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A Data-Driven Approach for Collision Risk Early Warning in Vessel Encounter Situations Using Attention-BiLSTM

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ABSTRACT Collision risk early warning is critical to sailing safety in vessel encounter situations because it provides ship officers with sufficient time to react to emergencies and take evasive actions in advance. In this study, we take spatiotemporal motion behaviors of encountering vessels into account since vessel motion behaviors have great influences on the occurrence of a dangerous situation. For this purpose, a data-driven approach is proposed to associate the motion behaviors with the future risk and early prediction of risk is achieved through classifying the behaviors into corresponding risk level. Specifically, we first derive a sequence of relative motion features between encountering vessels to characterize the spatial interactions that vary over time. Then a novel deep learning architecture, which combines bidirectional long short-term memory (BiLSTM) and attention mechanism, is developed to capture the spatial-temporal dependences of behaviors as well as their impacts on future risk. In particular, the BiLSTM is able to discover correlations among behaviors and the attention mechanism can emphasize the key information relevant to the risk prediction task. Exploiting the advantages of these two mechanisms makes the risk prediction more reasonable and reliable. Extensive experiments using ship trace data from the Yangtze River Estuary demonstrate that the proposed Attention-BiLSTM approach outperforms conventional LSTM in terms of accuracy and stability. Moreover, the real-time capability of the approach gives it a significant potential for use in predicting collisions at the early stages.

INDEX TERMS Collision risk, vessel encounter, early warning, spatial-temporal model, bidirectional LSTM, attention mechanism.

I. INTRODUCTION

Maritime transportation is the major mode of transportation for world trade. The continued growth of the global economy has increased the need for ships with larger cargo-carrying capacities and faster sailing speeds. However, the resulting increases in heavy traffic flow have made maritime accidents a complex problem in most waterways [1]. In busy water areas with dense traffic, ship-ship collisions are the most frequently occurring accidents and account for nearly 60% of all maritime incidents [2].

To prevent collisions and improve navigational safety, a variety of risk assessment models, including accident frequency [3], accident consequence estimation [4] and probability estimation models [5]) have been extensively studied. However, most of the models developed to date fail to incorporate methods for the early warning of collision risk and instead have tended to focus on the instantaneous assessment of collision risk. Even when a vessel officer is aware of an immediate collision risk, they often have neither the time nor the space to maneuver to avoid collision. For example,

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in 2018, the "Sanchi" and "CF crystal" were involved in a maritime collision in the East China Sea outside of the Yangtze River Estuary. According to the official accident report, the main cause of the collision was the lack of perception by either crew of the potential risk at the initial stage of the encounter. In particular, the International Regulations for Preventing Collisions at Sea (COLREGs) [6],proposed by International Maritime Organization (IMO) suggest that it is necessary to allow more time to assess individual situations and that collision avoidance action should be taken within a sufficient time frame. The evidence to date supports the idea that it is extremely important to warn officers as early as possible to allow them sufficient time to react to emergencies and take actions to avoid collision.

The factors enumerated above motivated this study on the use of early risk warning in collision avoidance techniques and decision support systems for safe vessel navigation. The main advantage of collision risk early warning lies in its ability to aid encountering vessels in avoiding a close-quarters situation [7], i.e., a situation in which a collision cannot be avoided through the efforts of only one vessel. Unfortunately, most existing risk assessment approaches do not have this capability.

A collision is the result of a sequence of motion behaviors of all vessels involved in an encounter situation [8]. In other words, the motion behaviors between vessel pairs have a potential impact on the future collision risk. For example, the relative angle between two ships can affect the probability of collision. A ship encounter is essentially a continuous series of movements on the part of the involved vessels. These spatiotemporal motion behaviors determine, to some extent, the subsequent risk status. It is therefore necessary to use motion behavior series in making reasonable risk predictions. However, influenced by the encountering vessels and waterway environment, the ship motion behaviors will exhibit a great of uncertainty during the encounter process. Specifically, the individual vessel may change its original course and velocity given the external pressures provided by the presence of encounter vessels (for example, the reactions to avoid collision). The uncertain motion behaviors increase the complexity of risk prediction task. To this end, we relate the motion behaviors within a specified time window to the possible risk that might occur in the future. By learning from historical data, the relationship between motion behavior and future risk can be established. Using this approach, the relationship between continuous motion behavior and future collision risk can be modeled as a time series classification task.

Recently, a number of learning-based technologies have been proposed for effectively solving complex problems in different fields [9], [10]. Among these, long short-term memory (LSTM) networks have been used to successfully perform various time series representing and classification tasks [11], [12]. The LSTM approach can be extended to the development of a collision risk early warning architecture. Because of their heavy masses and large inertias, ships require longer steering and acceleration processes than vehicles. The inertial properties of a ship also produce a strong correlation between its current motion and previous motion states. Effectively representing this contextual associated information on motion behavior is the key to improving risk prediction performance. To achieve this, the proposed model employs a bidirectional structure to capture the strong temporal correlation inherent in motion behaviors. This bidirectional structure overcomes the limitations of conventional structure of LSTM, which tends to ignore past relevant behavior information and result in the loss of contextual association. Besides, the motion behaviors occurring in various time segments also have different impacts on the future collision risk during the encounter process. For example, the acceleration or avoidance of a ship during one specific time segments can have a greater impact on the collision risk than actions undertaken during other time segments. It is therefore useful to distinguish the contributions of various motion behavioral features using weight coefficients. This approach has been shown to improve risk prediction accuracy. To impose such a weighting, we propose a deep learning architecture based on the application of an attention mechanism to the output of the bidirectional LSTM (BiLSTM), which is widely used in the field of natural language processing.

The main contributions of this article to ship collision risk early warning research are as follows:

- Owing to the situational complexities and uncertainties associated with motion behavior during ship encounters, determining the complex relationship between motion behavior and future collision risk is an exceedingly difficult task. In this article, we propose a data-driven approach to risk prediction based on the assessment of spatiotemporal motion behaviors. The relationship between behavior and risk is modeled using a time series classification architecture in which the collision risk level is applied as the class label of a given motion behavior sequence. By doing so, we transform the risk prediction problem into a time series classification task, which makes the prediction of risk more reliable and easier to implement.
- The performance of risk prediction is highly dependent on the validity of the models describing and understanding the spatiotemporal motion behaviors of vessels. Our risk prediction architecture adopts a bidirectional structure for LSTM to capture the temporal correlation between current and previous motion behaviors. As the motion behaviors in different segments have a varying impact on future collision risk, an attention mechanism is adopted to distinguish the contributions of behavior feature segments. By fully exploiting the advantages of these two sequential learning mechanisms, the temporal dynamics of motion behavior can be effectively modeled, making risk prediction more accurate and realistic.
- The proposed method enables collision risk prediction at earlier stages of the encounter process, thereby providing ship officers ample time and space to react to

emergencies and take evasive action. We believe that the outcome of this study can be applied to navigational support in densely trafficked waters and will encourage safe navigation in encounter scenarios to reduce the occurrence of ship collisions.

