Proceedings of the ASME 2024 43rd International Conference on Ocean, Offshore and Arctic Engineering OMAE2024
June 9-14, 2024, Singapore, Singapore

OMAE2024-126767

EXTRACTION OF SHIP COLLISION AVOIDANCE PATTERNS FROM AIS DATA

Akash Vijayakumar[1,*], Amar Nath Singh[1], Abhilash Somayajula[1]

[1]Marine Autonomous Vessels Laboratory (MAV Lab)
Department of Ocean Engineering
Indian Institute of Technology Madras, Chennai-600 036, India

ABSTRACT

The maritime industry faces constant challenges in preventing ship collisions and ensuring adherence to the Convention on the International Regulations for Preventing Collisions at Sea (COLREGs). This paper presents a comprehensive analysis of ship collision avoidance patterns utilizing Automatic Identification System (AIS) data. By examining AIS data parameters, including vessel speed, course, heading and the dynamic change in position, crucial insights into the avoidance of collision can be extracted. In this paper the encounters are extracted from the AIS data collected near Los Angeles Port. The raw data is preprocessed and visualised in a relative distance domain from the own ship. The encounters are filtered using a collision risk model and the encounter situations are labeled and classified into multiple classes using GRU-RNN deep learning technique.

Keywords: Automatic Identification System, COLREGs, GRU-RNN, Gated Recurrent Unit, Recurrent Neural Network, RNN, Collision Avoidance, Autonomous Ship, CRI, Encounter, DCPA, TCPA, Deep Learning, Collision, AIS Data

1. INTRODUCTION

The autonomous shipping industry is experiencing exponential growth, driven by technological advancements and the expansion of data resources in maritime domain . Automatic Identification System (AIS) was originally developed as a collision avoidance tool to enable commercial vessels to 'see' each other more clearly in all conditions and improve the helmsman's information about his surrounding environment. AIS does this by continuously transmitting a vessels identity, position, speed and course along with other relevant information to all other AIS equipped vessels within range. Combined with a shore station, this system also offers port authorities and maritime safety bodies the ability to manage maritime traffic and reduce the hazards of marine navigation [1].The volume of data stored from the Automatic Identification System (AIS) in maritime domain is growing rapidly. This expanding reservoir of AIS data presents a unique opportunity to significantly enhance the autonomous operations of unmanned ships, ushering in a new era of intelligent maritime navigation and safety. In this context, this research focuses on a comprehensive analysis of ship collision avoidance patterns, utilizing AIS data as a fundamental building block to refine and optimize the decision-making processes of autonomous vessels.

The maritime industry operates within a dynamic and challenging environment, where the prevention of ship collisions is of paramount importance to ensure the safety of vessels and compliance with international regulations. The Convention on the International Regulations for Preventing Collisions at Sea (COLREGs) [2] establishes the framework for safe navigation, outlining rules and guidelines for ship operators.

'Collision' is the main casualty event type from 2014 to 2022, with 21.6% of the occurrences according to annual overview of marine incidents and casualties 2023 by EMSA [3]. Around 14 articles regarding collisions incident between ships has been reported in FleetMon within 2023 [4]. More than 40 incidents from last 15 years of ship collisions has been investigated under Japan Transport Safety board [5].

The analysis primarily focuses on key parameters within AIS data, including vessel speed, course, heading and dynamic changes in position. These parameters serve as crucial indicators for understanding the intricate dynamics of ship movements and formulating effective collision avoidance strategies.

The ultimate goal of this research is to pave the way for the development of an Imitation Learning model that can revolutionize collision avoidance strategies in the maritime industry. The paper explores the potential of employing imitation learning algorithms, a powerful machine learning approach, enables algorithms to learn and mimic expert behaviors, making it a promising avenue for automating collision avoidance and rule adherence in

*Corresponding author: akashvnkm123@gmail.com
Documentation for `asmeconf.cls`: Version 1.36, March 22, 2024.

the maritime domain. By leveraging the expert decisions made by the ship captains for avoiding collisions between the ships, which can be extracted from the AIS data analysis, unmanned ships can be equipped with real life collision avoidance experiences.This research aims to contribute to the ongoing efforts in enhancing safety measures and regulatory compliance within the autonomous shipping industry.

1.1 RELATED WORKS

Several research endeavors have explored the application of Automatic Identification System (AIS) data for diverse purposes, encompassing the identification of encounter situations between ships, ship model identification, and the development of collision avoidance systems. X.Chen et al [6] delved into the classification of encounter situations through the utilization of a semi-supervised model where latitude and longitudes are directly used in the preprocessing step instead of using Cartesian coordinates and the whole trajectory is not fed into the network instead it is split into 60 seconds time interval. Instead feeding whole trajectory into the network is preferred. In a similar vein, Jin.Zhang et al [7] employed the Delaunay triangulation network algorithm to cluster trajectory pairs. The algorithm is comparatively computationally expensive since it is calculating meshes between all the trajectories to check similarity between the trajectory pairs.Also this paper is showing absolute trajectory of both own and target vessels , which apparently doesn't give an idea of how the target vessel went with respect to own vessel. In this paper since relative positions are considered that intuition is available. Additionally, Jia et al [8] contributed to the field by devising a collision avoidance system tailored for unmanned surface vehicles, incorporating the ship domain method as a collision risk method into their approach. This research is particularly done for creating an imitation learning model for collision avoidance in future which can incorporate all the real world scenarios including anomalous situations occured so that it is well versed to be deployed in real world. This primary goal of this research makes it different from the studies mentioned above.

