Collision Avoidance & Navigation System using AIS

Aman Bansal
Indian Institute of Technology Roorkee
amanb@mrc.foundationforuda.in

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Abstract:

The Collision Avoidance and Navigation System using Automatic Identification System (AIS) aims to enhance maritime safety by leveraging AIS technology. AIS provides real-time vessel information such as position, course, speed, and identification, which can be utilized to develop an intelligent system for collision avoidance and navigation in busy maritime environments. This research proposes a comprehensive system integrating AIS data with advanced algorithms and decision-making techniques to predict collision risks and aid in safe navigation. The system utilizes historical AIS data to analyze patterns and identify potential collision scenarios based on factors such as vessel proximity, course convergence, and relative speed. By employing machine learning and data analytics, the system can generate a Collision Risk Index (CRI) for each vessel, indicating the level of collision risk it may face. This information can be used to provide early warnings and recommendations to ship operators, allowing them to take proactive measures to avoid collisions. Additionally, the system incorporates intelligent routing algorithms that consider the predicted collision risks to suggest safer and more efficient vessel navigation paths. By considering real-time AIS data, weather conditions, and traffic density, the system can optimize vessel routes to minimize collision risks and improve overall maritime safety. The proposed Collision Avoidance and Navigation System using AIS holds significant potential to enhance safety in busy maritime environments. By leveraging AIS data and advanced algorithms, it enables proactive collision avoidance and intelligent routing decisions, reducing the likelihood of collisions and improving the efficiency of vessel navigation. Further research and development are required to validate and optimize the system's performance in real-world scenarios.

Introduction:

Collisions in Inland waterways represent the biggest threat to inland water transportation. Some studies have estimated that 80% of maritime accidents and 86–95% of ship collisions are due to human error; thus, the quantification of the impact of human error is of great importance to shipping safety. The European Maritime Safety

Agency (EMSA) has reported 20,616 marine casualties and incidents worldwide from 2011 to 2017. Among these conflicts, some have resulted in severe accidents that had a significant impact on the environment and resulted, tragically, in the loss of life.

Hence, it is crucial for the ship captains conducting maneuvers to understand their own future position with respect to target ships in a specific time span to solve close encounter situations more effectively.

Some standard components and features of a Collision Avoidance System in the marine domain:

- Radar
- Automatic Identification System (AIS),
- Electronic Chart Display and Information System (ECDIS),
- Alarm Systems
- Collision Avoidance Algorithms and Maneuvering Assistance

While Collision Avoidance System dramatically enhances safety and collision prevention, it is ultimately the responsibility of the ship's crew to exercise good seamanship and make appropriate decisions based on the information provided by these systems.

AIS and its application:

AIS (Automatic Identification System) is a critical component of vessel collision avoidance systems in the maritime industry. AIS is a transponder-based system that enables vessels to automatically exchange important information such as position, course, speed, and identification data.

The AIS transponder comprises a Very High Frequency (VHF) radio unit, Global Positioning System (GPS) receiver, a computer, a keyboard, and a display unit.

Here are some uses of AIS:

- Vessel Traffic Monitoring
- Collision Avoidance Systems
- Waterway Management

Available Solutions:

❖ ManhCuong Nguyen, Shufang Zhang, and Xiaoye Wang focused on creating a mathematical model to predict the likelihood of vessel collisions, utilizing AIS data. The study highlights the limitations of using the Distance of the Closest Point of Approach (DCPA) and Time to the Closest Point of Approach (TCPA) as the sole factors for calculating collision capability. It is noted that in the same lane scenario, DCPA is always zero, indicating an immediate collision, regardless of the distance between the ships. Additionally, when a ship moves slower than the target ship in the same lane, the possibility of collision is incorrectly disregarded.

The Collision Risk Index (CRI) is introduced as a valuable measure, where a higher TCPA value, shorter distance, greater speed, and larger angle between the ships indicate a higher collision risk. The dynamic visualization results indicate the practical applicability of the collision risk assessment model.

The study suggests integrating this model into the Automatic Identification System (AIS) to help sailors quickly and accurately assess collision risk and apply the COLREGS-72 collision avoidance principles. It is proposed to use a small-size embedded system equipped with the collision risk assessment model on small vessels and fishing vessels without an ARPA system. The model can also be utilized at base stations, VTS centers, and NoC to monitor, manage, and issue hazard warnings in the operating area.