II. RELATED WORK

Risk perception and assessment are important in the avoidance of collision in ship encounter situations. A number of studies have been devoted to risk assessment and collision detection. One output of this research has been the concept of ship domain, which is unique in its emphasis on the safety region. First proposed by Fujii [13], the ''ship domain'' represents the smallest geometric shape around a ship that allows ship officers to estimate the collision risk of the ship. Any violation of the ship domain is considered to be a threat to navigational safety and a potential source of collision accidents. The ship domain can be defined using three shapes, namely, circles [14], ellipses [15] and polygons [16], and is primarily determined by expert experience. In most cases, the shape and size remain unchanged during a voyage regardless of the actual traffic and encounter situation. To refine the ship domain concept, Wang [17] designed the so-called fuzzy quaternion ship domain, for which the size is determined in terms of parameters relating to the forward, backward, starboard radii and port-side radii. Nevertheless, the determination of the size and form of the ship domain is subject to a variety of factors, including the speed and length of the ship, the traffic flow density, the hydrometeorological conditions of the region, etc. Thus, determining a universal ship domain that can satisfy all situations remains an extremely challenging problem. Furthermore, because the ship domain represents the minimum-safety region, Szlapczynski and Szlapczynska [18] claimed that using ship domains with specialized shapes can result in risk warnings occurring too late for ship collision avoidance. Because of the factors described above, the ship domain is not an appropriate tool for use in a collision early warning index.

The collision risk index (CRI) [19], another critical indicator of ship collision risk, is a numerical value calculated using various influencing factors. When the CRI exceeds a preset threshold, a collision alarm should be triggered. Of the multiple definitions of CRI, the most widely used combines the distance closest point of approach (DCPA) and time closest point of approach (TCPA) parameters to measure collision risk. Specifically, Lisowski [20] defined the CRI as a weighted sum of the squares of DCPA, TCPA, and the ship-to-ship distance, with the weights of the respective parameters determined by the ship type. Beyond the DCPA and TCPA, there are numerous indicators that can estimate ship-ship collision risk. Zhao *et al.* [21] incorporated the values of relative distance and speed into the CRI. To assess risk in real time, Koldenhof *et al.* [22] proposed a CRI incorporating the encounter angle in different situations and assigning separate weights for each factor. Although the CRI is a practical measure of collision risk, it emphasizes immediate collision risk and fails to take into account motion behavior and the evolutionary process of encounters.

The wide adoption of Internet of Things (IoT) technology in the marine environment [23], [24] has led to the use of automatic identification systems (AISs) to provide huge amounts of data for modeling ship motion behavior. Li *et al.* [25] proposes an adaptive distance measure algorithm for time series, which aims at analyzing the similarity of ship motions from AIS trajectory data. Huang *et al.* [26] designs a GPU-accelerated compression algorithm to extract ship motion patterns behind massive AIS data. AIS can support ship motion pattern modeling and analyzing, and it can also provide real-time for motion prediction. Motion prediction is regarded as another fundamental approach to collision warning. Under this approach, any crossing of the predicted trajectories of encountering ship pairs indicates a high probability of collision. Li and Jilkov [27] used ship location, velocity, heading angle, and acceleration extracted from AIS data to predict upcoming ship positions. However, this model neglect ship maneuverability, which can significantly affect ship motion. Wiig *et al.* [28] proposed a compact vectorial representation to represent marine vessel maneuverability parameters such as mass, Coriolis force, damping matrix, restoring force, and disturbance to increase the accuracy of trajectory prediction. In most cases, however, these maneuverability parameters are difficult to access. In [29] Perera applied Kalman filtering to historical trajectory data to predict the future trajectories of ships.

Despite their advantages, current motion prediction models have certain problems. Although prediction models are efficient at short-term trajectory prediction, they are limited in their ability to model ship motion over longer periods of time, which can lead to failure in the prediction of future risk. For example, the Kalman filtering state is only directly accessible for subsequent time steps and ignores long-term dependencies spanning several time steps. More importantly, risk warning models based on motion prediction depend on the crossing of future trajectories. This simplified criterion fails to consider the complex relationship between spatiotemporal motion behavior and future collision risk.

Recently, LSTM networks [30], [31] have been used to model the temporal behavior of vehicles and humans. Ma *et al.* [32] developed an LSTM network for highway vehicle speed prediction in which samples of historical speed data ending at time t are input and an estimate of the speed over the interval Δt is output. Alahi *et al.* [33] proposed the Social-LSTM to predict the trajectories of individual pedestrians within a crowd based on the use of a social-pooling layer to explain the interactions between neighboring pedestrians. Ships, however, have unique dynamic characteristics that are not shared by vehicles or pedestrians. Huang *et al.* [34] noted that the high masses of ships have a significant impact on their motion: unlike vehicles, ships cannot abruptly stop, turn, accelerate, or decelerate. The longer times required for a ship to change its motion state provide a strong correlation between current and future

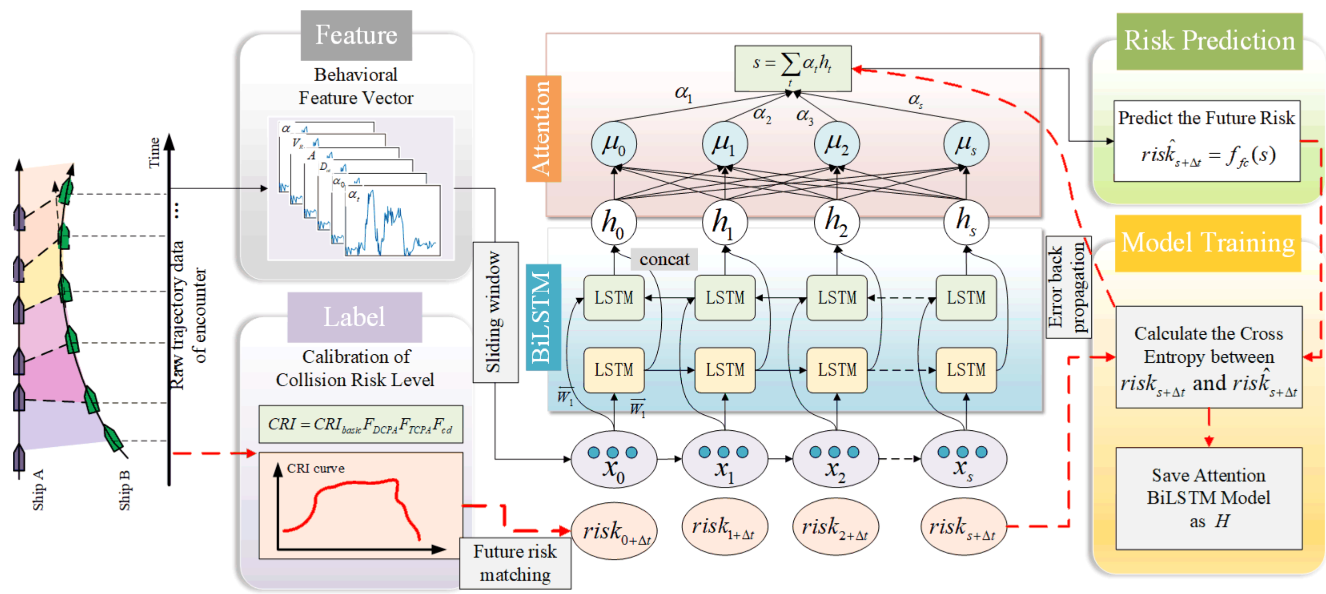

FIGURE 1. Overview of Attention-BiLSTM risk early warning architecture. In the risk prediction phase, motion behaviors are characterized by transforming AIS traces into a sequence of behavioral features via a combination of a fixed set of parameters. The behavioral features are then passed through sliding windows as input sequences X_s of the model, which contains a bidirectional structure and an attention mechanism. The output of the Attention-BiLSTM model is the estimate of the future collision risk level $\widehat{risk}_{s+\Delta t}$. In the model training phase, the estimated future collision risk level $\widehat{risk}_{s+\Delta t}$ is compared with the real risk level $risk_{s+\Delta t}$ by the cross-entropy. Through error backpropagation, the parameters of the Attention-BiLSTM model are trained.