1.2 AIS DATA

The regulation requirement of AIS to be fitted aboard all ships of 300 gross tonnage and upwards engaged on international voyages, cargo ships of 500 gross tonnage and upwards not engaged on international voyages and all passenger ships irrespective of size, became effective for all ships by 31 December 2004 [9]. AIS uses Global Positioning Systems (GPS) in conjunction with shipboard sensors and digital Very High Frequency (VHF) radio communication equipment to automatically exchange navigation information electronically .The technology works with transponders which automatically broadcast information at regular intervals by VHF transmitter. Vessel identifiers such as the vessel name and VHF call sign are programmed in during initial equipment installation and are included in the transmittal along with location information originating from the ship's global navigation satellite system receiver and gyrocompass [10]. The standard coverage range of an onboard transceiver typically spans 15-20 nautical miles (nm), subject to various factors including transceiver altitude/type and weather conditions.

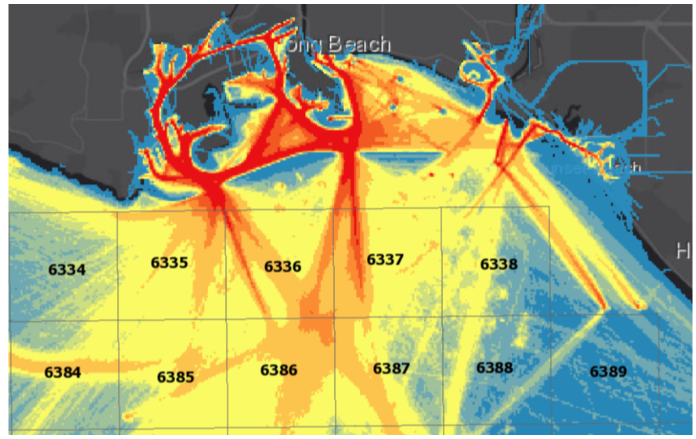


FIGURE 1: LOS ANGELES PORT IN MARINE CADASTRE[12]

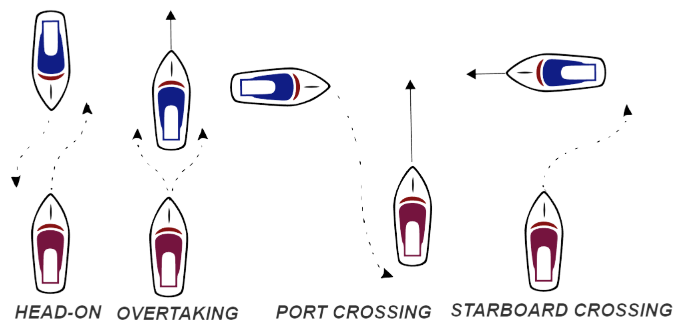


FIGURE 2: Encounters according to COLREGs

An onshore AIS station may boast a coverage range of up to 40 nautical miles. In open sea areas, a satellite-based receiver has the capability to encompass an expansive range of up to 1000 nautical miles. There are many free and paid versions of AIS data sources available. Some of them include USCG AIS Historical Requests, Marine Cadastre, FleetMon,AIS Exploratorium, IHS global, VT explorer, PROTEUS, SeaVision, Maritime Safetyand Security Information System (MSSIS),US Army Corps of Engineers AISAP [11]. In this paper the AIS data collected from a specified region near Los Angeles Port through Marine Cadastre has been utilised for analysis as shown in Figure 1.

1.3 ENCOUNTER SITUATIONS

In accordance with the International Regulations for Preventing Collisions at Sea (COLREGs) of 1972 [2], encounter situations can be classified into four distinct types: Head-on, Overtaking, Port Crossing, and Starboard Crossing as shown in Figure 2. When own ship is positioned on the starboard side of the target ship, it is incumbent upon the target ship to assume the role of the give-way vessel, and conversely, if own ship is on the port side, own ship should yield. In scenarios where both vessels are approaching head-on, the responsibility to yield rests with both ships to ensure the establishment of a safe passage. In overtaking situations, the overtaking vessel is required to act as the give-way vessel, maintaining a cautious distance behind the target ship to facilitate a safe overtaking maneuver according to COLREGs [2].

