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Verification of Collision Avoidance Utilizing Data-driven Fuzzy Logic

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Abstract

In all the hazardous accidents at sea, ship collision is always the most frequent one. It has been paid great attention, and International Regulations for Preventing Collisions at Sea (COLREG) are being complied with. With the development of technology, autonomous guidance and navigation for ship collision avoidance have been developed and used in practice for several years. However, there are still challenges when introducing autonomous navigation with the compliance of COLREG in consideration of human interpretation. To narrow this gap between vague and complex human interpretation and precise navigation, a non-linear system of fuzzy logic is introduced to represent the human decision under different situations when ship encounters.

However, the common approach of designing fuzzy logic verification and validation system of ship collision avoidance is still by utilizing domain expertise and based on assumptions and conjecture, which is good for interpretability and understandability, but is yet imprecise and lacks a certificate. In recent years, proposals have been brought that AIS can be included to have a thorough improvement of the fuzzy logic system, by the means of helping decide significant parameters and derive the shape of fuzzy membership functions, but have not been implemented and tested. To improve the knowledge-based fuzzy logic model to a novel data-driven fuzzy logic model, machine learning methods can be used, such as unsupervised learning and neural networks. One more concern is, it is also possible to not only improve the parameters and functions but integrate the whole system, which includes fuzzifier, If-Then rules, and defuzzier, into one fuzzy black box using fuzzy neural network.

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Abbreviations

AGN Autonomous Guidance and Navigation

AIS Automatic Identification System

ANFIS Adaptive-Network-based Fuzzy Inference System

ANN Artificial Neural Network

ASV Autonomous Surface Vehicles

CAS Collision Avoidance System

COLREG Convention on the International Regulations for Preventing Collisions at sea

CPA The Closest Point of Contact

CPD Change Point Detection

DBSCAN Density-based Spatial Clustering of Applications with Noise

DCPA Distance to Closest Point of Approach

DOF Degrees of Freedom

DRL Deep Reinforcement Learning

FMF fuzzy Membership Function

FNN Fuzzy Neural Network

GW Give-way

IMO International Maritime Organization

MASS Maritime Autonomous Surface Ships

MMSI Maritime Mobile Service Identity

MPC Model Predictive Controller

MSMS Maritime Safety Management System

NFN Neural Fuzzy Network

OS Own-ship

PFM Potential Field Method

SBMPC Simulation-Based Model Predictive Control

SO Stand-on

TCPA Time to CPA

TS Target Ship

V&V Validation and Verification

1 Introduction

1.1 Background

The maritime industry is a vital component of global trade and transportation. It serves as a critical conduit for connecting people, goods, and services across different countries and continents. The industry's contribution to the global economy is significant, and maritime transportation is announced as "Backbone of Global Trade and the Global Economy" by United Nations (2016) . However, despite its importance, maritime industry faces several challenges, particularly in terms of safety and reliability. These challenges can lead to casualties that cannot be overlooked, and in all these hazards, ship collisions are the most frequent and dangerous. According to Acejo et al. (2018), ship collisions accounted for 35.8 % of all 693 maritime accidents that occurred between 2002 and 2016, making it the leading cause of such incidents. This high number of collisions can be attributed to several factors, including poor visibility, adverse weather conditions, and navigational errors. However, human error is considered the primary cause of ship collisions, accounting for between 75% to 96% of all such accidents (Zhang et al., 2013). Human factors such as fatigue, lack of training, and complacency can compromise the ability of crew members to operate ships safely and effectively.

The alarming rate of ship collisions underscores the urgent need for comprehensive safety measures to be put in place. To address this issue, numerous rules and regulations have been developed, such as the Collision Regulations of 1960 and Convention on the International Regulations for Preventing Collisions at sea (COLREG) of 1972 that replaced it. These regulations provide a framework for the safe operation of vessels by establishing rules for navigation, vessel traffic services, and maritime communication. Additionally, many maritime organizations have implemented Maritime Safety Management System (MSMS) that promote a proactive approach to safety by identifying hazards and implementing appropriate measures to mitigate risks (Thai and Grewal, 2006).

However, although the aforementioned efforts has been made, there is still high percentage of navigational accidents for conventional vessels which are caused by human erroneous operations . As a consequence, autonomy is naturally introduced to maritime industry, such as autonomous shipping, where autonomy refers to "the ability of a ship to independently control its own actions while transporting goods from one port to another" (Munim, 2019). In 2018, International Maritime Organization (IMO) has taken the first action to address Maritime Autonomous Surface Ships (MASS), together with the four different autonomy levels, from low to high are (IMO, 2018):

- Ship with automated processes and decision support, to give a most common instance, CAS.

- Remotely controlled ship with seafarers on board.
- Remotely controlled ship without seafarers on board.
- Fully autonomous ship, meaning that he operating system of the ship can be able to make decisions and determine actions.

In recent years, autonomous ships are being trialled for short voyages in some areas under the interim guidelines from IMO (IMO, 2023), but the international shipping are not allowed due to law regulations (Ziajka-Poznańska and Montewka, 2021). However, several maritime companies already have a future vision with vessels majority on water are autonomous. For instance, in 2014, Norwegian ship classification society DNV has proposed the autonomous container-ship concept named ReVolt with autonomous steering technology, and a small container-ship scale model was constructed and sails in Trondheim water area four years later (DNV, 2021), as shown in Fig.1. This ReVolt project was motivated to ease the burden on land transportation, reduce cost of operations and promote safety at sea (Munim, 2019). The latest milestone of autonomous vehicle is the trails of autonomous ferry. In October 2022, the world's first trail of an urban autonomous passenger ferry MilliAmpere 2, designed and operated by NTNU, as shown in fig 2. In December the same year, Denmark's first driverless harbour bus 'GreenHopper' sailed successfully (Katrine Damkjar, 2022). In April 2023, a Swedish autonomous ferry is scheduled to finish its construction, which is an electric catamaran with a capacity of 25 people (Nick Blenkey, 2023). In addition, it is interesting to know that the AIS dataset analyzed in this thesis contains a vessel categorized as "unspecified", named "OCEAN SPACE DRONE1." This robust autonomous surface vehicle was developed by Kongsberg in collaboration with NTNU and Sintef and was first tested in May 2017, as illustrated in fig.3. (Mats Krokstrand, 2017)

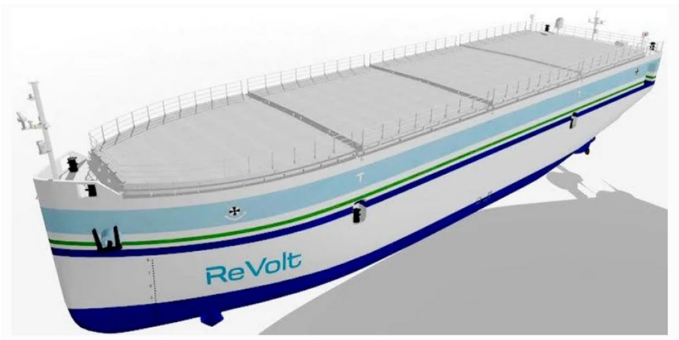


Figure 1: ReVolt (DNV, 2021)

The incorporation of autonomous systems in maritime vessels holds promising prospects, encompassing enhancements in operational safety and efficiency both on board and offshore through more accurate perception of the environment and assist on decision-making. Another significant benefit lies in the potential reduction of fuel consumption and the associated decrease in CO_2 emissions. This objective is

Figure 2: Autonomous passenger ferry MilliAmpere 2 (Idun Haugan, 2022)

Figure 3: Ocean Space Drone 1 (Mats Krokstrand, 2017)

primarily pursued through the adoption of reduced-speed operations, which, however, increases the transport time for goods, especially for long international travels. This long duration trip is not viable for traditional ships since crew members onboard need to switch shifts regularly. With autonomous ships, there is a reduced need for personnel, which enables the ship to sustain prolonged at sea. In spied of all the advantages brought by autonomous ship, the commercialization of autonomous on a global scale faces significant challenges, particularly related to the regulatory framework (Vagale et al., 2021). Specifically, the convention on COLREG was designed for human-controlled ships (Benjamin and Curcio, 2004), so its considerable flexibility and vagueness render it inadequate for evaluating the collision avoidance behavior of ASV. To illustrate this point, there are many instances of imprecise and ambiguous terminology within COLREG reciprocal describing situations and actions, such as ”nearly reciprocal courses” and ” in any doubt” in rule 14, ” so far as possible” in rule 16, and ”as soon as it becomes apparent” in rule 17, which are apparently appropriate for human-operated vessels but hard for a CAS to understand and be accessed. Consequently, there is a pressing need for more effective evaluation methods to assess how ASVs perform collision avoidance maneuvers in compliance with COLREG. As a result, V&V of collision avoidance has been focused and utilized for ASV since 2016 (Helle et al., 2016), aiming at ensuring ship's CAS is functioning properly and effectively preventing collisions by evaluating how much the ship is maneuvering subjective to COLREG, and this is of significant importance. Since then, scoring systems for each rule COLREG was designed respectively by (Woerner, 2016). Field tests and simulation-based tests have been used by different methods (Kufoalor et al., 2020; Torben et al., 2022).

Simultaneously, the advent of robust fuzzy logic technology has presented a promising solution to act as a ”translator” of the COLREG, converting their objectivity into an understandable computer language with subjectivity, represented by a degree between 0 and 1, instead of relying solely on Boolean values. In the maritime industry, researchers such as Kijima and Furukawa (2001) and Perera et al. (2011) have employed fuzzy logic to design the controller and decision-making function in ship CAS, They take into account fuzzy inputs as, respectively, collision risk, and collision distance, collision region, relative speed ratio and relative collision angle. This approach enhances the trustworthiness and reliability of the CAS for ASVs concerning compliance with the COLREG. Furthermore, fuzzy logic has also found utility in the V&V of CAS since the year of 2021 by Trodahl (2021) and Løvoll (2022).