motion states. To address this issue, we adopt the BiLSTM to capture this correlation between motion behaviors. Another important factor is the dependence of the collision risk on the critical motion behavior at a given moment. To quantify the differential impact of motion behavior over different time segments, we introduce an attention mechanism, which can learn the importance of different time segments and capture underlying interactions among features [35], [36]. Originally, the attention mechanism was used to measure the contribution of words or sentences to text semantics.

III. METHOD

To model the relationship between spatiotemporal motion behavior and future collision risk, a data-driven approach with a novel deep learning architecture for collision risk early warning was developed. An overview of the proposed architecture is shown in Fig.1. The entry point is the AIS data produced by the encountering ships, which are analyzed to obtain spatiotemporal information relating to motion behavior. From these data, behavioral features can be extracted and the collision risk level calibrated. The proposed Attention-BiLSTM is then used to relate sequences of behavioral features to future collision risk level. In this architecture, the BiLSTM is used to capture the temporal dependence of motion behavior, and the attention mechanism is then used to establish a more precise collision risk prediction model based on the varying influence of motion behavior on risk.

A. FEATURE EXTRACTION AND COLLISION RISK CALIBRATION

Ship encounter is essentially a stochastic process comprising the motion behaviors of the encountering ships.

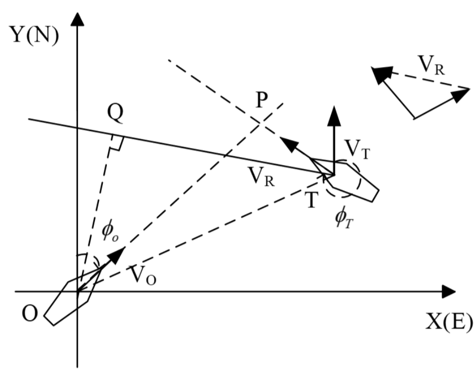

FIGURE 2. Geometric representation of encounter ships.

Many studies [37] point out that valuable information can be extracted from spatiotemporal behavior data. Following this rationale, the ship encounter process can be represented by transforming their AIS traces into a sequence of behavioral features that represent the spatial dependencies between the two ships. By applying a widely used dynamic CRI [1], the collision risk can then be related to the motion behavior sequence over each time interval. In machine learning, these two steps correspond to feature extraction and label calibration, respectively.

The behavior feature vector comprises the relative velocity, course difference, relative distance, and three types of azimuth obtainable via geometric calculation. As shown in Fig. 2, a rectangular coordinate system in which the X- and Y-axes represent east and north, respectively, is established. Expressing the own ship coordinates, course over ground, and velocity as $S_o(lng_o, lat_o)$, ϕ_o and V_o, respectively, and the corresponding target ship values as $S_T(lng_T, lat_T)$, ϕ_T, and V_T, the six motion parameters can be obtained as:

$$V_R = |V_o - V_T| \tag{1}$$

$$\begin{cases} a = sin(lat)sin(lat_t) \\ g = cos(lat_o)cos(lat_t)cos(lng_t - lng_o) \\ D_{ot} = R * arc\,cos(a+b) * \pi/180 \end{cases} \tag{2}$$

$$A = \begin{cases} \phi_o - \phi_T & |\phi_o - \phi_T| \leq 180° \\ 360° - (\phi_o - \phi_T) & |\phi_o - \phi_T| \geq 180° \end{cases} \tag{3}$$

$$\alpha = \begin{cases} arc\,cos(\frac{a}{D_{ot}}) & a \geq 0 \\ 360° - arc\,cos(\frac{a}{D_{ot}}) & a \leq 0 \end{cases} \tag{4}$$

$$\alpha_o = \alpha - \phi_o \tag{5}$$

$$\alpha_t = \alpha - \phi_T \tag{6}$$

where V_R is the relative velocity, D_{ot} is the relative distance, A is the relative course, α is true azimuth, $alpha_o$, $alpha_t$ are own and target ship azimuths, respectively. These six inter-ship motion parameters are then input as features into a risk prediction module in which the feature vector at time t is denoted by x_t, and $x_t = [V_R^{(t)}, D_o t^{(t)}, A^{(t)}, \alpha^{(t)}, \alpha_o^{(t)}, \alpha_t^{(t)}]$.

The COLREGs suggest that the CRI can be used to evaluate the probability of inter-vessel encounters. In this study, the CRI was used to calibrate the collision risk in individual time windows using the optimally effective DCPA and TCPA indicators. DCPA and TCPA can be obtained by geometric calculation as follows:

$$DCPA = D_{ot} \times sin(\angle OTQ) \tag{7}$$

$$TCPA = D_{ot} \times cos(\angle OTQ)/V_R \tag{8}$$

In practice, small values of DCPA or TCPA indicate a high probability of collision risk. To measure collision risk, the CRI combines DCPA and TCPA using the following equation:

$$CRI_{basic} = \left[a_{dcpa} \left(\frac{DCPA}{D_s} \right)^2 + a_{tcpa} \left(\frac{TCPA}{T_s} \right)^2 + a_d \left(\frac{D_{ot}}{D_s} \right)^2 \right]^{-\frac{1}{2}} \tag{9}$$

Although this basic definition of CRI is typically used to quantify the risk of ship collision, the value of using this model as a decision support system for real-time risk assessment has been questioned, and a number of improvements have been proposed to meet efficiency requirements. In this study, we used the CRI proposed in [1] as the index for evaluating dynamic collision risk in a more timely manner than Eq. 9. Compared with Eq. 9, the dynamic CRI in Eq. 10 takes the impacts of different encounter situations into consideration. As investigated on the historical casualty data, the crossing encounters are much more dangerous than other encounter situations.

$$CRI = CRI_{basic} F_{DCPA} F_{TCPA} F_{cd} \tag{10}$$

$$F_{TCPA} = exp^{-TCPA/10} \tag{11}$$

$$F_{DCPA} = exp^{-DCPA} \tag{12}$$

where CRI and CRI_{basic} are the dynamic and basic collision risk indices. F_{TCPA}, F_{DCPA} are the weights of TCPA and DCPA respectively. F_{cd} is a multiplier reflecting the encounter danger degree in different encounter situations. Specifically, according to the different angle of encounter, the encounter situations can be divided into three categories and corresponding value of each multiplier F_{cd} is obtained: overtaking(encounter course is 0-60°, $F_{cd} = 1$), crossing(encounter course is 60-150°, $F_{cd} = 8.5$) and head-on(encounter course is 150-180°, $F_{cd} = 2.34$).

