime traffic or to guide the selection of collision-free paths for unmanned surface vehicles.

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