1.2 Motivation

This thesis is primarily motivated by the research conducted by Trodahl (2021) and Løvoll (2022). Trodahl (2021) successfully implemented fuzzy logic in the evaluation system of CAS subject to COLREG. By modeling the linguistic variables in COLREG as mathematical variables utilizing FMF, the output is an appropriate degree of truth between 0 and 1, providing scores of compliance for every rule. Trodahl (2021) cleverly designed this system as three subsystems, which decide the role of Own-ship (OS) and Target Ship (TS) as either a Give-way (GW) vessel or a Stand-on (SO) vessel, and evaluated the compliance of the GW and SO vessels, respectively. Finally, an overall score for a whole ship encounter situation is provided, as illustrated in Fig.4. His fuzzy V&V system has undergone successful testing in scenario-based simulations in open-water area, including head-on, crossing, and overtaking situations of two ships encountering. Based on Trodahl (2021)'s promising results, Løvoll (2022) has extended the fuzzy V&V system by combining the COLREG-compliance block with two blocks of evaluating perceived safety and encounter safety, and finally gives a combined overall safety score, as shown in fig. 5. In addition, he employed Change Point Detection (CPD) technique which results a higher accuracy of calculating the fuzzy inputs. The system of Trodahl (2021) is designed for open-water area, so Løvoll (2022) improved this to an urban and semi-restricted operational domain, and tested with multiple ships encountering scenarios (one OS with three TSs).

Nonetheless, both of the evaluation systems designed by Trodahl (2021) and Løvoll (2022) utilized knowledge-based fuzzy logic, which means that the FMFs were all assumed to have trapezoidal shapes, and the values of the fuzzy variables were

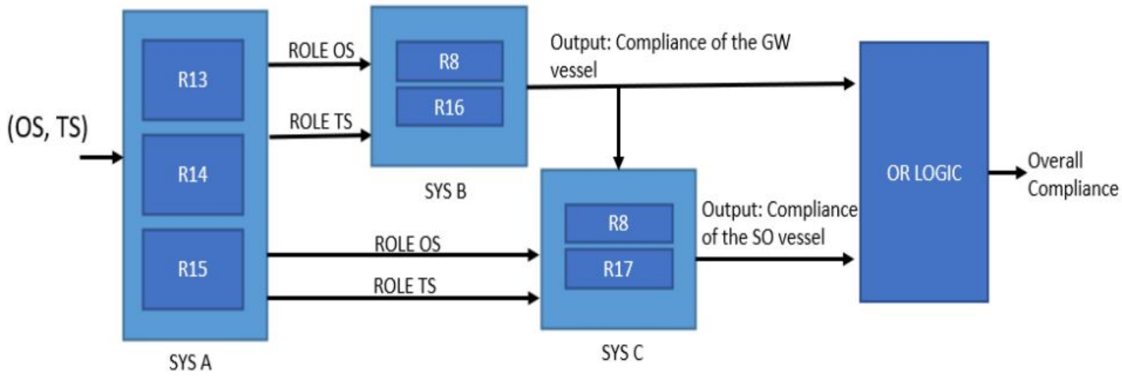


Figure 4: Fuzzy V&V system of collision avoidance from Trodahl (2021)

based on domain knowledge and previous literature. For example, in the fuzzifier of Løvoll (2022), relative bearing and contact angles are used for representing the term 'reciprocal or nearly reciprocal' in COLREG rule 13, by the experience from literature. This simplification was made aiming at facilitating the verification process and demonstrating the efficacy of the V&V process. However, (Løvoll, 2022) emphasized the importance of quantifying parameters when evaluating CAS in adherence to COLREG, particularly in the context of ASV, which has yet to be thoroughly investigated. As the accuracy of the FMF is crucial for the effectiveness of fuzzy logic-based evaluation systems, the tuning of the FMFs parameters or adapting different shapes of the FMFs are necessary for a better incorporation of COLREG compliance.

In the recent years, a technique named data-driven fuzzy logic has emerged based on knowledge-based fuzzy logic, and has been implemented in many other fields, for example, for predicting the remaining useful life in dynamic failure scenarios of a nuclear system (Zio and Di Maio, 2010) and for the prediction of rock burst intensity (Adoko et al., 2013), all of which demonstrate the effective integration of fuzzy logic and measurement data. In Adoko et al. (2013)'s work, fuzzy inference system (FIS) and adaptive neuro-fuzzy inference systems (ANFIS) were both implemented and the results were compared, showing that data-driven models outperform knowledge-based models, indicating the superior performance of the former. While in ship collision avoidance domain, proposals have emerged recently to enhance the reliability and interpretability of fuzzy logic systems by integrating Automatic Identification System (AIS) data. Inspired by this, two of the possible approaches to improve the knowledge-based fuzzy logic model used by (Løvoll, 2022; Trodahl, 2021) to a data-driven fuzzy logic model can thus be:

- Improve the FMFs by enabling the identification of significant parameters and obtaining more realistic parameter values. This can be conducted through analyzing extensive AIS data. By leveraging large-scale AIS datasets, it becomes possible to extract valuable insights and refine the understanding of key

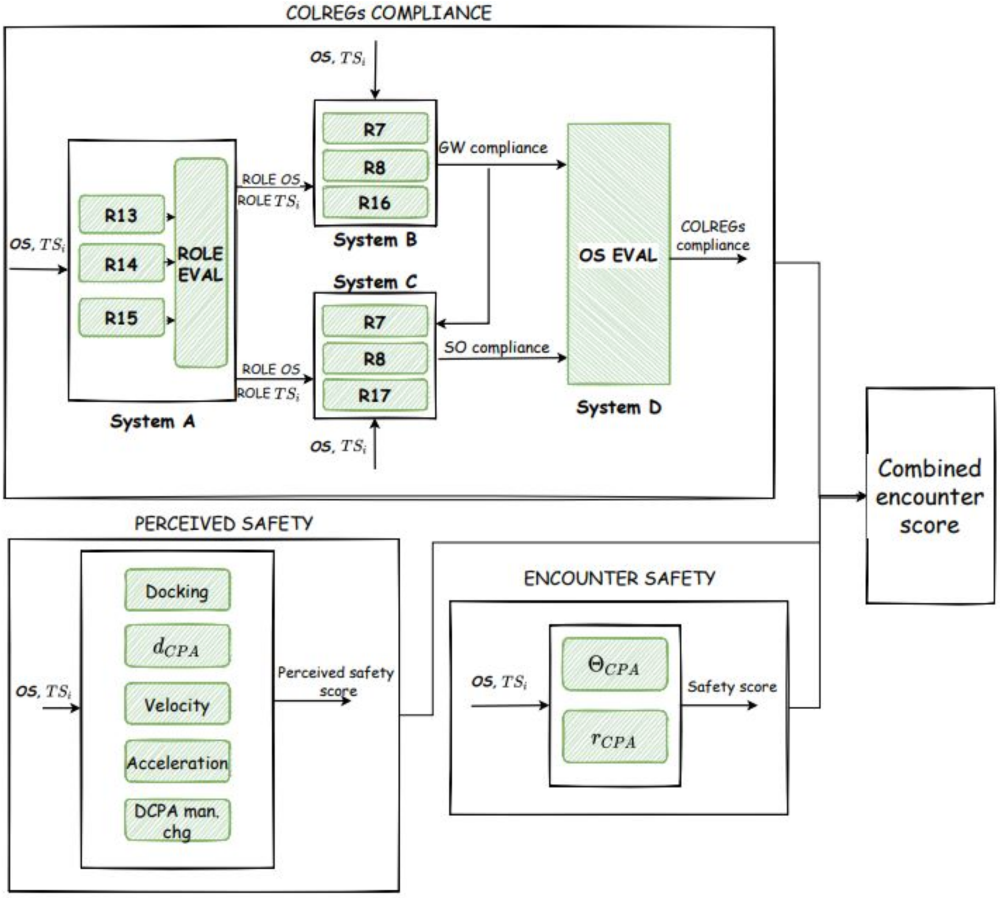


Figure 5: Fuzzy V&V system of collision avoidance from Løvoll (2022)

parameters.

- To enhance the original shapes of the FMF which are all trapezoidal, other types of shapes can be utilized.

- fuzzy neural netwok can be used to convert the current fuzzy system into a 'black box'.

  traditional forms such as trapezoidal, triangular, or Gaussian, an approach involves deriving the FMF based on the calculation of fuzzy degrees from extensive AIS data is proposed. Specifically, the fuzzy degrees of diverse cases are calculated, and neural network is employed to train these fuzzy degrees. The resulting fuzzy degrees are used to generate the curve of the FMF through regression analysis.

1.3 Literature Review

1.3.1 Collision Avoidance Algorithm

Collision avoidance is interpreted as "a process in which one ship departs from its planned trajectory to avoid a potential undesired physical contact at a certain time in the future" (Huang et al., 2020). According to his research, the whole process of collision avoidance includes two sub-stages: conflict detection and conflict resolution. For a manned ship, modern bridge system such as an Integrated Navigation System (INS) is engaged mainly in conflict detection stage to support human to make decision of how to control the ship to evasive collision, i.e. conflict resolution. For an unmanned ship, collision avoidance is executed by a Guidance and Control System. There are many different categories of collision avoidance, such as route planning, path planning and reactive collision avoidance. Route planning takes place on large scale map; path planning is to look for a collision-free path with static obstacles in some local area; reactive collision avoidance focuses on collision avoidance of moving obstacles. In the research area of this thesis, the verification of collision avoidance is reactive, i.e. collision avoidance with other ships with respect to COLREG.