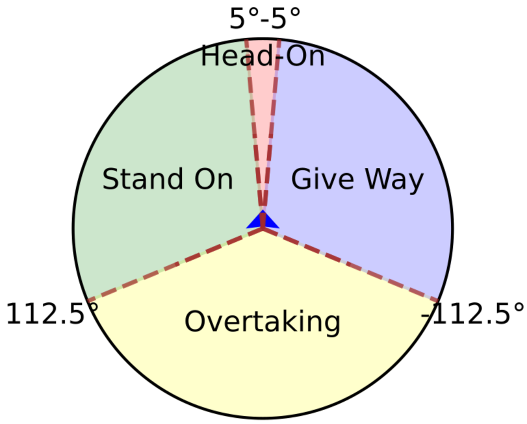


FIGURE 3: Vessel Domain

2. AIS DATA PREPROCESSING

The raw AIS data encompasses numerous extraneous data points that hold no relevance to the analysis of ship encounters. To refine the dataset for meaningful analysis, a series of preprocessing steps is employed to extract the specific features that contribute to the characterization of encounter situations.

2.1 PRELIMINARY STEPS

The Automatic Identification System (AIS) data obtained from Marine Cadastre encompasses essential maritime information, including the Maritime Mobile Service Identity (MMSI) Value, Coordinated Universal Time (UTC) date and time, Latitude, Longitude, Speed Over Ground (SOG), Course Over Ground (COG), Heading, Vessel Name as per the station radio license, International Maritime Organization (IMO) vessel number, Callsign assigned by the Federal Communications Commission (FCC), Vessel Type defined by the National AIS (NAIS) specifications, Navigational Status as per the International Regulations for Preventing Collisions at Sea (COLREGs), Vessel Length, Width, Draft, Cargo Type, and AIS Transceiver Class.The AIS data utilized in this research is sourced from a specifically chosen geographic region adjacent to the Los Angeles port, USA. The dataset spans from January to June 2023 and has been obtained through the Marine Cadastre platform.

The raw AIS dataset comprises features that do not contribute to the extraction of encounter scenarios between ships. It encompasses both static and dynamic information. To streamline the dataset, the removal of unnecessary features involves retaining only static information, such as the MMSI number and length of the vessel, along with all dynamic information.

The data points were extracted from a selected rectangular region in proximity to the Los Angeles port. For analysis purposes, the latitude and longitude information is converted to Cartesian coordinates based on the WGS 84 reference system, utilizing the nearby lighthouse as the datum.

2.2 COLLISION RISK

There are a lot of encounter scenarios which are unnecessary for the analysis because the interest of this research is on the collision avoidance maneuver taken by the target and own ships.For the same , the data need to be filtered further to extract a closer and more riskier encounter. A collision risk model is employed for this purpose. It will indicate how riskier the encounter is at each time step, in the sequence of trajectories. Several collision risk model are available for identifying risky encounter between two ships. An exponential collision risk index model (CRI) as shown in Equation 4 similar to Ji.Ha et al [13] , is employed in this paper that incorporates the parameters of Distance to Closest Point of Approach (DCPA) Equation 1 as in paper by Chanhee Seo et al [14], Time to Closest Point of Approach (TCPA) Equation 2, and relative heading between vessels. DCPA represents the distance between the own ship and the closest point both ships will reach if they continue to move at the same velocities. TCPA indicates the time own ship will take to reach the closest point of approach between the vessels. DCPA and TCPA can be obtained through geometric calculations of ship encounter situations where the dashed-dotted lines represent the extended line of the relative velocity V_R as shown in Figure 4.

The location coordinates, velocity, and course of the own ship are $S_O(x_O, y_O)$, V_O, and ψ_O, and those of the target ship are $S_T(x_T, y_T)$, V_T, and ψ_T. D_R, V_R, and ψ_R are the relative distance, velocity, and course, respectively. a_T is the azimuth of the target ship, and q_T is the relative bearing. The equations for DCPA, TCPA, D_R, and θ_T are defined in the following equations.

$$\mathrm{DCPA} = D_R \cdot \sin(\psi_R - a_T - \pi) \tag{1}$$

$$\mathrm{TCPA} = \frac{D_R \cdot \cos(\psi_R - a_T - \pi)}{V_R} \tag{2}$$

The expression for D_R is defined as:

$$D_R = \sqrt{(x_T - x_O)^2 + (y_T - y_O)^2} \tag{3}$$

$$\psi_R = \begin{cases} \tan^{-1}\left(\frac{V_R x}{V_R y}\right), & \text{if } V_R x >= 0, V_R y >= 0 \\ \tan^{-1}\left(\frac{V_R y}{V_R x}\right) + 90^\circ, & \text{if } V_R x >= 0, V_R y <= 0 \\ \tan^{-1}\left(\frac{V_R x}{V_R y}\right) + 180^\circ, & \text{if } V_R x <= 0, V_R y <= 0 \\ \tan^{-1}\left(\frac{V_R y}{V_R x}\right) + 270^\circ, & \text{if } V_R x <= 0, V_R y >= 0 \end{cases}$$

The components of $V_R x$ and $V_R y$ are given by:

$$V_R x = V_T x - V_O x$$
$$V_R y = V_T y - V_O y$$

Where:

$$V_O x = V_O \sin \psi_O$$
$$V_O y = V_O \cos \psi_O$$
$$V_T x = V_T \sin \psi_T$$
$$V_T y = V_T \cos \psi_T$$

$$V_R = \sqrt{V_R x^2 + V_R y^2}$$
$$\theta_T = a_T - \psi_O$$

The expression for CRI is given by:

$$CRI = \exp\left(-\frac{|\mathrm{DCPA}|}{k1}\right) \cdot \exp\left(-\frac{|\mathrm{TCPA}|}{k2}\right) \cdot \frac{(\psi_O - \psi_T)}{\pi} \tag{4}$$