❖ In the paper by Haiqing Shen, they utilized deep reinforcement learning (DRL) to automate collision avoidance for multiple ships. It introduces a training methodology and algorithms that consider ship maneuverability, human expertise, and navigation rules, utilizing the AIS database.

The method was extensively investigated through numerical simulations and model experiments involving three self-propelled ships. The validation process involves using Theano and Keras, which are deep-learning libraries, to implement the proposed approach. Additionally, Pygame generates real-time visual representations of the simulation results.

This design choice aims to enhance the learning speed and enable the development of an efficient RL (Reinforcement Learning) model. By leveraging deep Q-learning techniques, the approach offers a promising solution for realizing autonomous collision avoidance capabilities in ships, contributing to the advancement of autonomous ship technology in the future.

❖Visual analytic-based ship collision probability modeling for ship navigation safety.

This study introduces a visual analytic tool that utilizes AIS data to analyze maritime traffic in a spatio-temporal context. The tool offers a novel approach for understanding the macroscopic safety structure of both fairways and individual ships, supported by evidence at a microscopic level. The system's effectiveness is demonstrated using a 7-day AIS trajectory dataset from the Mexican Gulf. The analysis reveals that the spatio-temporal position patterns of encountered ships in Port Houston vary significantly over time. The study also finds that the spatial distribution of ship accidents aligns with the proposed near-miss density areas. Additionally, the tool proves capable of identifying real accident cases. Field experiments conducted with domain experts confirm that the approach enables realistic inferences about the navigational safety behavior of both individual vessels and water areas.

❖ The assessment by Perera worked on a system that incorporates a fuzzy theory-based decision-making mechanism for collision avoidance. A Bayesian network module is employed to convert these decisions into sequential actions. The emphasis lies in integrating intelligent collision avoidance capabilities into ocean navigation systems using AIS data. By conducting simple corrective measures such as minor speed and heading adjustments, close encounters can be prevented, reducing the overall risk and improving traffic flow. This study focuses on proactive collision avoidance to enhance the safety of autonomous ship operations. The research suggests that such proactive actions should be taken as early as 30 minutes before the closest point of approach. It is observed that ship navigators rely on high-level situation awareness to make these predictions. The study investigates the mechanisms involved in developing prediction models and finds that mental models play a crucial role. These models categorize ship behavior and have specific transition functions that capture future dynamics. By matching patterns, a novel trajectory can be classified into existing categories, and the appropriate model can be applied to predict the future behavior of a vessel.

However, these prediction models heavily rely on the experience of the navigator. To address this limitation, the study proposes leveraging historical AIS data to represent navigational experience. Additionally, it is discovered that machine learning techniques closely resemble the mechanisms used in developing mental models for situation awareness. Categorization is achieved by clustering historical AIS trajectories, and transition models are built using relevant machine-learning regression techniques. Pattern matching can also be facilitated through machine learning using appropriate classification methods. By emulating the mechanisms used by humans to develop high-level situation awareness, autonomous ships can effectively predict long-range ship trajectories and enable proactive collision avoidance.

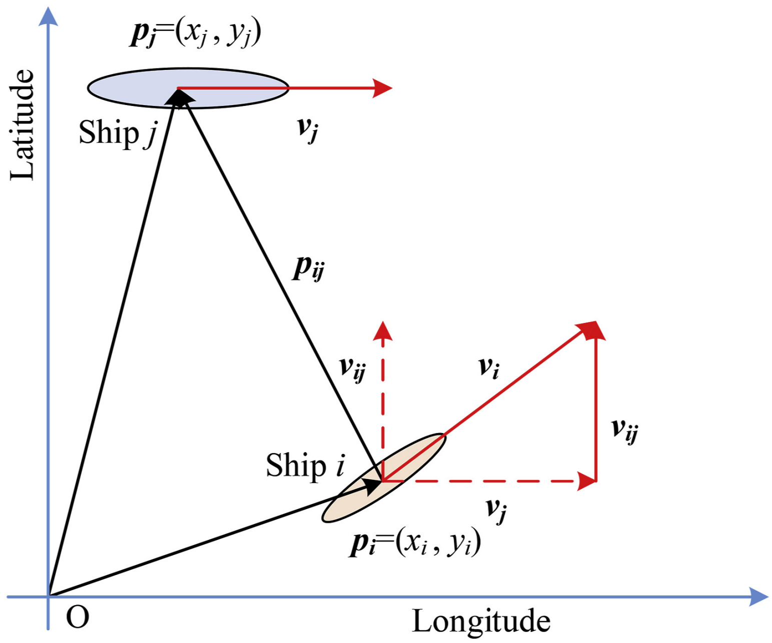
❖The judgment of the Collision Risk Index (CRI) is crucial in ensuring safe navigation for autonomous ships. To make informed decisions for collision avoidance, real-time navigation information is now readily available. Many researchers have proposed inference models based on fuzzy theory, utilizing this collected navigation information to enhance navigation safety. However, conventional inference models have limitations:

(i) they establish a membership function solely based on the Distance of the Closest Point of Approach (DCPA) and Time to the Closest Point of Approach (TCPA), without considering other ship dynamic parameters, and (ii) they rely on simulated results using virtual navigation information. To overcome these limitations, this study introduces an inference model using Artificial Neural Network (ANN) that learns from an input vector consisting of various parameters such as own ship's speed, target ship's speed, own ship's course, target ship's course, bearing between own ship and target ship, distance between own ship and target ship, and target vector. By considering actual near-collision situations, the proposed model can effectively express different CRI values while maintaining desirable TCPA and distance measures to determine appropriate collision avoidance actions. The proposed method demonstrates superior decision-making capabilities compared to conventional models.

AIS in Collision Avoidance System

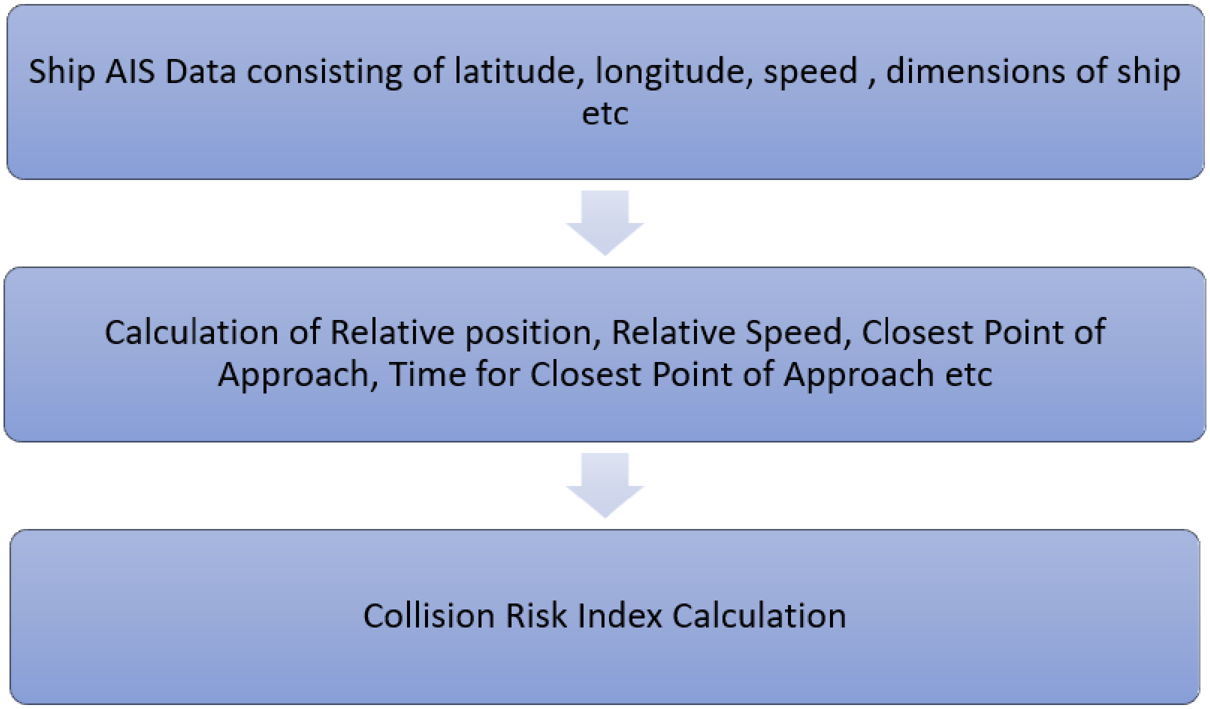
The proposed method uses the static and dynamic information of Automatic Identification System (AIS) data. Considering it to be a near collision situation, we first find the closest points of ship-ship collision (CPC) based on the ship specifications (e.g., ship length and breadth) and the geographical positioning of ships.