The present study focuses on the verification of collision avoidance for an Autonomous Surface Vehicle (ASV), with potential implications for the verification of conventional ships by leveraging their Automatic Identification System (AIS) data. To achieve this goal, the collision avoidance system (CAS) model is extracted from prior research, and various collision avoidance algorithms and their underlying principles are succinctly introduced in this section.

In the work conducted by Huang et al. (2020), an assessment of different state-of-the-art techniques is undertaken. Initially, the author enumerates several prominent methods. Rule-based methods (Perera et al., 2012; Tam and Bucknall, 2013) are highlighted as one such approach, involving the integration of specific rules COLREG into the rule system. This integration enables the selection of rule-compliant actions for the own ship (OS). Additionally, the artificial potential field method (Lyu and Yin, 2019) is described, wherein the motion of the ship is guided by a resultant virtual force. Furthermore, the velocity obstacle algorithm (Huang et al., 2018; Wiig et al., 2017) is introduced, which identifies and gathers all potential collision velocities to aid in navigation.

Another important category of collision avoidance techniques is based on optimization approaches. For instance, Model Predictive Controller (MPC) (Chen et al., 2018; Ferranti et al., 2018; Papadimitrakis et al., 2021) is a powerful and general method designed to determine the optimal control input for a ship by solving an optimization problem. MPC has been utilized not only in marine field, but also other industries such as ground vehicles and aircrafts (Hagen et al., 2018). Typically, this problem formulation incorporates a cost function and various constraints.

The cost function often consists of quadratic terms associated with control input and vessel states, while the constraints are derived from vessel dynamics, environmental forces and collision-free conditions. Other constraints such as risk, fuel efficiency, operational constraints and destination time.etc. can also be included easily. Solving the optimization problem yields a set of optimal control inputs for a predicted time horizon, with only the first control input being employed at the current time step (Ferranti et al., 2018). This process is repeated at regular intervals to continuously update the control actions. Nevertheless, it is worth noting that MPC methods entail the formulation of complex optimization problems, which can result in substantial computational demands (Huang et al., 2020).

To evade this problem, Johansen et al. (2016) improved MPC method through representing the solution-space by a limited number of predictive scenarios. The obstacle motion is predicted based on simple holonomic model, while the control scenario of OS are defined by course and speed selection with 3-Degrees of Freedom (DOF) ship's dynamics model, this new control method is named SBMPC, and is illustrated as fig.6. By employing simulated predicted trajectories of OS and TS, it becomes possible to evaluate and select the optimal maneuvering action that adheres to COLREG. This evaluation and selection process can thus be accomplished through a hazard cost function. The primary equations in his work are presented below:

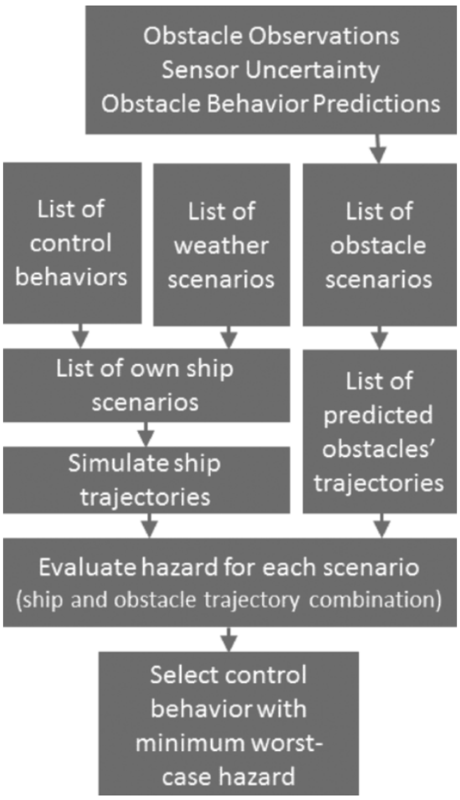


Figure 6: SBMPC CAS by Johansen et al. (2016)

$$k^*(t_0) = arg\min_k \mathcal{H}^k(t_0) \tag{1}$$

$$\mathcal{H}^k(t_0) = \max_i \max_{t\in D(t_0)} \left(\mathcal{C}_i^k(t)\mathcal{R}_i^k(t) + \kappa_i\mu_i^k(t)\right) + f\left(P^k, \chi_{ca}^k\right) + g\left(P^k, \chi_{ca}^k\right) \tag{2}$$

where the total cost $\mathcal{H}^k(t_0)$ in scenario k at time t_0 can be calculate by various factors: COLREG compliance term $\kappa_i\mu_i^k(t)$, cost of collision $\mathcal{C}_i^k(t)$, risk of collision $\mathcal{R}_i^k(t)$, penalty for path and speed deviation $f(P^k, \chi_{ca}^k)$ and risk of grounding $g(P^k, \chi_{ca}^k)$. Compared to traditional MPC, this method is computationally simpler for real-time operation, and it is also versatile by considering environmental forces and uncertainty from sensors and predictions. In contrast to conventional MPC approaches, this method exhibits computational simplicity, rendering it well-suited for the implementation of real-time operations.

Kjerstad (2020) expanded upon this MPC method by incorporating information regarding the intentions of other ships. He conducted a metrics-based safety evaluation and confirmed that the collision avoidance performance was enhanced. The simulation model for OS, as proposed by Kjerstad (2020), was extracted and applied in this thesis to generate data inputs for testing the V&V system. Figure 7 illustrates the various components of the OS's simulation model. The guidance system encompasses the Line of Sight (LOS) guidance law, reference models for both speed and heading, as well as SBMPC, which incorporates information regarding the intentions of other ships. This method selects the optimal propulsion command and heading angle offset that minimize potential cost. These selected values are then inputed to a feedback linearizing controller.

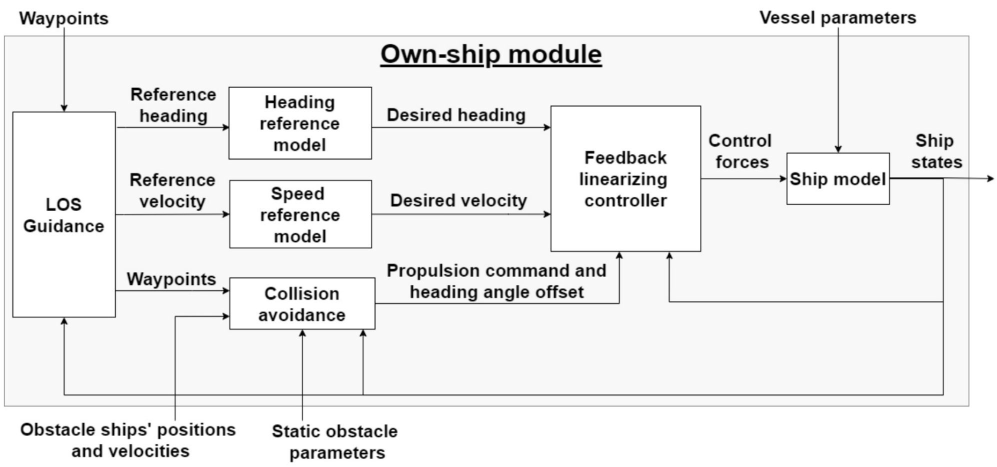


Figure 7: Guidance and control systems with SBMPC CAS (Kjerstad, 2020)

1.3.2 Verification and Validation of collision avoidance systems

The growing adoption of autonomy in ASVs and the integration of various CAS methods in recent years have been met with enthusiasm. These developments have significantly improved the overall performance and functionality of ASVs. However, as software complexity increases, ensuring the trustworthiness and reliability of safety-critical systems utilized in ASVs has become challenging, thereby hindering public acceptance of ASV implementation in the maritime domain. Collision, being the most frequent and severe hazard in the maritime field, has garnered significant attention for resolution. Consequently, researchers have dedicated considerable effort to the V&V of ship collision avoidance with compliance of COLREG, especially the recognizing the limitations of conventional V&V methods that prove inadequate in accommodating the non-deterministic characteristics of autonomous systems capable of continuous learning and adaptation (Helle et al., 2016). Specifically, V&V procedure for autonomous systems encompasses comprehensive testing and evaluation to guarantee their correct operation and efficient collision prevention. This generally entails conducting simulations or on-site tests on the systems across diverse scenarios and subsequently comparing the obtained outcomes with predetermined criteria to ascertain the adherence of the system to its intended design and functionality. Since 2016, various state-of-art approaches of V&V of ship collision avoidance with adherence to COLREG have been proposed. A flow chart of the process of V&V is illustrated as fig.8 (Bolbot et al., 2022; Kufoalor et al., 2020; Løvoll, 2022; Porres et al., 2020; Stankiewicz and Mullins, 2019; Trodahl, 2021; Woener and Benjamin, 2015; Woerner, 2016; Woerner et al., 2019).

1.3.3 Fuzzy logic

Fuzzy logic, proposed by Zadeh (1988), is a mathematical framework that enables the representation and manipulation of uncertainty and imprecision. It diverges from traditional binary logic by accommodating approximate reasoning and allowing for statements to possess degrees of truth or falsehood. In contrast to the misconception surrounding its name, Zadeh (2008) argued and substantiated that the key contribution of fuzzy logic lies in its capability to precisely handle imprecision and approximate reasoning. The underlying principles of fuzzy logic and how it is employed in the V&V system will be elucidated in Section 3.