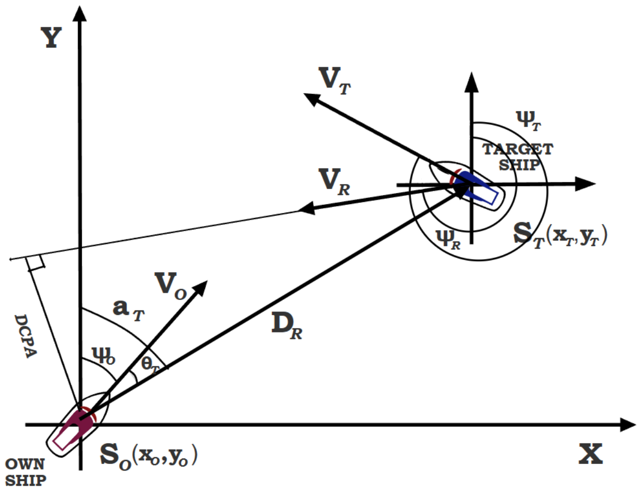


FIGURE 4: CLOSEST POINT OF APPROACH

This index was utilized as a critical component in our data analysis framework for data filtration. Subsequently, a predefined threshold for the Collision Risk Index and the inter-vessel distance was established. Vessel pairs exceeding this threshold were earmarked for further scrutiny and subsequent analysis.

To enhance the quality of the filtered data set, a systematic removal of redundant points was executed. Specifically, series characterized by difference between consecutive points in both the x and y dimensions exceeding a predefined threshold were systematically excluded from the filtered data.This will ensure to remove the sudden jump in the spatial data of the vessels which is not possible in real world. The resultant filtered trajectory pairs of own ship and target ship encounter were then organized and stored, utilizing vessel ID pairs as unique keys for efficient retrieval and subsequent analysis.This encounter trajectory pairs stored are used for further analysis and classification.

3. GRU RNN

The preprocessed sequential data has to be classified with some technique for further analysis. There are numerous methods available to classify sequential data . Unsupervised classification methods like KNN, ARIMA models, Dynamic Time Warping techniques(DTW) and there are deep learning supervised classification techniques like using Recurrent Neural Networks(RNN), Long Short Term Memory (LSTM) networks, Gated Reccurent Units (GRU).Since the relation within the sequential data can be captured well enough through a neural network , a deep learning technique GRU is employed in this paper. If a fair amount of user labeled encounter scenarios between ships can be fed into the neural network , this trained network can be used for classifying the remaining data.

Within sequence modeling techniques, the Gated Recurrent Unit (GRU) represents a more recent addition following the development of Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM). Consequently, it presents enhancements over the capabilities of the preceding RNN and LSTM architectures.GRU was introduced by Kyunghyun Cho et al in the year 2014[15] as a simpler alternative to Long Short-Term Memory (LSTM) networks.Like LSTM, GRU can process sequential data such as text, speech, and time-series data.

3.1 ARCHITECTURE

The fundamental concept of GRU (Gated Recurrent Unit) involves employing gating mechanisms to selectively update the hidden state of the network at each time step. These gating mechanisms play a crucial role in regulating the flow of information into and out of the network, allowing for more nuanced and adaptive processing of sequential data. A GRU cell comprises two primary gates, in contrast to the three gates found in an LSTM cell as shown in Figure 5. LSTM has three gates (Input, Forget, and Output gates), while GRU has two gates (Reset and Update gates).in the GRU architecture, the reset gate serves the function of deciding how much of the previous hidden state should be forgotten, allowing the network to selectively discard irrelevant information. Meanwhile, the update gate determines the extent to which the new input should be incorporated to update the hidden state, facilitating the adaptation to current input patterns.

The output of the GRU is subsequently calculated based on the modified hidden state. This mechanism enables the model to retain relevant information over time and adapt its internal representation to capture long-term dependencies in sequential data.

The first gate is the Reset gate, it determines how much of the past knowledge to forget. It is analogous to the combination of the Input Gate and the Forget Gate in an LSTM recurrent unit.The equation for the Reset gate is as follows:

$$r_t = \sigma(W_r \cdot x_t + U_r \cdot h_{t-1} + b_r) \tag{5}$$

$$r_t \in (0,1)^e : \text{reset gate vector}$$

$$x_t \in \mathbb{R}^d : \text{input vector}$$

Similarly, an Update gate is employed for long-term memory.It determines how much of the past knowledge needs to be passed along into the future. It is analogous to the Output Gate in an LSTM recurrent unit. Its equation is given by:

$$z_t = \sigma(W_z \cdot x_t + U_z \cdot h_{t-1} + b_z) \tag{6}$$

$$z_t \in (0,1)^e : \text{update gate vector}$$

To determine the hidden state (H_t) in a GRU, a two-step process is undertaken. The first step involves generating the candidate hidden state, as expressed by the equation:

$$\tilde{h}_t = \tanh(W_h \cdot x_t + U_h \cdot (r_t \odot h_{t-1}) + b_h) \tag{7}$$

$$\tilde{h}_t \in \mathbb{R}^e : \text{candidate activation vector}$$

This process incorporates both the input and the hidden state from the previous timestamp ($t-1$), multiplied by the reset gate output (r_t). Subsequently, this information is passed through the hyperbolic tangent ($tanh$) function, yielding the candidate hidden state. Crucially, the reset gate value controls the influence of the previous hidden state on the candidate state. If r_t equals 1, the entire information from the previous hidden state ($H_t - 1$)