It is obvious from Eq. 10 that CRI is a continuously valued function. However, the continuous CRI values do not directly indicate the urgency of ship collision; that is, even if the value of the CRI is known, the level of danger it represents remains uncertain. Inspired by [38], we divide continuous CRI into 5 discrete levels to rank the severity of the vessel encounters. We sort the CRI values of all samples and adopt the Cumulative Distribution Function (CDF) to determine the threshold for each level, so that the number of samples in each level is the same. The five risk levels are: low (L, $CRI \in [0, 0.15]$); low-middle (LM, $CRI \in [0.15, 0.17]$); middle (ML, $CRI \in [0.17, 0.25]$); middle-high (MH, $CRI \in [0.25, 0.4]$); and high (H, $CRI > 0.4$).

After calculating the behavioral features x_t for each time point over the entire ship-pair trace, the trace can be split into multiple samples (snippets) with a given observation length by a sliding window technique. For each snippet, $X_t = (x_{t-s+1}, x_{t-s+2}, \cdots, x_t)$ is defined as the behavior sequence leading up to time t. At the same time, the ship collision risk level, $risk_t$, at time t can be calculated using Eq. 10. To achieve early risk warning, the risk level must be predicted in advance, making it insufficient to obtain the instantaneous collision risk level $risk_{t+\triangle t}$. Instead, our goal is to predict the collision risk level beyond time interval $\triangle t$ given a behavioral sequence X_t. To do this, the current sequence of the behavior feature should be matched with the future collision risk level to form a time series sample with a label given by $(X_t, risk_{t+\Delta t})$. Using the proposed Attention-BiLSTM algorithm, the relationship between X_t and $risk_{t+\Delta t}$ can be established.

B. SEQUENTIAL MODELING OF MOTION BEHAVIORS USING BIDIRECTIONAL LSTM

As discussed in the preceding sections, the motion behaviors of encountering ships over a specific time interval will have a significant impact on the future collision risk. Accordingly, the proposed model focuses on employing the behavior sequence constructed as discussed in Section IIIA to identify the potential risk, which is also the key to achieving early warning of collisions. For this purpose, the model applies the concept of time series classification to establish the relationship between each behavior sequence and its corresponding risk.

LSTM networks have been shown to be effective in performing many sequential data classification tasks. Unlike feed-forward neural networks, which can only predict output labels based on current input features, LSTM can hold important and relevant information obtained from historical inputs. An LSTM unit performs remembering and forgetting functions by controlling three gates [39] that can remember relevant information obtained in previous time steps and ignore irrelevant data. This process is carried out using the following functionalities and calculations:

1) The forget gate f_t is responsible for filtering past period information on ship motion behavior. Not every action undertaken by a ship during a voyage (in particular, constant actions) will affect the level of risk. The purpose of the forget gate is to filter out, under supervision, information useless to risk determination to reduce the operational time and storage requirements:

$$f_t = \sigma(W_f * [h_{t-1}, x_t] + b_f) \tag{13}$$

where h_t is the vector encoding the ship motion state from times 0 to time $t-1$, which serves as a representation of the ship motion behaviors during this period; x_t is the ship motion behavior feature, which is input at time t; W_f and b_f are the weights and biases in the forget gate, respectively; and σ is the sigmoid function.

2) The input gate comprises i_t, which determines which ship motion behavior information needs to be updated at time t, and $\widetilde{C}_t$, which temporarily records the current input information. If, for example, the ship turns at the current time, t, the input gate allows this information to be updated. The motion state C_t that can be updated includes historical information (before time $t-1$) and the current input information. In this process, C_{t-1} is used in the calculation of C_t; in this recursive manner, information on motion behaviors is stored:

$$\begin{aligned} i_t &= \sigma(W_i * [h_{t-1}, x_t] + b_i) \\ \widetilde{C}_t &= \tanh(W_c * [h_{t-1}, x_t] + b_c) \\ C_t &= f_t * C_{t-1} + i_t * \widetilde{C}_t \end{aligned} \tag{14}$$

3) The output gate o_t selects the ship motion state information that has a significant impact on the risk, and outputs the final ship motion state h_t at time t.

$$\begin{aligned} o_t &= \sigma(W_o * [h_{t-1}, x_t] + b_o) \\ h_t &= o_t * \tanh(C_t) \end{aligned} \tag{15}$$

The ship motion state h_t is the output of the LSTM structure and the input of the attention layer and is used to construct a representation of the motion behaviors between the encountering ships:

$$H(h_t) = \mathbf{arg}\min \sum_{i=1}^{N} (Risk\_Level - H(h_t))^2 \tag{16}$$

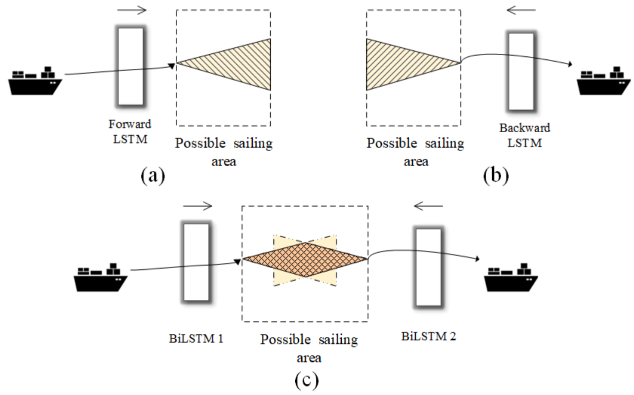

FIGURE 3. Representation of ship motion state with bidirectional motion. (a) Forward, (b) backward, and (c) bidirectional LSTM. Traversing the contextual motion behaviors in both directions enables the capture of temporal dependencies.

Ship motion states tend to be relatively stable owing to the weight and inertia of the vessel. Accordingly, it takes a long time for a ship to transition from one motion state to another, which produces a strong degree of correlation between the current and previous motion states. To model this strong correlation in the time series, a comprehensive network structure must be used to perceive the motion state.

In natural language processing terms, BiLSTM is used to capture the temporal dependencies of contextualized information. It overcomes the limitations of conventional LSTM, which tends to ignore past relevant information, by remembering input information from the past time frames and applying information from the current frame using two separate LSTMs (forward and backward pass). In a manner similar to natural language, ship motion behaviors exhibit high temporal dependencies, and BiLSTM capitalizes on this by capturing the temporal dependencies between the past and current motion states.