The application domains of fuzzy logic are extensive and encompass mostly on control systems, as well as aerospace development, marine, artificial intelligence.etc. Its effectiveness becomes evident in scenarios where determining an exact truth value for a statement presents challenges, particularly when dealing with ambiguous or imprecise data. For instance, Chen et al. (1993) proposed a fuzzy-PID control system, and the stability analysis is performed. The Lyapunov's method was employed to establish a satisfactory criterion for ensuring stability. His work paved the way of the designing of fuzzy-PID control system and can be applied to non-fuzzy control model as well. In the work of Tanaka et al. (2001), fuzzy logic is employed in Lyapunov function as a 'Fuzzy Lyapunov function' by fuzzily blending quadratic functions. Through this, stability conditions for open-loop fuzzy systems are derived

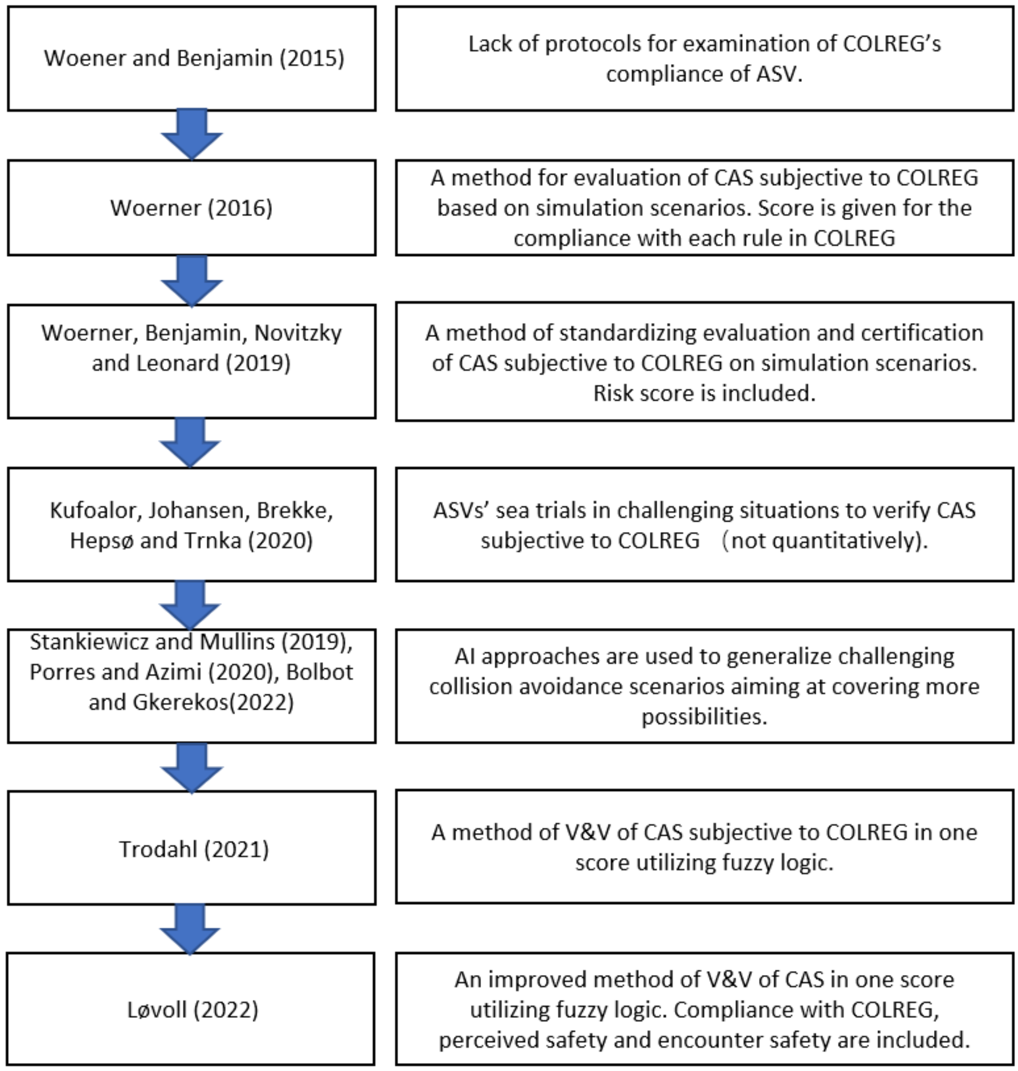


Figure 8: The process of V&V of collision avoidance of ASV

and discussed in his Takagi-Sugeno fuzzy model.

Fuzzy logic has been extensively utilized in the maritime domain since the early 21st century, particularly in the design of CAS and the assessment of collision risk. For instance, Kijima and Furukawa (2001) proposed a fault control method that integrated fuzzy logic to regulate the rudder for achieving the desired course change. The author employed TCPA and DCPA as fuzzy inputs for the fuzzy logic system. In a similar vein, Lee et al. (2004) presented a modified virtual force field method for ship track-keeping and collision avoidance. In his work, fuzzy rules were developed to provide explanations for the application of COLREG. To give a specific example, Perera et al. (2011) devised a collision avoidance decision-making system that can be seamlessly integrated with an Autonomous Guidance and Navigation (AGN) system. The author introduced a fuzzy inference system, visually presented in Fig.9, which incorporates various inputs such as the speed, course, and position of both the own vessel and the target vessel. This information is subsequently utilized to compute and fuzzify estimated relative speed and course values, employing a set of four FMFs.

The FMFs are specifically designed to capture essential aspects related to collision distance, collision region, relative speed ratio, and relative collision angle. Drawing upon the regulations stipulated by COLREG, a set of fuzzy rules is formulated in the form of if-then statements. These rules provide valuable outputs in the form of collision risk assessments and fuzzy decisions. To facilitate further analysis, the decisions are then subjected to defuzzification, primarily focusing on course change and speed change. Ultimately, the resulting defuzzified values serve as vital control inputs for the AGN system of the own vessel. To validate the proposed system, comprehensive simulation-based tests were conducted under critical collision conditions utilizing MATLAB. The outcomes of these tests successfully demonstrated that the incorporation of the fuzzy logic-based decision-making system, acting as a controller on the own vessel, effectively facilitated proper maneuvering in accordance with COLREG.

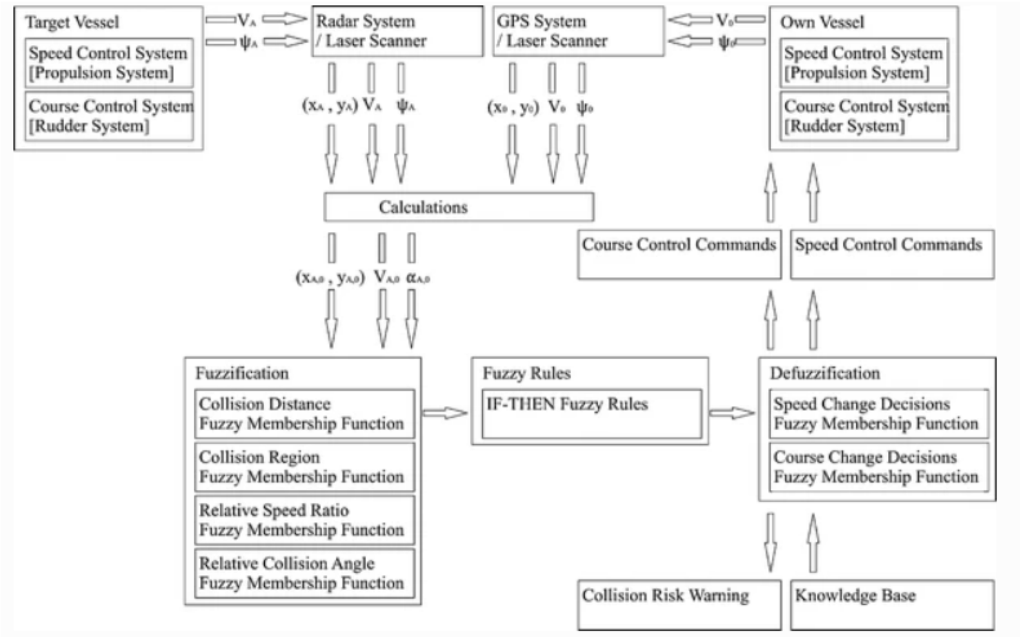


Figure 9: Fuzzy inference system (Perera et al., 2011)

1.3.4 AIS data

As a foundational element within the international shipping industry, AIS serves as an automated tracking system employed to discern and accurately determine the identities and positions of maritime vessels through the exchange of messages. Initially introduced during the 1990s, the primary objective of AIS is to reduce the risk of vessel collisions and improve overall navigation safety (Yang et al., 2019). By equipping ships with AIS technology, a wealth of information regarding the ship itself and neighboring vessels that are within 20 nautical miles range to it can be obtained via satellite or nearby coastal base stations. The mandatory implementation of AIS was introduced in 2002 for maritime vessels exceeding 300 gross tonnages engaged in international voyages, as well as for cargoes surpassing 500 gross tonnages in any body of water and all passenger vessels (Tu et al., 2017).