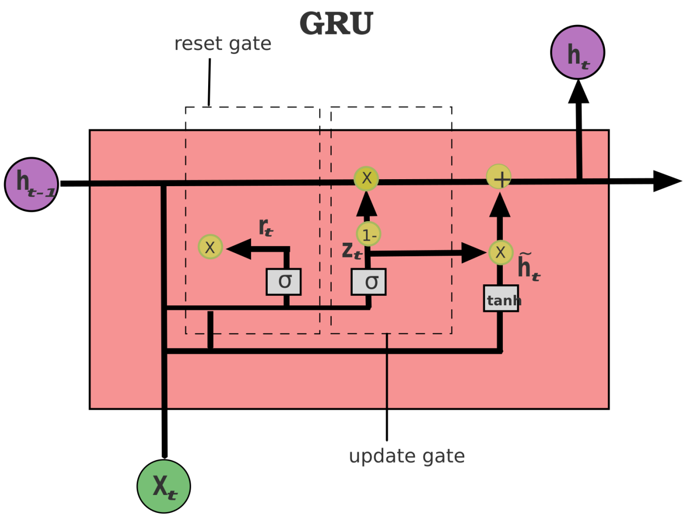


FIGURE 5: GRU cell structure

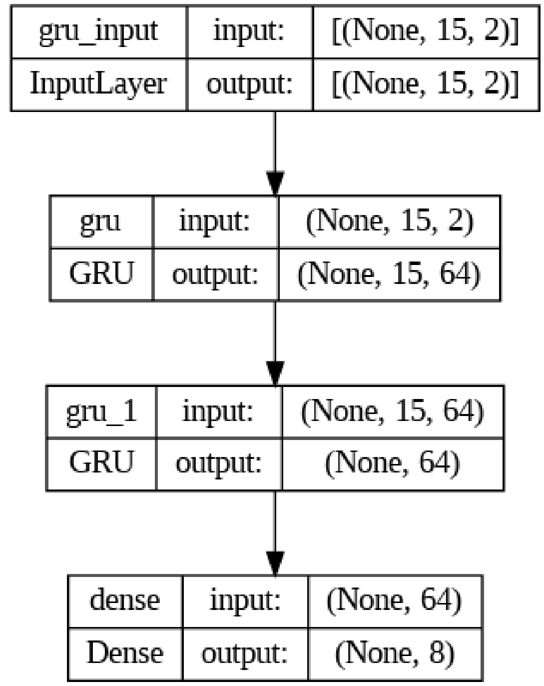


FIGURE 6: MODEL ARCHITECTURE

is considered. Conversely, if r_t equals 0, information from the previous hidden state is entirely disregarded. Once the candidate state is obtained, it is utilized to generate the current hidden state (H_t), with the Update gate playing a pivotal role. In GRU, a single update gate governs both historical information ($H_t - 1$) and new information from the candidate state. The equation for the hidden state at output is given by:

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \tag{8}$$

$$h_t \in \mathbb{R}^e : \text{output vector}$$

$$W \in \mathbb{R}^{d \times e}, \quad U \in \mathbb{R}^{e \times e}, \quad \text{and} \quad b \in \mathbb{R}^e$$

are parameter matrices and vector which need to be learned during training.

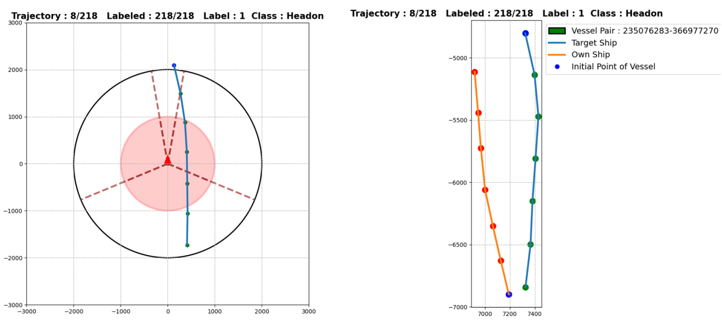
Assuming the value of z_t is approximately 0, the first term in the equation diminishes, indicating that the new hidden state will lack significant information from the previous hidden state. Conversely, if the value of z_t is close to 1, the second term becomes almost 0, signifying that the current hidden state will primarily consist of information from the candidate state.