The time required for the Closest Point of Approach (CPA) is computed and used as input to a mathematical or machine learning model. This model utilizes these parameters to calculate the Collision Risk Index (CRI). If the calculated CRI exceeds a predefined threshold value, an alarm is triggered, alerting the ship's crew.



By employing fundamental principles of kinematics, we can determine the relative speed, position, and acceleration of the vessels involved. Utilizing these parameters, we can calculate the time for a collision to occur. Consequently, we compute the Collision Risk Index (CRI) by considering this collision time, where the CRI is inversely proportional to the calculated time for collision. By comparing the obtained CRI with a predetermined threshold value, we can provide timely alerts to the ship crew.

Flow Chart for the work:



First, the Data from Marine Traffic are used to calculate the position, speed, CPA , and TCPA, and with these parameters being fed in a Machine Learning/Mathematical model, CRI is Calculated, and with this CRI, an alarm is triggered.

Way Forward:

Integrating AIS data, along with parameters such as Closest Point of Approach (CPA), Distance to Closest Point of Approach (DCPA), and Time to Closest Point of Approach (TCPA), with a machine learning model that leverages historical data can potentially improve the overall accuracy of trajectory prediction. By incorporating these variables into the machine learning algorithm, the model can learn from past patterns and behaviors to predict safe trajectories. This combination of real-time AIS data and historical data-driven predictions has the potential to enhance accuracy and provide more reliable trajectory information for collision avoidance systems.

Intelligent Automation: The integration of AIS with autonomous and semi-autonomous navigation systems can enable intelligent automation in collision avoidance. Vessels with AIS and advanced algorithms can autonomously detect and avoid collision risks, optimizing navigation routes and ensuring safe operations. (Just like Self Driving Cars)

Enhanced Data Integration: AIS data can be integrated with other sensor technologies, such as radar, lidar, and cameras, to create a more comprehensive and accurate picture of the vessel's surroundings. This integration can improve collision risk assessment and enable more effective decision-making.

Limitations of AIS Data:

While AIS data is valuable for collision avoidance systems, there are some limitations to consider:

1. Data Availability and Coverage: AIS data relies on vessels having operational AIS transponders and a functioning AIS network. However, not all vessels must have AIS, and there may be areas with limited AIS coverage. This can result in incomplete or unavailable data, leading to gaps in situational awareness.

2. Data Accuracy and Integrity: AIS data can be prone to transmission errors, reception errors, and intentional or unintentional data manipulation. Outliers and incorrect information can impact the accuracy of collision risk assessments and trajectory predictions.

3. Limited Information on Small Craft and Non-Cooperative Vessels: AIS data is primarily available for larger vessels that are required to have AIS transponders. Smaller craft, fishing vessels, and non-cooperative vessels may not continuously transmit AIS data, making it challenging to detect and track their movements accurately.

4. Update Rate and Latency: AIS data is typically updated at intervals ranging from a few seconds to a few minutes. This update rate, combined with potential network latency, means that the information may not always reflect real-time vessel positions and dynamics. In rapidly changing situations, such as high-traffic areas or during maneuvering, the delay in data can impact the effectiveness of collision avoidance measures.

5. Limited Information on Intention and Navigational Decisions: AIS data provides information on vessel positions, courses, and speeds but lacks details regarding a vessel's intentions, navigational decisions, or response to collision warnings. Understanding the intentions of other vessels is crucial for accurate collision risk assessment and effective collision avoidance maneuvers.

6. Vulnerability to Jamming and Spoofing: AIS signals can be susceptible to jamming or intentional spoofing, where malicious actors manipulate the AIS data to deceive other vessels or disrupt the system's operation. These activities can undermine the reliability and integrity of the AIS information, leading to potential safety risks.