With the considerable benefits offered by AIS data and together the advancing maturity of big data processing capabilities, AIS data has found extensive applications within the maritime industry, both facilitating the optimization of seaway navigation management and the safe operation of maritime vessels. Since the beginning of the 21st century, researchers have directed their attention towards collision risk assessment of seaways based on AIS data. Firstly, assessing collision risk holds critical importance in determining the safe routing of ships through waterways. By collecting and analyzing historical AIS data specific to a particular waterway, the potential for ship collisions can be derived, thereby facilitating maritime traffic management and aiding in the design or improvement of these water areas. For instance, Mou et al. (2010) conducted a statistical analysis of AIS data in the Traffic Separation Scheme (TSS) off Rotterdam Port. To assess the risk in this water area, a dynamic method based on the SAMSON model is developed utilizing AIS data. The data was analyzed by calculating the DCPA along with other essential indices such as ship dimensions, speed, and course. A linear regression model was employed to investigate the correlations between these variables. Similarly, Feng et al. (2022) developed a quantitative collision risk assessment system using an information entropy method combined with K-means clustering on historical AIS data from Ningbo-Zhoushan Port. This system generated different groups of waterway legs with varying collision risk levels, as depicted in figure 10, thereby benefiting waterway management and assisting ships in prioritizing their maneuvers.

In ship's domain, AIS data has been employed for various purposes such as anomaly detection, trajectory prediction, collision assessment and path planning. Notably, Deep Reinforcement Learning (DRL), known for its efficacy in addressing continuous control problems, has been extensively utilized in research studies to construct data-driven autonomous path planning models. In a study conducted by Guo et al. (2020), the authors developed a path planning model using deep deterministic policy gradient algorithm by incorporating ongoing environmental interactions and historical AIS data, enabling the agent to acquire the optimal action policy. In his work, the fundamental principle is to maximize the reward obtained from a predefined reward function, that is, to minimize the distance between OS to target point and minimize the distance between OS to the range of obstacles (including static and dynamic obstacles). The specific equation of the reward function is as below:

$$R = \begin{cases} 2 & d_{t-goal} < D_{g-min} \\ -1 & d_{t-obs} < D_{o-min} \\ d_{t'-goal} - d_{t-goal} - 0.1 & other \end{cases} \tag{3}$$

where t and t' are the time of this step and the last step. d_{t-goal} and $d_{t'-goal}$ are the distance between OS to target point at time t and t', while d_{t-obs} represents the dangerous distance to the obstacle. D_{g-min} and D_{o-min} are the preset threshold to target and minimum distance threshold to obstacle. With the model, simulated scenarios were conducted utilizing a 2-dimensional map of 800 $\times$ 600 pixels (one pixel represents 10 meters in real environment) to replicate the range of ship motion. An essential determinant in deciding whether the ship collides is the assessment of whether it traverses the boundaries of this map. In the system's design process, AIS data played an indispensable role. This data was incorporated in the training of the deep learning framework, leading to the optimization of the neural network's structure and parameters.

In the terms of anomaly detection utilizing AIS data, it aims to find typical vessel motion patterns from AIS data and identify potential navigation safety hazards (Tu et al., 2017). Tu et al. (2017) classified ship anomaly into three groups: position anomaly when a ship appears in a restricted or unexpected water area, speed anomaly when the ship speed is significantly above or below regular speed, and time anomaly for the unexpected ship visiting time. Rhodes et al. (2005) use the normalcy box method to detect the speed anomaly by defining a set of region box based on the distance to the port, like dock region, dock perimeter region, inner harbor region and open water region. The learning system use the location and speed information from historical AIS data to learn the acceptable speeds limits of each region box. Rhodes et al. (2009) later improves system performance by replacing the rectangle region with hyper-ellipsoid. The normalcy box has good online ability and efficiency in updating the models with new data, but it cannot connect normal speed with static AIS information like vessel types. Osekowska et al. (2013) introduces the Potential Field Method (PFM) to maritime anomaly detection, where AIS data is used and different local charge is assigned to vessel's passed locations. The amount of a local charge is influenced by the number of vessels and time period.

$$\mathcal{C}_{lat_k,lon_l}(t) = \sum_{t=0}^{\tau} d(t)c_{lat_k,lon_l} \tag{4}$$

where lat_k, log_l are the geographical latitude and longitude coordinates at point (k, l), $d(t)$ is a non-increasing decay function over time and c_{lat_k,lon_l} is the charge carried by a vessel at the location. Then the potential field is build up with a two-dimensional Gaussian smoothing equation with standard deviation. Areas with high potential represents the normal behaviour, and the anomalous is considered when the observed vessel behaviour is not conform to the normal pattern. The potential field can be displayed on a map and is intuitive for users to detect both spatial and temporal anomalous.

1.3.5 Data-driven fuzzy logic

In a fuzzy logic system, the design of fuzzy sets, fuzzy membership functions, and fuzzy rules largely relies on experiential knowledge, leading to a significant degree of subjectivity (Nilashi et al., 2017). Conversely, machine learning has emerged as

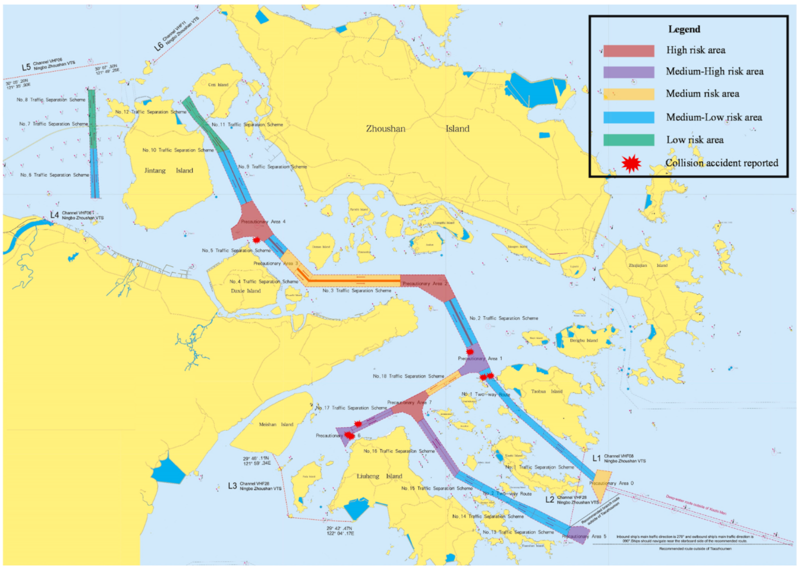


Figure 10: AIS trajectory plot in legs of water areas with different ship collision risk (Feng et al., 2022)

a powerful approach that leverages the analysis and learning of large-scale datasets, providing an automated means to enhance decision-making effectiveness. One of the most significant advantages derived from machine learning is the ability to achieve high accuracy when dealing with complex natural systems that involve large input data sets (Abiodun et al., 2018; Wang et al., 2017). While machine learning offers high accuracy, it still lacks interpretability in terms of comprehending the underlying rationale for decision-making processes. To provide an illustration, in a classical set A utilized in machine learning, each element x can only correspond to one of two scenarios: either x is in A or not in A. In contrast, a fuzzy set B can encompass elements that are partially included. The characteristics of a classical set are defined by its characteristic function $\mu(x)$, whereas a fuzzy set is characterized by its membership function $\chi(x)$, given by

$$\mu(x) : A \to [0, 1] \tag{5a}$$
$$\chi(x) : A \to \{0, 1\} \tag{5b}$$

Since the 1980s, ANN has emerged as a prominent research topic, aiming to simulate the intricate processes of information transmission within the neurons of the human brain (Dong and Hu, 1997). It consists of interconnected nodes (or neurons), while Each node corresponds to an activation function responsible for producing specific outputs. The connections between nodes represent weights assigned to signal propagation (Jenkins and Tanguay, 1995). To provide a comprehensive overview of ANN and fuzzy logic, a simple of comparison has been made as Table 1.

	Fuzzy logic	Neural network
knowledge acquisition	expert knowledge	big data
learning mechanisms	induction	weight adjustment
reasoning mechanisms	heuristic search	parallel Computing
error tolerance	low	high
reasoning speed	low	high
natural language flexibility	high	low

Table 1: Comparison between fuzzy logic and ANN

Given the previously mentioned benefits of fuzzy logic machine approaches, it is a logical progression to consider their integration. In the year 1990, (Takagi, 1990) first proposed a discussion and the future of the integration of these two methods. As a milestone, Jang (1993) first introduced Adaptive-Network-based Fuzzy Inference System (ANFIS). By leveraging both human knowledge in the form of fuzzy logic and specified input-output data pairs, ANFIS demonstrates the capability to establish mappings between inputs and outputs. This integration sets the stage for subsequent rapid advancements in the field of data-driven fuzzy logic, facilitating its improved performance and further development.

de Campos Souza (2020) made a review on data-driven duzzy logic using ANN. He highlights that there are two distinct strategies in the academic literature, namely FNN and Neural Fuzzy Network (NFN).

FNN

FNN is a specific type of neural network architecture that incorporates fuzzy neurons (de Campos Souza, 2020). Introducing the learning capability of neural networks into fuzzy systems provides a significant avenue for achieving self-organization and self-learning in fuzzy systems. By representing the fuzzy system's fuzzification, fuzzy inference, and defuzzification computations through distributed neural networks, a FNN becomes instrumental in facilitating the self-organization and self-learning processes of fuzzy systems. In a FNN, the input layer and output layer nodes of the neural network are employed to represent the input and output signals of the fuzzy system, respectively, in a fuzzy manner. The hidden layer nodes of the neural network are used to represent the composition of fuzzy rules. It is proved that leveraging the parallel processing capabilities of neural networks greatly enhances the inference capability of fuzzy systems. For instance, Lin et al. (2006) employed a independent component analysis based FNN to design an adaptive alertness estimation program. His FNN is illustrated as Figure 11, with 5 layers. Layer 1 receives the input and transfers it to second layer. Layer 2 projects the input into the independent axes by employing the independent component analysis, thus representing the the fuzzification process, in other words, the FMFs. Layer 3 aims at simulating the fuzzy rules, where each node represents one fuzzy rule and its precondition. Layer 4 is a consequent layer, with the black circles representing a fuzzy set of the output rule, and white circles transferring FMFs in layer 2 and rules in layer 3. Acting as a defuzzifier, the last layer provides the out put as one variable y_1.