The forward and backward LSTM layers embedded within BiLSTM connect with the sub-section layer to provide more comprehensive and sequenced information for the output layer. As shown in Fig. 3, this architecture allows BiLSTM to facilitate a deeper understanding of ship behavior and temporal correlation. In addition to the single-direction LSTM model parameters mentioned above, it is necessary to input backward time series, x_t, and initialize and train parameters $\{\overleftarrow{W}\}$ and $\{\overleftarrow{b}\}$ for backward LSTM. The output of the resulting model h_t will then contain the available information on ship motion behavior:

$$h_t = [\overrightarrow{h_t}, \overleftarrow{h_t}] \tag{17}$$

C. ATTENTION MECHANISM

As mentioned in the previous sections, critical motion behaviors in certain time segments will affect the probability of potential collision. In particular, the acceleration, deceleration, steering, and avoidance actions taken within a certain time interval can have a more significant impact on the potential for ship collision than actions taken during other time periods. More formally, within the time window $X_t = (x_1, x_2, \cdots, x_t)$, the behavior at a specific time point $\widetilde{x_t}$ will have a larger contribution to the determined risk and the prediction results. If, however, only the output of the BiLSTM network at time t, $[\overrightarrow{h_t}, \overleftarrow{h_t}]$, which represents the final motion state (after t time steps) of the ships, is used to predict the future risk (as shown in Eq. 18), the impact of motion behaviors at the individual time points might be lost. The attention mechanism is used to quantify the different impacts of these individual encounter behaviors on collision risk.

The attention mechanism was first proposed for use in machine translation tasks [40]. The primary concept underlying this mechanism is that words and sentences make different contributions to the emotion and meaning of a text. Using the attention mechanism, different attention weights can be assigned to various words to improve the understanding of text semantics. The momentary motion behaviors over the course of a ship voyage can be likened to the words in a text, with the future collision risk corresponding to the emotion and semantics of the text. Using this metaphor, the attention mechanism can be used to quantify the different effects of ship motion behavior on the risk at various time frames:

$$\begin{aligned} p(risk_{t+\Delta t}|x_1, x_2, \ldots, x_T) &= p(risk|\overrightarrow{h_t}, \overleftarrow{h_t}) \\ (\overrightarrow{h_t}, \overleftarrow{h_t}) &= BiLSTM(x_1, x_2, \ldots, x_T) \end{aligned} \tag{18}$$

This approach differs most significantly from the basic LSTM and BiLSTM approaches in that it does not attempt to use the last-moment output state *ht* to summarize the motion behavior over an entire period. Instead, it focuses on the critical motion behaviors of ships at specific time points that produce changes in the risk. As shown in Eq. 19, the motion states at each moment $[h_1, h_2, \ldots, h_t]$ are input to the attention layer. The degree of contribution of each frame is represented by the corresponding attention weight in $[\alpha_1, \alpha_2, \ldots, \alpha_t]$, which is calculated using Eq. 21 based on Bahdanau's attention computational approach [40]. The overall attention is calculated as follows:

$$\begin{aligned} p(risk_{t+\Delta t}|x_1, x_2, \ldots, x_T) &= p(risk_{t+\Delta t}|\overrightarrow{h_1}, \overrightarrow{h_2}, \ldots \overrightarrow{h_t}, \\ &\qquad \overleftarrow{h_2}, \ldots, \overleftarrow{h_t}, \alpha_1, \alpha_2, \ldots \alpha_t) \\ (\overrightarrow{h_1}, \overleftarrow{h_1}, \ldots, \overrightarrow{h_t}, \overleftarrow{h_t}) &= BiLSTM(x_1, x_2, \ldots, x_T) \end{aligned} \tag{19}$$

$$\mu_t = \tanh(W_w h_t + b_w) \tag{20}$$

$$\alpha_t = \frac{\exp(W_\mu \mu_t^T)}{\sum_t \exp(W_\mu \mu_t^T)} \tag{21}$$

$$s = \sum_t \alpha_t h_t \tag{22}$$

where $h_t = [\overrightarrow{h_t}, \overleftarrow{h_t}]$; W_w and W_μ are the weights of the respective fully connected layers; s is the weighted sum of all time steps $[h_1, h_2, \ldots, h_t]$, which represents the motion state of the overall encounter process; and α_t is the normalized weight of each motion state of the ship, i.e., the attention score. Whereas in conventional natural language processing, the attention score is used to describe the contribution of each word to the semantic or emotion of the text, in our early risk warning task, the attention score is applied to quantify the importance of the motion behavior features to the future risk. From this process, the future risk is obtained as $risk = f_{fc}(s)$, where f_{fc} is the fully connected layer. By comparing the cross entropy between the predicted and real risk levels and applying the back-propagation algorithm, the corresponding parameters in the model can be trained. A pseudo-code of the Attention-BiLSTM training process is given as Algorithm 1.

Algorithm 1 Attention-BiLSTM Algorithm for Collision Risk Early Warning

```
Input:AIS data collection C(n)
Output:Risk prediction model H
Compute behavioral features X(k) and risk level of
  encounter ship from C(n)
Generate the training data set M_train and M_test from X(k)
For mini batch M in M_train
    For T time window data M_T in M
        For t=1 to T
            Using forward LSTM to encoder h_t
            Using backword LSTM to encoder h_t
        End For
        Compute Attention score α_t and s
        Compute risk_level from s
    End For
    Training the model H with back propagation
  algorithm
End For
Save the prediction model H
```

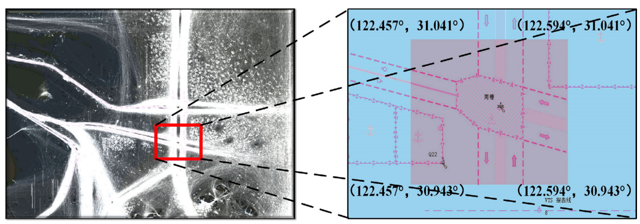

FIGURE 4. Dense traffic flow and nautical chart of Nancao channal.

IV. EXPERIMENT AND RESULTS

A. DATA SET AND MODEL PARAMETERS

From the AIS dataset for the East China Sea, the encountering ship-pair trace data from the Yangtze River Estuary covering January to April 2019 were selected for analysis. The region, covering the longitude range between 122°457′E and 122°594′E, and latitude between 31°41′N and 30°943′N, is a typically busy waterway with dense traffic flow, as shown in Fig. 4. To process the AIS trace data, we used time windows with a length of 20 s and a step of 10 s to separate the overall track into different time intervals. Using the method described in Section III, the six motion behavioral features and the CRI values were calculated, and the results saved in a database with 75,115 records.

TABLE 1. Network structure and parameter.

parameter name	parameter value	parameter name	parameter value
sliding window length	20s	batch size	850
sliding step length	10s	learning rate	exponential decay
prediction horizon	30s	optimizer	Adam
lstm size	27	attention size	20
lstm layers	3	grad clip	5
epochs	1000	drop out	0.5

The architecture was designed based on Bahdanau's attention LSTM structure using the network parameters listed in Table 1, which were the optimal parameters determined using the cross-validation set. The input had the dimensions [850, 20, 6], where 850 was the batch size, 20 was the number of time points, and 6 was the behavior feature dimension. The learning rate was adjusted by applying the Adam method in accordance with the convergence speed during the iterative process. The initial learning rate was 10^{-4}.