3.2 TRAINING SCHEME

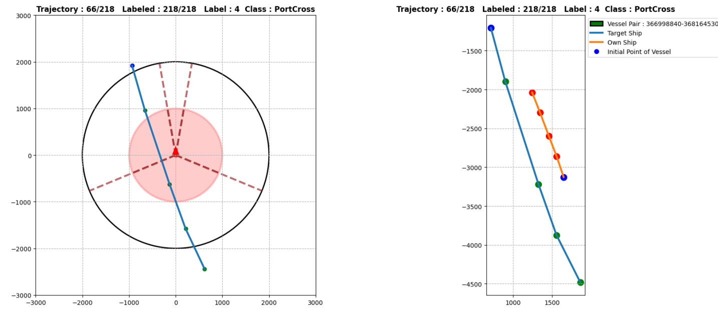
The encounter situations according to the COLREGs 1972 are Head-On, Overtaking, Port Crossing and Starboard Crossing. For in depth analysis of encounter between ship, this classification has been expanded to 7 classes namely Head-On in Figure 7a, Overtaking in Figure 7b, Port Crossing in Figure 7c, StarBoard Crossing in Figure 7d, Port to Port maneuver in Figure 8a, StarBoard to StarBoard maneuver in Figure 8b, Stern Crossing in Figure 8c , where the red trajectory represent own ship's trajectory and blue trajectory represents target vessel's trajectory. Blue point represents the starting point for both target and own ships . The circles in all the figures are the close field of the own ship, inside which risk of collision is higher.The red colored circle has radius of 1 kilometer and the outer circle has a radius of 2 kilometers. The circles have been divided into different regions according to the regions for collision avoidance maneuver defined by COLREGs[2]. Additionally an unclear class has been created for redundant and anomalous sequences in the data set. The representation of trajectories utilizing the concept of relative distance is a pivotal aspect of this study. This approach illuminates the spatial relationship between the target ship and the own ship, facilitating a more nuanced classification of encounter scenarios. The trajectory pairs of own and target ship encounters , curated through data preprocessing, are presented visually in a relative distance domain manner and have undergone supervised labeling for training purposes.In this manner how the target ship went with respect to the own ship is evident and it can be labeled accordingly.

Given the inherent variability in time series lengths across different trajectory pairs, a uniform input length is ensured through padding. Consequently, all inputs fed into the model are standardized to a (15, 2) dimension, wherein 15 denotes the sequence length, and 2 signifies the number of features at each time step. Notably, these features represent the relative distance in the x and y directions of target ship with respect to own ship.The neural network here is essentially learning the spatial relation showing how the target ship went with respect to the own ship.

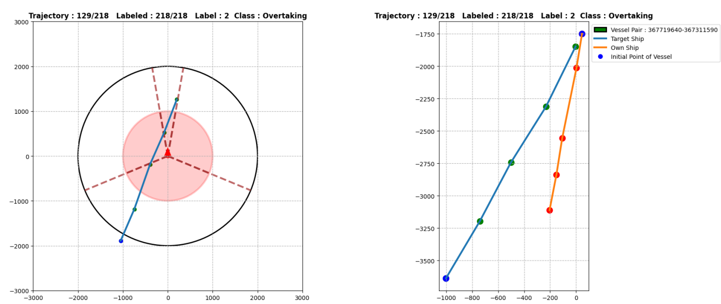
The GRU model employed in this research comprises two layers, each housing 64 GRU units as in Figure 6. Rectified Linear Unit (ReLU) activation functions are applied in both layers. This design choice is grounded in the ability of ReLU to capture complex patterns and nonlinear relationships within the trajec-