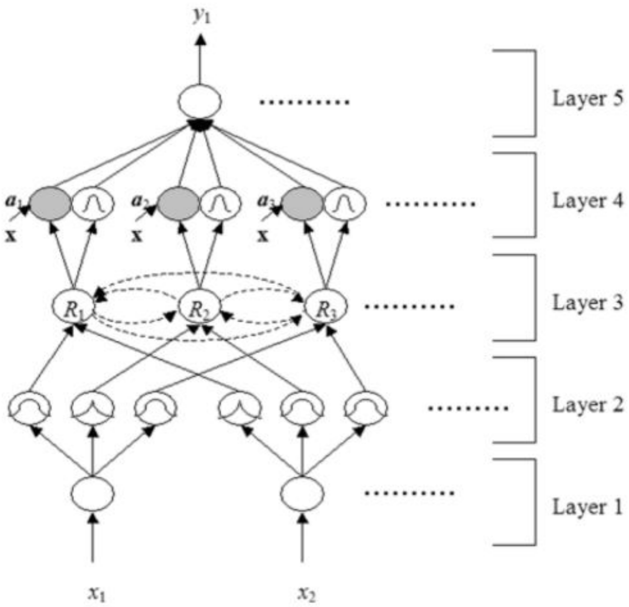


Figure 11: FNN

NFN

NFNs set themselves apart from FNN through the incorporation of neural network training for specific components, such as fuzzification or fuzzy rules. (de Campos Souza, 2020) The primary objective of NFNs is to effectively handle intricate mathematical relationships thus improving this fuzzy component, such the changing the FMF parameters and shapes, and the amount and content of fuzzy rules. Throughout the training process, algorithm provided by an intelligent model can be employed. Except for ANN, other techniques of data analysing or machine learning have also been applied. For example, in order to generate the improved FMFs, ANN is used by Takagi and Hayashi (1991), fuzzy c-means clustering is employed by Adoko et al. (2013), histogram and decision tree by Yadav and Yadav (2015) and genetic algorithms by Karr and Gentry (1993).

1.4 Objective and Scope

Based on the literature reviewed above, it can be concluded that:

- The rapid development of autonomous ships in recent years has presented challenges in accurately applying the V&V process to the CAS of autonomous vessels.
- COLREG was established with a primary focus on manned ships, resulting in terminologies and concepts that may be vague and not readily applicable

to autonomous ships. To bridge this gap and facilitate better adherence to COLREGs by autonomous vessels, the integration of fuzzy logic as a powerful tool is highly promising, which can effectively address the challenges posed by the imprecise and uncertain nature of autonomous systems, enabling a more nuanced and context-aware interpretation of COLREG for autonomous ships.

- Several researches have been carried out showing a promising usage of fuzzy logic on the V&Vof CAS, but all are based on expert knowledge and experience. For better evaluating collision avoidance, AIS data has emerged as a promising strategy. By incorporating AIS data, the utilization of data-driven fuzzy logic can significantly enhance the interpretability, reliability, and accuracy of the fuzzy logic system.
- Data-driven fuzzy logic is not a novel concept, and numerous methods utilizing data-driven fuzzy logic have been developed and proved powerful.However, their adoption and implementation in maritime applications remain relatively limited.

Motivated by the above research gaps and the investigations carried out by Trodahl (2021) and Løvoll (2022), the primary objective of this thesis is to further advance the existing the V&V model with the utilization of large-scale AIS data. This advancement is achieved by employing data-driven fuzzy logic. It involves enhancing the parameters and shapes of fuzzy membership functions through the analysis of AIS data using machine learning approaches such as classification and regression. Based on this, a fuzzy C-Mean based Takagi–Sugeno fuzzy inference system can be derived to replace the original knowledge-based fuzzy system. The final stage of this research entails conducting simulation-based tests to evaluate the performance of the enhanced data-driven fuzzy V&V system. .

1.5 Contribution

The contribution of this thesis is listed as following:

1. Data preprocessing for raw AIS vessel data: A comprehensive data preprocessing methodology is developed to handle raw AIS vessel data and contribute to the generation of high-quality datasets for subsequent analysis and modeling.
2. Data analysis for head-on scenario in COLREG: The study focuses on analyzing head-on scenarios in COLREG, specifically addressing important parameter recognition and correlative analysis, providing valuable insights for collision avoidance strategies.

3. Investigating a data-driven approach combining fuzzy logic system and neural network: A novel approach to optimize the Fuzzy Membership Functions (FMFs) is developed, which could provide a more accurate representation of the system dynamics, enhancing the overall performance of the fuzzy logic system. The research contributes by demonstrating the potential of integrating fuzzy logic systems and neural networks to overcome the limitations of traditional rule-based systems in COLREG analysis.

1.6 Outline

The rest of this thesis is organized as follows: Chapter 2 presents some relevant basic theory for the following work. Chapter 3 introduces the methodology used for verification, including data pre-processing, data analysis and data-driven fuzzy model. In Chapter 4, the proposed method is tested by simulations of various scenarios, and the results are displayed and compared with that of tradition fuzzy logic V&V system, then the challenges and limitations are pointed out. In Chapter 5, the work of this thesis is concluded, and potential future work is listed.

2 Basic Theory

2.1 AIS

As a foundational element within the international shipping industry, AIS serves as an automated tracking system employed to discern and accurately determine the identities and positions of maritime vessels through the exchange of messages. By equipping ships with AIS technology, a wealth of information regarding the ship itself and neighboring vessels that are within 20 nautical miles range to it can be obtained via satellite or nearby coastal base stations. The mandatory implementation of AIS was introduced in 2002 for maritime vessels exceeding 300 gross tonnages engaged in international voyages, as well as for cargoes surpassing 500 gross tonnages in any body of water and all passenger vessels Tu et al. (2017). The AIS data encompasses various types of information, including static details such as the ship's name, Maritime Mobile Service Identity (MMSI)-number, ship type, and sometimes the ship's dimensions are available as well. In addition to static information, the high-frequency kinetic messages transmitted through AIS data at intervals of typically 3 to 10 seconds (3 minutes when the ship is at anchor) enable dynamic monitoring of vessel movements and maritime traffic analysis, including historical vessel trajectories and port navigational channels. This dynamic information encompasses elements such as time, positional coordinates, speed, heading, course, and rate of course change Mou et al. (2010). Table 2 presents an illustrative instance of the AIS data employed in this thesis, while Table 3 provides explanations for each indicator within the dataset.AIS data can be categorized into two types: historical AIS data and live AIS data, with historical AISS data generally accessible through numerous maritime information databases. The information provided by AIS plays a crucial role in enhancing situational awareness, making it an indispensable resource for studying maritime traffic and addressing related critical situations, particularly vessel-to-vessel collisions Rong et al. (2022). By utilizing the latitude and longitude information present in AIS data, ship trajectories can be visualized, providing a more intuitive understanding of vessel movements for subsequent analysis purposes. Figure 12 is an example plot of the trajectories of cargo ships and tankers in Trondheim water area on 15th January 2020.

mmsi	unixtime	latitude	longitude	heading	sog	nav	cog	rot
209318000	1577849253	63.7961	9.5702	207	8.5	0	208.10	-7.54
209318000	1577849264	63.7921	9.5698	206	8.5	0	204.69	-2.18
209318000	1577849295	63.7981	9.5688	205	8.5	0	201.10	0.71

Table 2: Example of AIS data

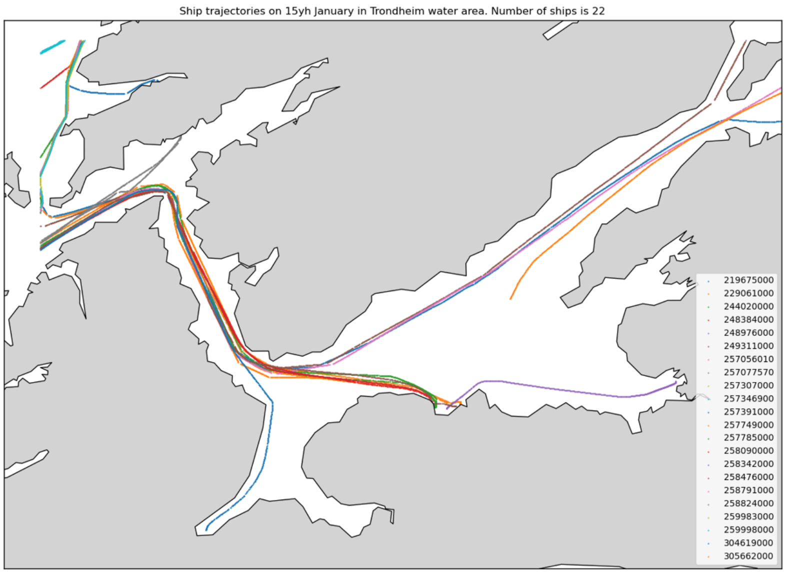


Figure 12: ship trajectories plot in Trondheim water area on 15th January 2020

Indicator	Description	Unit/Accurancy
mmsi	Maritime Mobile Service Identity number	
unixtime	timestamp in second	1 second
latitude	longitudinal position	10 m
longitude	latitudinal position	10 m
heading	nose heading	deg
sog	speed over ground	knot
nav	navigation status	
cog	course over ground	deg
rot	rate of rotating	deg/min

Table 3: Explanation of indicators in AIS data

2.2 COLREG

COLREGs represent the "International Regulations for Preventing Collisions at Sea" published by IMO, a comprehensive set of rules and regulations designed to mitigate the occurrence of vessel collisions in maritime environments. These regulations establish a standardized framework for vessels' actions and responsibilities at sea to ensure secure navigation and avoid collisions.