B. EXPERIMENT AND RESULTS

The proposed model introduces two augmentations to conventional LSTM: BiLSTM and the Attention mechanism. To determine which improvement has a greater impact on prediction performance, LSTM, Attention-LSTM, BiLSTM, and the Attention-BiLSTM algorithm were compared.

Fig. 5 shows a comparison of the respective algorithms' classification accuracies on the training set during the training process. The following are noted in terms of final accuracy and speed of convergence, respectively:

(1) It is seen from the final prediction results in Fig. 5 that the Attention-BiLSTM algorithm (red line) achieves the best prediction accuracy, with the highest point of stability. The accuracy of BiLSTM (green line) is lower than that of Attention-BiLSTM but higher than those of the remaining two algorithms. Relative to the original LSTM, BiLSTM offers features with higher dimensionality for the decision-making model and enables the representation of strong temporal correlations in motion state. The results obtained by the Attention-LSTM algorithm (yellow line) do not differ significantly from those of the conventional LSTM algorithm. Attention-LSTM takes into account the differences in influence of various ship motion behaviors on risk. However, because it lacks a sufficient perception of ship motion behavior, it is difficult for the attention model to exert these advantages. From a machine learning standpoint, the complex Attention-LSTM model feeds into a relatively reduced number of dimensions, resulting in inaccurate prediction results that are only slightly better than those obtained by the LSTM.

(2) A comparison of the rates of change of the four curves in Fig. 5 reveals that the Attention-BiLSTM algorithm has the fastest learning rate during the early training period (the red line has the highest gradient over the first 93 iterations). This demonstrates the effectiveness with which the relationship between motion behavior and the future collision risk is trained by Attention-BiLSTM. In the latter stage of

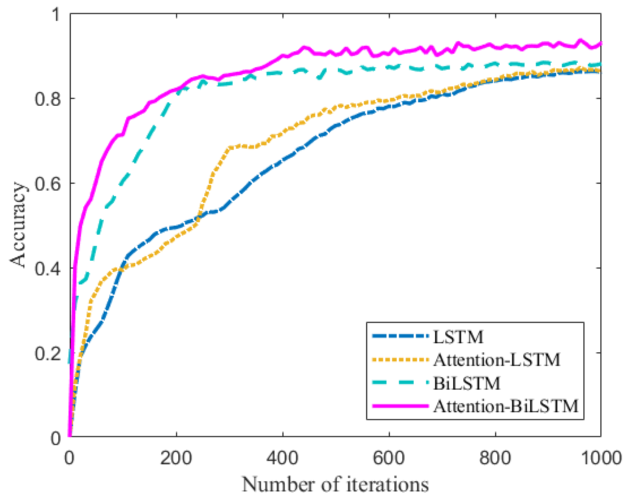

FIGURE 5. Accuracy curves of models on the training set. The convergence rate and accuracy of a model can be obtained from the gradient and peak value of its curve.

training, the prediction accuracy of BiLSTM rises at a similarly rapid rate, although the model tends to converge after about 300 iterations. In terms of model structure, BiLSTM traverses ship behaviors in the forward and backward directions to increase the number of feature dimensions. However, it is relatively simple compared with Attention-BiLSTM and terminates the iteration process prematurely, which is an under-fitting phenomenon. By contrast, the Attention-LSTM model fluctuates significantly in terms of learning speed because it does not fully perceive ship motion behavior information. When the representation created by the model does not completely reflect the motion state of the ship, the performance of the model becomes unstable, especially under the complex model formulation applied using the attention mechanism.

To quantitatively analyze the respective algorithm prediction performance at different risk levels, the recall rate was applied as an evaluation index on the test set. The results in Table 2 and Fig. 6 indicate that all LSTM-based risk prediction models achieved higher recall rates when the collision risk was high. Over five risk levels from low to high, the recall rate of Attention-BiLSTM reached 78.95%, 72.51%, 73.61%, 84.24%, and 87.98% respectively, possibly because the motion behavior of the ship is more typical in high-risk situations. Among the LSTM-based algorithms, Attention-BiLSTM performed the best in terms of average recall rate. These results suggest that the BiLSTM and attention mechanism augmentations are effective in early risk warning.

The stabilities of the four models are compared using box-plots in Fig. 6. In this case, a box-plot with a smaller length corresponds to a higher degree of stability of the model, while the vertical position of the box is proportional to the mean value of the recall rate. Under these criteria, Attention-BiLSTM is relatively stable, as confirmed by the variance values in brackets in Table 2 and the length of the box

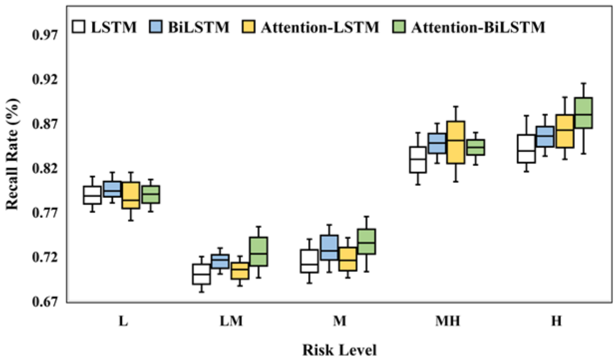

FIGURE 6. Box-plots of recall rate on the test set representing the stabilities of the models at various risk levels.

TABLE 2. The recall rate of risk prediction.

mean(variance)	LSTM	BiLSTM	Attention-LSTM	Attention-BiLSTM
L	78.89 (1.14)	**79.59** (1.03)	78.72 (1.63)	78.95 (1.05)
LM	70.00 (1.23)	71.54 (0.87)	70.42 (0.99)	**72.51** (1.65)
M	71.39 (1.43)	72.89 (1.72)	71.75 (1.40)	**73.61** (1.04)
MH	82.91 (1.71)	84.74 (1.32)	**84.80** (2.57)	84.24 (1.69)
H	84.22 (1.88)	85.51 (1.39)	86.20(2.02)	**87.98** (2.18)

in Fig. 6. A separate analysis of the two mechanisms reveals that, while the recall rate variance of BiLSTM is relatively small, it has a small mean. This suggests that a bidirectional structure is indeed a more comprehensive representation of motion behavior and offers adequate feature dimensions for the model. However, because of its lack of sophistication, BiLSTM has difficulties in fitting the relationship between ship behavior and risk. As mentioned earlier, BiLSTM considers only the last-moment ship motion state $[\overrightarrow{h_t}, \overleftarrow{h_t}]$ as the basis for predicting future risk while ignoring the influence of ship behavior at each prior time point. By contrast, Attention-LSTM has a high variance and an unstable recall rate. As the attention mechanism takes into account the ship behavior at each time step, the model can produce an unstable prediction effect owing to individual differences in behavior. The combination of the two mechanisms not only enriches the bidirectional feature expression but also increases the high-dimensional fitting degree of the model. As a result, Attention-BiLSTM achieves the best prediction effect in terms of accuracy and stability.

C. CASE STUDY AND INTERPRETABILITY OF ATTENTION

From the above experiments, we have verified that the Attention-BiLSTM algorithm has good prediction performance in the overall sample. To further study the concrete examples, in this part, we analyze the difference between the predicted risk level and the true value in the naturalistic ship encounter scenario. Then, through the calculated attention weight, the interpretability of the risk prediction model is analyzed.