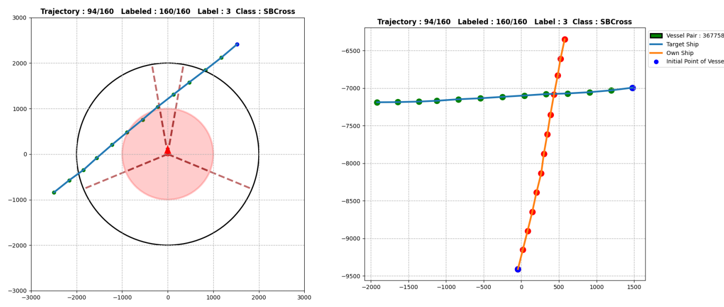
(a) HEAD-ON



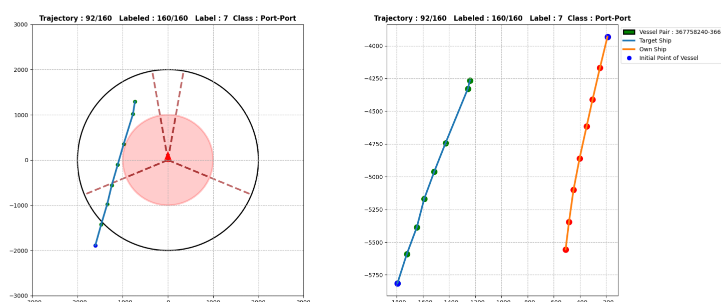
(c) PORT CROSS



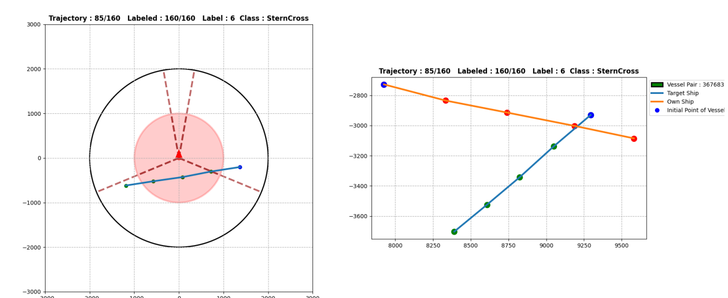
(b) OVERTAKING



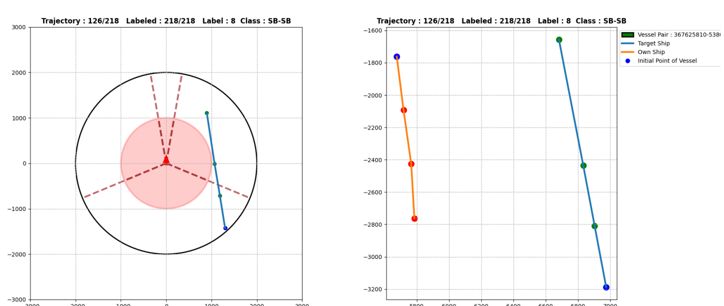
(d) STARBOARD CROSS



(a) PORT TO PORT



(c) STERN CROSS



(b) STARBOARD TO STARBOARD

tory data. The subsequent dense layer, comprising 8 units, serves as the final classifier, distinguishing trajectories into the predefined set of 8 encounter scenario classes. This comprehensive model architecture is tailored to effectively capture and classify encounter scenarios defined under analysis.

4. RESULTS AND DISCUSSION

The raw AIS data was of dimension (917742 rows × 17 columns) spanning from January to June 2023 in a selected region near Los Angeles Port.After data preprocessing it becomes (447473 rows × 7 columns). More than 1000 encounters scenarios have been used for labeling and training the neural network. The model has been trained with 95% accuracy .The statistics of encounter scenarios classified from all encounters extracted is shown in Figure 9.Most of the encounter situations were crossing scenarios compared to other cases. Head on situation was the least occurring scenario . There were many anomalous sequences and violation of COLREGs scenarios present in the dataset which came into notice while visualizing the trajectory pairs. Especially smaller vessels equipped with AIS tend to move not according to the regulations. A filter based on length of the vessels can be employed , so that encounter between bigger ships can be extracted for analysis. In some of the Port crossing scenarios , it was observed COLREGs was not obeyed as target ship has to give priority to own ship according to the COLREGs , but in some situations it is observed that target vessel crossed the own ship as seen in starboard crossing . In head-on situations also there were cases where vessels went in the direction opposite to direction which it was supposed to move according to COLREGs. Some cases were there when target vessel took turn around the own ships, which will cover multiple regions in the trajectory domain making it difficult to label.

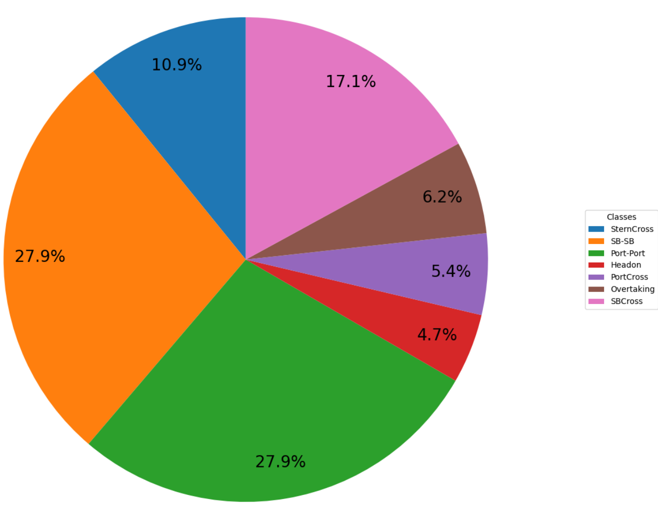


FIGURE 9: ENCOUNTER STATISTICS

5. CONCLUSION

In summary, this research aimed to extract ship encounter scenarios from AIS data, employing a different approach for identifying the encounter scenarios with flexibility. In particular, a GRU RNN is utilized in this study to classify trajectory pairs based on encounter classes, in which an accuracy of 95% was obtained. The results demonstrated the effectiveness of the GRU RNN in successfully categorizing trajectory pairs, showcasing its potential for improving the understanding of maritime encounters.The major advantage of visualizing the trajectory pairs of the own and target vessels in a relative distance domain is that , it can be seen how the target vessel went with respect to the own ship , if the observer is inside the ship. This essentially means it shows how the captain of the own ship would have observed the motion of the target vessel from the bridge. He would have taken maneuvering decisions of the own ship accordingly and that can be utilized for creating collision avoidance models with imitation learning. This visualization makes it easier to identify the type of encounter rather than visualizing both trajectories in absolute coordinates without having the idea of how the target vessel went with respect to own ship which will be confusing to label in the training data.