However, the COLREG rules are primarily written for human operators(Benjamin and Curcio, 2004), which presents challenges when integrating them into the CAS of ASV (Woerner, 2016). For example, COLREG rules are designed to address encounters between two vessels, whereas in practical scenarios, an ASV may simultaneously assume both stand-on and give-way roles, potentially leading to conflicts where one rule has to be disregarded. Therefore, conducting evaluations is important as they enable a deeper understanding of the performance of CAS by quantifying to what extent the algorithms comply with the COLREG (Woerner, 2016). These evaluations provide valuable insights into the system's adherence to the COLREG rules, allowing for improvements and adjustments to ensure better compliance and safety.

Among the rules defined in the COLREG, Rules 13, 14, and 15 primarily serve to determine the specific type of encounter situation and prescribe the appropriate actions to be taken in order to avoid collisions, illustrated as Figure 13. Conversely, Rules 8, 16, and 17 provide guidance on the specific actions to be taken in various circumstances. A more detailed explanation of these rules is provided below.

- Rule 8 - Action to avoid the collision. It outlines the necessary actions to be taken by vessels to prevent potential collisions. According to this rule, any alteration in course and/or speed should be substantial enough to be perceptible to other vessels, ensuring a safe passing distance is maintained. Course alteration is often considered as the most effective means to evade a close-quarters situation.
- Rule 13 - Overtaking. An overtaking scenario occurs when one vessel approaches another from a direction that is more than 22.5 degrees behind the overtaken vessel's beam. In such circumstances, the vessel undertaking the overtaking maneuver takes the responsibility of maneuvering and maintaining a safe distance from the vessel being overtaken.
- Rule 14 - Head-on situation. Head-on situations occur when two vessels are approaching each other on reciprocal or nearly reciprocal courses. In such instances, both vessels are obligated to alter their course to starboard to ensure that they pass each other on the port side.
- Rule 15 - Crossing situation. When two vessels are approaching each other within a certain angle, the vessel that has the other vessel on its starboard side bears the responsibility of giving way and avoiding crossing ahead of the other vessel.
- Rule 16 - Action by GW vessel. Rule 16 of the COLREGs addresses the actions to be taken by a GW vessel, which refers to a vessel that is required to keep out of the way of another vessel. According to this rule, the GW vessel must initiate timely and significant maneuvers to avoid a potential collision.
- Rule 17 - Action by SO vessel. According to this rule, when one of two vessels is designated as the give-way (GW) vessel, the other vessel should assume the stand-on status and maintain its current course and speed.

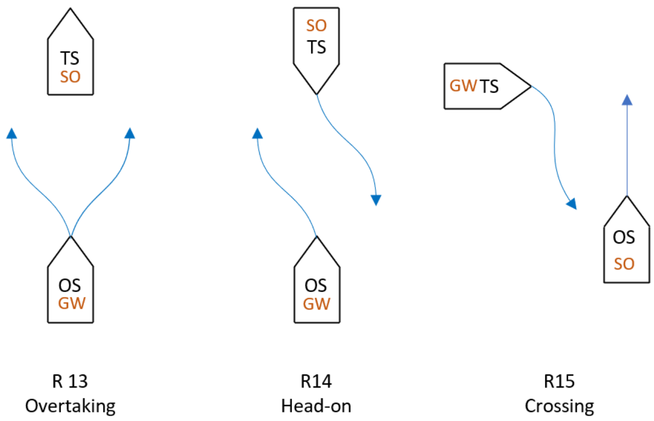


Figure 13: An illustration of rule 13, 14, 15

Entry criteria

The determination of appropriate actions in accordance with the COLREG relies on the critical contact angle, denoted as α_{crit}, which serves as a pivotal parameter. This critical angle plays a vital role in assessing and evaluating the specific COLREG situation encountered by a vessel. The incorporation of a critical contact angle offers flexibility in the evaluation process, allowing designers to customize and optimize this angle to closely align with the decision-making practices of human ship operators, as suggested by Woerner et al. (2019).

2.3 Collision avoidance notation

This section introduces basic notation used in ships' collision avoidance, which consists of general notation of one ship as well as notation of ship encounter situation.

One ship notation

The ship under investigation is referred to as own ship (OS), and its maneuverability is the main focus of study and validation. To describe the pose of a ship, essential parameters such as speed, position, and angle are required.

Ship position: The coordinates of OS is noted in a earth-fixed frame as $[x_{OS}, y_{OS}]^{\mathrm{T}} \in \mathbb{R}^{2\times 1}$. The AIS data employed in this thesis includes position information in the form of longitude and latitude coordinates. To align these coordinates with an earth-fixed frame of reference, an arbitrary origin is defined and utilized for the transformation process.

Ship direction: There are multiple methods available to describe the direction of a ship, among which the following three are commonly utilized: heading (yaw) ψ , course χ and sideslip (drift) λ. According to Xu (2022), it is worthy to distinguish these different parameters, as they are used interchangeably and confusedly in much of researched in marine field. Heading ψ is defined as the angle from NED x-axis to the body x-axis, course χ is the angle from the NED x-axis to the velocity vector U of the ship. Heading and course have a difference as there might exists a sideslip (drift) λ, which is the angle from body x-axis to the velocity vector of the vessel (Fossen, 2011). The sideslip can be caused by nonzero sway velocity as a consequence of environmental forces. Note all the terms satisfy the positive rotation about z-axis frame by the right-hand screw convention (Fossen, 2011). Simply, the relation between these three ship direction terms is:

$$\chi = \psi + \lambda \tag{6}$$

The draft of one ship notation is illustrated in fig.14. Within the AIS dataset, two parameters, namely heading or nose heading ψ, and course over ground χ, are employed to represent the direction of a ship.

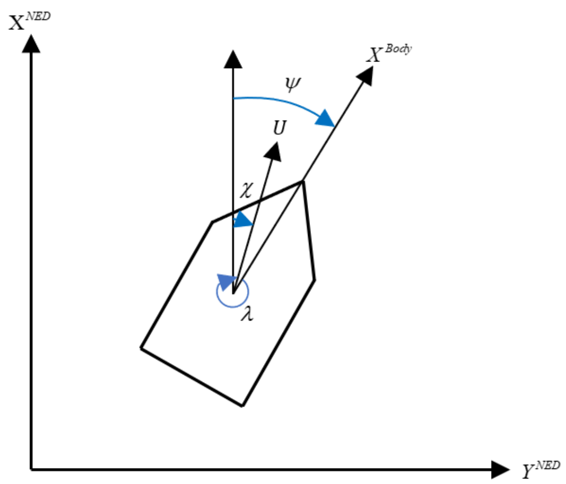


Figure 14: One ship notation

Ship encounter notation

In a ship encounter situation, the counterpart of OS is TS, which representing potential obstacles that pose collision risks to the OS. To effectively depict and assess such scenarios, various factors including relative position, relative angles, and expert-based indices have been introduced by Benjamin (2017) and Løvoll (2022).

Taking a one-to-one ship encounter scenario as an example, the positions of the OS and TS are denoted as $[x_{OS}, y_{OS}]$ and $[x_{TS}, y_{TS}]$, respectively, within an earth-fixed frame of reference. The headings of the ships are denoted as ψ_{OS} and ψ_{TS}, while U_{OS} and U_{TS} represent the respective speeds of the OS and TS. These positional, heading, and speed values can be obtained from the AIS data set. Utilizing the aforementioned indices, the relative range r_{TS}^{OS} between OS and TS, which represents the linear distance between the two ships, can be calculated as follows:

$$r_{TS}^{OS} = r_{OS}^{TS} = \sqrt{(x_{OS} - x_{TS})^2 + (y_{OS} - y_{TS})^2} \tag{7}$$

In addition to the relative range, two significant indices, namely the relative bearing ($\bar{\beta}$) and the relative contact angle ($\bar{\alpha}$), have been introduced to depict the relative angle between OS and TS, inspired by Nguyen et al. (2023). The following formulas can be utilized to calculate the prerequisite parameters, as well as the relative bearing and relative contact angle. It is important to note that all angle parameters are measured in a positive clockwise direction.