As stated in the literature [6], encounter situations between ships can be divided into three categories: crossing, head-on, and overtaking. In different encounter situations, the impact of motion behavior on future collision risk might differ. Figs. 7(a), (b), and (c) show the changes in ship risk and the evolution of motion behavior under the respective situations. It is worth noting that the risk levels shown in the figure represent the collision risks after 30 s. We then compared the risk levels predicted by the three models with the ground-truth risk level and found that the risk predicted by Attention-BiLSTM was the most consistent with the ground truth. In particular, the real collision risk level changed as the two ships met and departed. The LSTM was not able to catch this change in a timely manner and tended to maintain the risk level in the previous period. By contrast, Attention-BiLSTM was able to track the change in the real value in a timely manner, thus yielding a better real-time prediction performance.

Using Eq. 21, we calculated the attention scores at each time interval of motion behavior. This score represents the contribution of encounter behavior at a given time to the risk level, with a higher score representing a greater impact of ship behavior on risk. The respective attention score results are shown in the sub-images on the right in Figs. 7(a), (b), and (c). From the results, it is seen that a high score reflects the portion of motion in which the state changes to some extent. Intuitively, an area with a high attention score will essentially represent a turning point of the trace or the point at which the two ships begin to approach. The results indicate that the attention mechanism is very sensitive to changes in the ship motion state and is therefore useful in predicting the collision risk in a timely manner. It is, in fact, apparent that the changes in the attention score are more significant in high-risk windows, which also explains why the proposed model has a higher recall rate for high-risk situations and demonstrates how the attention mechanism can effectively quantify the differential influence of encounter behavior on risk.

To further assess the effectiveness of the Attention-BiLSTM risk prediction algorithm, we focused on the areas in which the risk changes under different situations. In Fig. 8, the corresponding areas in Figs. 7(a), (b), and (c) have been enlarged to enable a more detailed analysis of the risk prediction results. The far-left histogram shows the future risk level, which is the ground truth. The degree to which a histogram of predicted risk is consistent with the ground truth is proportional to the prediction accuracy of the associated algorithm. It is seen that the Attention-BiLSTM model is more consistent than the LSTM with the change in true risk. In Fig. 7(a), the risk level MH lasts for two minutes and, while LSTM does not detect it, Attention-BiLSTM senses this risk level a minute and a half in advance. These results are confirmed in Figs. 8(b) and (c), in which the Attention-BiLSTM algorithm demonstrates better risk prediction performance than LSTM in both head-on and overtaking situations. The original LSTM does not update as the risk changes and tends to retain the risk predicted during the previous moment, an approach that is inappropriate for the early risk warning task.

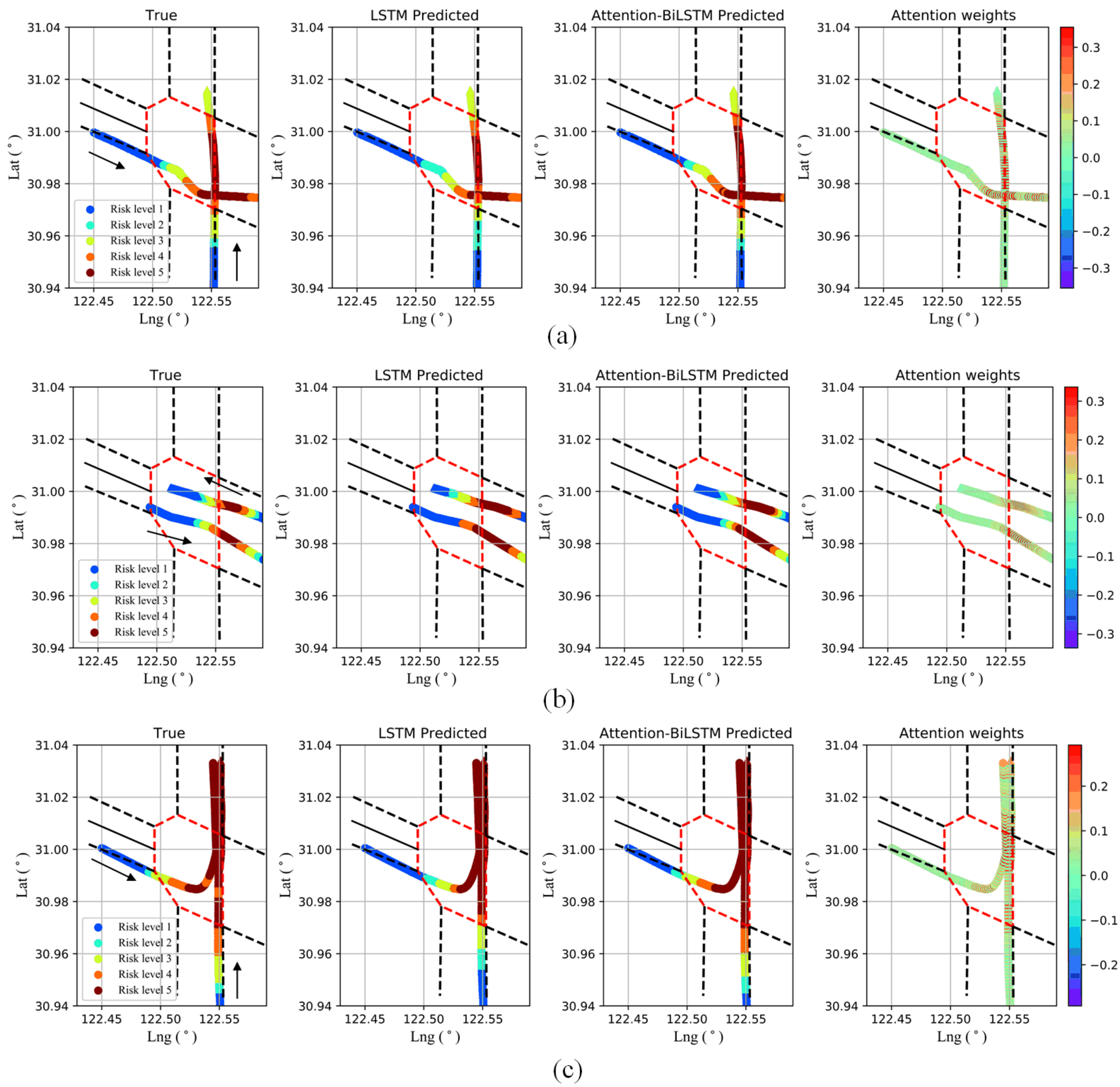

FIGURE 7. **Comparison of the predicted results between original LSTM and Attention-BiLSTM in various encounter situation. In the order from left to right, the first picture shows the real risk level of the future, the second picture represent the predicted risk level by original LSTM, the third picture show the predicted risk level by Attention-BiLSTM, the fourth picture represent the attention weight calculated by attention mechanism. (a) The crossing situation. (b) The head-on situation. (c) The overtaking situation.**

The results in Fig. 7 and 8 validate the early risk prediction performance of Attention-LSTM. Here, we further analyze the mechanism underlying the attention mechanism, discuss the interpretability of the model, and explore the relationship between attention score and ship motion behavior. In the field of text classification, the attention score can be used to represent high-level model information. For example, words with high attention scores contribute significantly to the text category because high-scoring words better reflect the high-level semantic information related to the text. Inspired by the text classification task, we can evaluate the relationship between the calculated attention score and ship motion behaviors in different encounter scenarios. The maximal information coefficient (MIC) is a nonlinear correlation coefficient used to calculate the correlation between an input motion feature and the calculated attention score. It is worth noting that this score is calculated under a supervised process in which the label is the future risk level. Therefore, a higher MIC correlation with the score will correspond a greater degree of contribution of the motion behavior to the future risk.