It is essential to consider these limitations and complement AIS data with other sensors, such as radar, sonar, and visual observations, to enhance situational awareness and improve the overall effectiveness of collision avoidance systems.

References:

Harsh Kumar Sharma 1, Dr (Cdr) Arnab Das 2, Collision Avoidance In Inland Waterways By Using AIS Data https://mrc.foundationforuda.in/collision-avoidance-in-inland-waterways-by-using-ais-data/

Zhao Liu 1, Boyuan Zhang 2, Mingyang Zhang 3, Helong Wang 4, Xiuju Fu 5, A quantitative method for the analysis of ship collision risk using AIS data, 2023

https://www.sciencedirect.com/science/article/pii/S0029801823002901

Dr. Aghil Rezaei Somarin 1, Dr. Ng Szu Hui 2, THE VESSEL COLLISION AVOIDANCE SYSTEM (VCAS)

https://www.porttechnology.org/wp-content/uploads/2019/09/UNI-OF-SINGAPORE.pdf

https://shipping.nato.int/nsc/operations/news/2021/ais-automatic-identification-system-overview#:~:text=The%20Automatic%20Identification%20System%20

Ho Namgung 1, Jung Sik Jeong 2, Joo-sung Kim 3 and Kwang-Il Kim 4,
Inference Model of Collision Risk Index based on Artificial Neural Network using Ship Near-Collision Data , 2019

https://iopscience.iop.org/article/10.1088/1742-6596/1357/1/012044

Brian Murray 1, Lokukaluge Prasad Perera 2,Proactive Collision Avoidance for Autonomous Ships: Leveraging Machine Learning to Emulate Situation Awareness, 2021

https://www.sciencedirect.com/science/article/pii/S2405896321014695

Ülkü Öztürk 1, Hasan Alp Boz 2, Selim Balcisoy 3, Visual analytic-based ship collision probability modeling for ship navigation safety, 2021

https://www.sciencedirect.com/science/article/abs/pii/S0957417421001962

Haiqing Shen 1, Hirotada Hashimoto 2, Akihiko Matsuda 3, Yuuki Taniguchi 4, Daisuke Terada 5, Chen Guo 6 , Automatic collision avoidance of multiple ships based on deep Q-learning, 2019

https://www.sciencedirect.com/science/article/abs/pii/S0141118718302293

Zhao Liu 1, Boyuan Zhang 2, Mingyang Zhang 3, Helong Wang 4, Xiuju Fu 5, A quantitative method for the analysis of ship collision risk using AIS data, 2023
https://www.sciencedirect.com/science/article/pii/S0029801823002901

For more uses of AIS :

Refer to the functionality and Capability part
https://gmdsstesters.com/radio-survey/ais/shipborne-automatic-identification-system-ais.html

Refer to the Applications part
https://www.frontiersin.org/articles/10.3389/fmars.2019.00537/full

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Advantages of Using ML in Collision Avoidance and Navigation System over Existing Models:

Improved situational awareness: ML algorithms can analyze data from various sensors, such as radar, sonar, AIS (Automatic Identification System), and satellite imagery, to provide a comprehensive understanding of the maritime environment. ML models can detect and track other vessels, identify potential collision risks, and provide real-time situational awareness to maritime operators. This enables timely decision-making and proactive collision avoidance.

Pattern recognition and anomaly detection: ML algorithms can recognize patterns and learn from historical data to identify anomalies or abnormal behavior in vessel movements. This capability allows ML models to detect potential collision risks, such as vessels deviating from their usual paths or exhibiting erratic behavior. By detecting anomalies, ML-based systems can issue warnings or alerts to avoid collisions.

Sensor fusion and data integration: ML techniques can integrate data from multiple sensors, including radar, sonar, and AIS, to create a holistic maritime situational picture. By fusing information from diverse sources, ML models can improve the accuracy and reliability of collision detection and avoidance. Sensor fusion enhances the system's ability to track vessels, detect obstacles, and make informed navigation decisions.

Continuous learning and adaptation: ML models can learn from new data and continuously update their knowledge and algorithms. As new information becomes available, ML-based collision avoidance and navigation systems can refine their understanding of vessel behavior, improve collision risk assessments, and adapt to changing maritime conditions. This continuous learning ensures that the systems remain up to date and effective.