Although the classification has been done with decent amount of accuracy there are some shortcomings, which lies in the labeling of the training data set. The major challenge in labeling of the encounter scenarios is that the encounter scenarios are not clearly separated, some of them has overlap between each other, there is no fine line separation between some of these scenarios. It depends on the intuition of the user who labels the encounter data.The model will predict class labels of new scenarios based on the learning from this labeled data set.There comes one of the limitations of this method, which depend on the user labels. Here experience of the ship captains or an expert trainee data can be leveraged for resolving this shortcoming. That's where the importance of the analysis and data extraction done till now can be used. The future work is set to be carried out by developing an imitation learning model where the model can learn from the encounter scenarios in AIS data as well as bridge simulation training data by experts, so that the model can experience all sort of real world encounter cases with supervision of an expert.

By exposing autonomous vessels to real-world scenarios, including anomalous situations, this research provides valuable insights that can contribute to the development of more robust and adaptive autonomous collision avoidance systems. Future research can build upon these findings, exploring additional applications and refining the model to enhance the safety and efficiency of maritime transportation.

REFERENCES

[1] NATO. "AIS (Automatic Identification System) overview." (2021). Accessed January 5, 2024, URL https://shipping.nato.int/nsc/operations/news/2021/ais-automatic-identification-system-overview#:~:text=The%20Automatic%20Identification%20System%20(AIS,both%20vessels%20and%20shore%20stations.

[2] IMO. "Convention on the International Regulations for Preventing Collisions at Sea, 1972 (COLREGs)." International Maritime Organization (2019). Accessed January 5, 2024, URL https://www.imo.org/en/About/Conventions/Pages/COLREG.aspx.

[3] Agency, European Maritime Safety. "Annual Overview of Marine Casualties and Incidents 2023." European Maritime Safety Agency (2023). Accessed January 5, 2024, URL https://www.emsa.europa.eu/emcip/items.html?cid=141&id=5052.

[4] FleetMon. "Search results for "collision"." FleetMon (2023). Accessed January 5, 2024, URL https://www.fleetmon.com/maritime-news/search/?q=collision.

[5] Board, Japan Transport Safety. "Marine Accident and Incident Reports." Japan Transport Safety Board (2020). Accessed January 5, 2024, URL https://www.mlit.go.jp/jtsb/marrep.html.

[6] Xiang Chen, Kamalasudhan Achuthan Xinyu Zhang Jinhai Chen, Yuanchang Liu b. "A semi-supervised deep learning model for ship encounter situation classification." *Ocean Engineering* Vol. 239 (2021). DOI https://doi.org/10.1016/j.oceaneng.2021.109824.

[7] Jinfen Zhang, Spyros Hirdaris Mingyang Zhang Wuliu Tian, Jiongjiong Liu. "An interpretable knowledge-based decision support method for ship collision avoidance using AIS data." *Reliability Engineering System Safety* Vol. 230 (2022). DOI https://doi.org/10.1016/j.ress.2022.108919.

[8] hui Shi, Jia and jiang Liu, Zheng. "Deep Learning in Unmanned Surface Vehicles Collision-Avoidance Pattern Based on AIS Big Data with Double GRU-RNN." *Journal of Marine Science and Engineering* (2020)DOI https://doi.org/10.3390/jmse8090682.

[9] IMO. "Regulations for carriage of AIS." International Maritime Organization (2019). Accessed January 5, 2024, URL https://www.imo.org/en/OurWork/Safety/Pages/AIS.aspx#:~:text=The%20regulation%20requires%20AIS%20to,passenger%20ships%20irrespective%20of%20size.

[10] statistics Wiki, UN. "Overview of AIS dataset." Version 1.0. United Nations Statistics (2020). Accessed January 5, 2024, URL https://unstats.un.org/wiki/display/AIS/Overview+of+AIS+dataset.

[11] Centre, Defense Technical Information. "AIS Data: An Overview of Free Sources." (2023). Accessed January 5, 2024, URL https://apps.dtic.mil/sti/trecms/pdf/AD1193822.pdf.

[12] Cadastre, Marine. "Access AIS." Version 1.0. Marine Cadastre (2024). Accessed January 5, 2024, URL https://marinecadastre.gov/accessais/.

[13] Jisang Ha1, Myung-I Roh and Lee, Hye-Won. "Quantitative calculation method of the collision risk for collision avoidance in ship navigation using the CPA and ship domain." *Journal of Computational Design and Engineering,* (2021)DOI https://doi.org/10.1093/jcde/qwab021.

[14] Chanhee Seo, Misganaw Abebe Young-Jin Kang Sunyoung Park Cheolhyeon Kwon, Yoojeong Noh. "Ship collision avoidance route planning using CRI-based A* algorithm." *International Journal of Naval Architecture and Ocean Engineering* (2023)DOI https://doi.org/10.1016/j.ijnaoe.2023.100551.

[15] Kyunghyun Cho, Caglar Gulcehre-Dzmitry Bahdanau Fethi Bougares Holger Schwenk Yoshua Bengio, Bart van Merrienboer. "AIS Data: An Overview of Free Sources." (2014). Accessed January 6, 2024, URL https://arxiv.org/abs/1406.1078v3.