Figs. 9 (a), (b), and (c) present heat maps of the correlation coefficients between the set of ship behavior features and

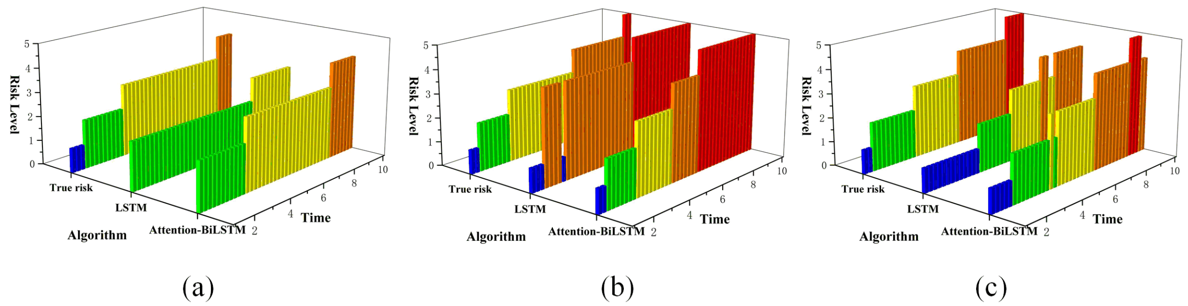

FIGURE 8. The histogram of the predicted results original LSTM and Attention-BiLSTM. (a) The crossing situation. (b) The head-on situation. (c) The overtaking situation.

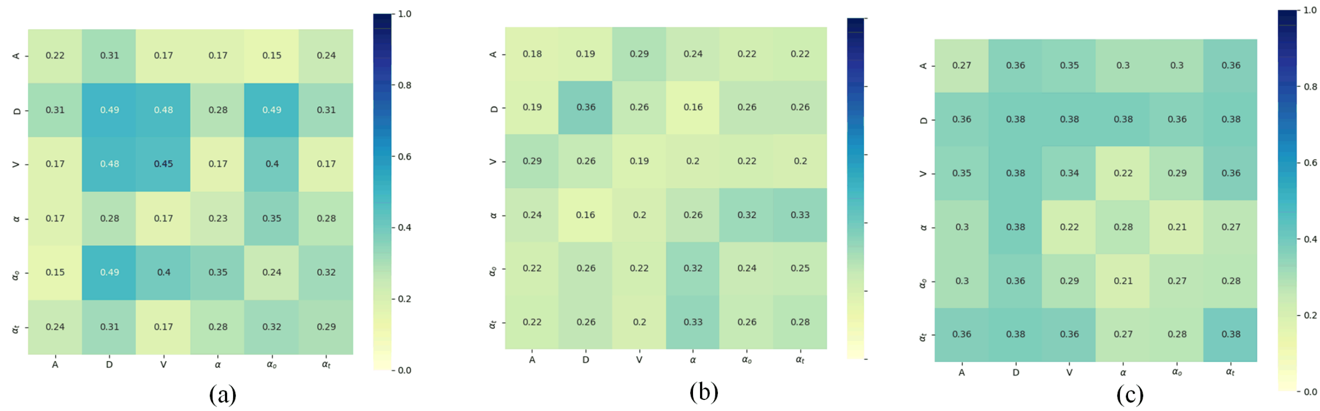

FIGURE 9. Heat map of the correlation coefficient MIC between the motion behaviors and the attention score. (a) The crossing situation. (b) The head-on situation. (c) The overtaking situation.

the set of attention scores $\{\alpha_t\}$ in the crossing, head-on, and overtaking scenarios, respectively. The diagonal elements of the heat map represent the MIC values between the respective attention scores and the individual features. For example, the value of 0.22 in the first row/first column of Fig. 9(a) represents the MIC between the relative course A and the attention scores $\{\alpha_t\}$ in the crossing situation. The non-diagonal elements represent the MICs between the products of the abscissa and ordinate features and the attention scores. For example, 0.31 in the first row/second column represents the correlation between the attention score and $A * D$. Higher MIC values in the heat map correspond to a greater degree of contribution of the corresponding motion feature to the risk prediction in the corresponding scenario. For example, it is seen from Fig. 9(a) that V and D have a greater impact on future risk, a result that is consistent with the fact that the distance and relative speed are important in determining whether a collision will occur between two ships involved in a crossing situation. In the encounter case (Fig. 9(b)), both the distance and the azimuth of the ship-pair have a significant contribution to the risk prediction. In this case, it is more meaningful to consider the azimuth of the two ships synthetically than it is to consider each angle separately because $0.32 > 0.24$ and $0.33 > 0.28$. The overtaking situation is more complex. As seen from Fig. 9(c), the MIC value distribution is relatively uniform at each position, indicating that the impacts of the six different motion features on future risk are balanced, and it is difficult to obtain the most prominent one or two factors to explain the formation of risk. The value range of MIC across all scenarios in Fig. 9 is $[0.17 - 0.49]$, indicating that there is a nonlinear correlation between motion features and attention scores. This means that the attention score reflects the influence of different behaviors on risk. By using the attention mechanism, the Attention-BiLSTM can capture the complex and uncertain relationship between motion behavior and future risk.

V. CONCLUSION

In this study, an approach to collision risk early warning based on deep learning techniques was investigated. Based on the consideration that the motion behavior can determine the subsequent collision risk, a novel deep learning architecture was proposed as a method for modeling the complex relationship between spatial-temporal motion behaviors and future risk. Under this approach, the motion behavior sequence over a specified time interval is labeled with its corresponding near-future risk level. Time series classification is then employed to classify the behavior sequence that results in a predicted risk. Using this approach, effective and timely risk prediction is achieved. In particular, the spatial dependencies of encountering ship pairs can be represented by transforming AIS data into a sequence of behavioral features. The bidirectional structure of LSTM is incorporated by the proposed architecture to capture the temporal correlation among motion behaviors, while the attention mechanism is adopted to quantify the different effects of ship behavior on risk at different time frames. The Attention-BiLSTM algorithm was experimentally validated in terms of its prediction accuracy, stability, and real-time performance. The approach developed in this study should be applicable in the early risk warning of ship collision accidents, and future research should provide more valuable insights into situational perception.

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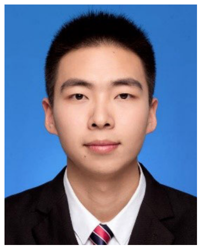

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