The bearing (β), ranging from 0 to 360°, represents the angle from the north of OS to the linear distance towards TS. The relative bearing ($\bar{\beta}$), also ranging from 0 to 360°, denotes the angle from the heading of OS to the linear distance towards TS.

$$\beta = atan2(y_{OS} - y_{TS}, x_{OS} - x_{TS}) \tag{8a}$$

$$\bar{\beta} = \begin{cases} 360° - abs(\beta - \psi_{OS}) & \beta - \psi_{OS} < 0° \\ \beta - \psi_{OS} - 360° & \beta - \psi_{OS} \geq 360° \\ \beta - \psi_{OS} & else \end{cases} \tag{8b}$$

An alternative approach to describe the angles involves utilizing contact angle (α) within the range of $[0, 360°)$. In contrast to bearing angle, contact angle initiates from the north of TS and extends towards the linear distance to the OS. Obtaining contact angle can be achieved by simply adding π to the bearing angle. The calculation of relative contact angle ($\bar{\alpha}$) follows the same methodology as that of relative bearing. A visual representation of the notations for a ship encounter scenario involving two ships is illustrated in fig.15.

$$\alpha = \beta + \pi \tag{9a}$$

$$\bar{\alpha} = \begin{cases} 360° - abs(\alpha - \psi_{TS}) & \alpha - \psi_{TS} < 0° \\ \alpha - \psi_{TS} - 360° & \alpha - \psi_{TS} \geq 360° \\ \alpha - \psi_{TS} & else \end{cases} \tag{9b}$$

Additional parameters crucial for the verification against COLREG are listed as follows. For a specific ship denoted as ship i, course alteration $|\Delta\chi_i|$ and speed alteration $|\Delta U_i|$ are considered. The relative heading $\delta\psi \in [0, 360°)$ and the relative course $\Delta\chi$ from the perspective of OS are calculated using the following equations:

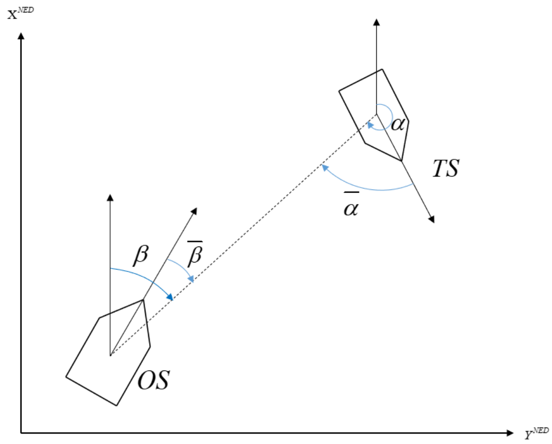


Figure 15: 2 ship encountering notation

$$\Delta\psi = |[\psi_{OS} - \psi_{TS}]_{180^\circ}| \tag{10a}$$
$$\Delta\chi = mod(\chi_{OS} - \chi_{TS}, 360^\circ) \tag{10b}$$

Notice that until now, all the angular variables are not relevant about the ship speed, except for course over ground.

The closest point of contact

Inspired by Benjamin (2017) and Nguyen et al. (2023), another important definition used for assessing the collision risk is CPA. It is the point on the track of OS, where the range between OS and TS is at its minimum. Since CPA is a closest point that does not exist in reality, two expert-based variables are introduced to numerically estimate the risk of collision, that are TCPA and DCPA. TCPA is the estimated time for the ships to reach this point, assuming the speed and heading of the ships are constant. This can be calculated through setting the first order derivative of range as 0 and solving for time (Nguyen et al., 2023). DCPA is the range between OS and TS when they are at the time of TCPA, estimated. The calculation of the two variables related to CPA can be accomplished through various approaches established in previous research. In this thesis, the methodology proposed by Benjamin (2017) is employed, which relies on the positional information, headings, and speeds of the ships.

$$DCPA = \sqrt{k_2 TCPA + k_1 TCPA + k_0} \tag{11a}$$
$$TCPA = \begin{cases} 0 & \dot{r} \geq 0 \\ -\frac{k_1}{k_2} & otherwise \end{cases} \tag{11b}$$

where k_0, k_1, and k_2 are given by:

$$k_0 = (y_{OS} - y_{TS})^2 + (x_{OS} - x_{TS})^2$$

$$\begin{aligned} k_1 = {} & 2\cos(\psi_{OS})U_{OS}y_{OS} - 2\cos(\psi_{OS})U_{OS}y_{TS} - 2\cos(\psi_{TS})U_{TS}y_{OS} + 2cos(\psi_{TS})U_{TS}y_{TS} \\ & + 2\sin(\psi_{OS})U_{OS}x_{OS} - 2\sin(\psi_{OS})U_{OS}x_{TS} - 2\sin(\psi_{TS})U_{TS}x_{OS} + 2sin(\psi_{TS})U_{TS}x_{TS} \end{aligned}$$

$$k_2 = \big(\cos(\psi_{OS})U_{OS} - cos(\psi_{TS})U_{TS})^2 + (\sin(\psi_{OS})U_{OS} - \sin(\psi_{TS})U_{TS}\big)^2$$

3 Methodology

3.1 Fuzzy logic

A fuzzy logic system is a computational framework that aims to model and emulate human reasoning under conditions of uncertainty and imprecision. It is based on fuzzy set theory, which allows for the representation and manipulation of vague or fuzzy concepts. In a fuzzy logic system, information is processed using fuzzy logic, which extends traditional binary logic to incorporate degrees of truth and membership. Theoretical foundations of fuzzy logic encompass four essential components: fuzzy sets, fuzzifiers, fuzzy rules, and defuzzifiers. These elements collectively constitute the fuzzy logic system, as depicted in Figure 16. The subsequent introduction of the fuzzy system is based on (Klir and Yuan, 1995) and (Ross, 2009).

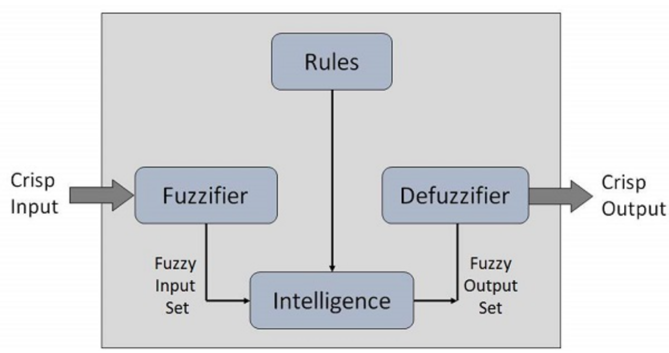


Figure 16: Fuzzy logic system

Fuzzy set

The fundamental notion of the fuzzy set was originally proposed by (Zadeh, 1965). A fuzzy set, denoted as A, is characterized by the membership function $\mu_A(x)$, which assigns a degree of membership to an element x in the range between 0 and 1. Unlike traditional sets that categorize elements as either completely in or completely out, the concept of fuzzy sets allows for a continuum of membership values, thereby accommodating varying degrees of uncertainty. The representation of fuzzy set A is expressed as follows:

$$A = \{x, \mu_A(x) | x \in X\} \tag{12}$$

where the symbol X represents the universe of discourse, encompassing all relevant elements under consideration. The function $\mu_A(x)$ corresponds to the fuzzy membership function (FMF) associated with element x. The value assigned by $\mu_A(x)$ reflects the degree of truth, ranging between 0 and 1, thereby quantifying the extent to which x belongs to the fuzzy set A.

Fuzzifier

Fuzzification is the process of converting a crisp input value x into a fuzzy input set A by assigning them degrees of membership utilizing a set of FMFs. Since fuzzy sets operate within a universe of discourse X consisting of a large or infinite number of elements x, explicitly defining all pairs to establish a FMF becomes impractical. As stated by Ali et al. (2015), the selection of the FMF shape is a critical aspect in the architecture of a fuzzy logic system because it directly influences the degree of truth for each x. Previous research employing fuzzy logic has commonly employed triangular, trapezoidal, and Gaussian FMF shapes, as illustrated in Figure 17. Other shapes, such as exponential, generalized bell, sigmoid, and 2-D FMFs, are also viable alternatives (Samanta, 2018).

Ali conducted a comparative analysis of the three most commonly used FMF shapes to determine their impact. For this purpose, a fuzzy logic controller was developed for the Antenna Azimuth Position Control System. The study concluded that while the triangular and trapezoidal FMFs exhibit similar response characteristics in terms of rising time and overshoot, the triangular FMF outperforms in steady-state behavior. Conversely, when dealing with systems involving probabilistic and statistical data, the Gaussian FMF is generally preferred.

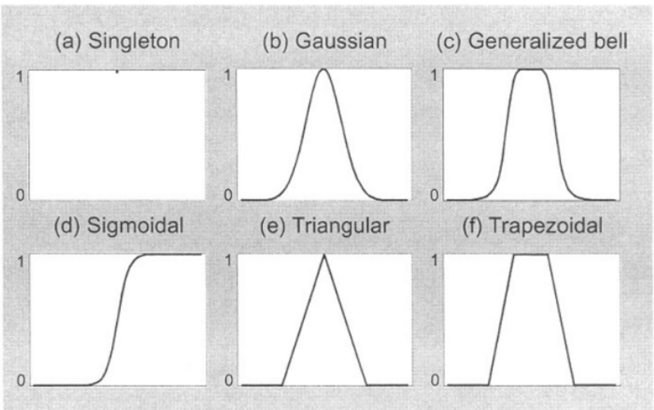


Figure 17: FMF shapes (Ali et al., 2015)

Regarding V&V of collision avoidance system, Trodahl (2021) and Løvoll (2022) have chosen the commonly used trapezoidal FMF due to its simplicity and effectiveness in demonstrating the functioning of the V&V system. An example of a trapezoidal FMF is depicted in Figure 18, where the variable x represents the relative bearing course of the own ship, ranging from 0 to 360 degrees with a 2-degree interval. The fuzzy membership degree $\mu(x)$ ranges from 0 to 1. By setting the x-coordinates of the four folding points on the blue line as a, b, c, and d, the trapezoidal FMF can be constructed using the MATLAB language through the expression $y = \text{trapmf}(x, [a, b, c, d])$. This approach facilitates the interpretation of Rule 14, part (a) in COLREGs, which states that "When two power-driven vessels are meeting on reciprocal or nearly reciprocal courses so as to involve risk of collision, each shall alter her course to starboard." Here, the term "reciprocal or nearly reciprocal courses" is represented by a range of relative courses from 168 degrees to 192 degrees, rather than precisely 180 degrees.

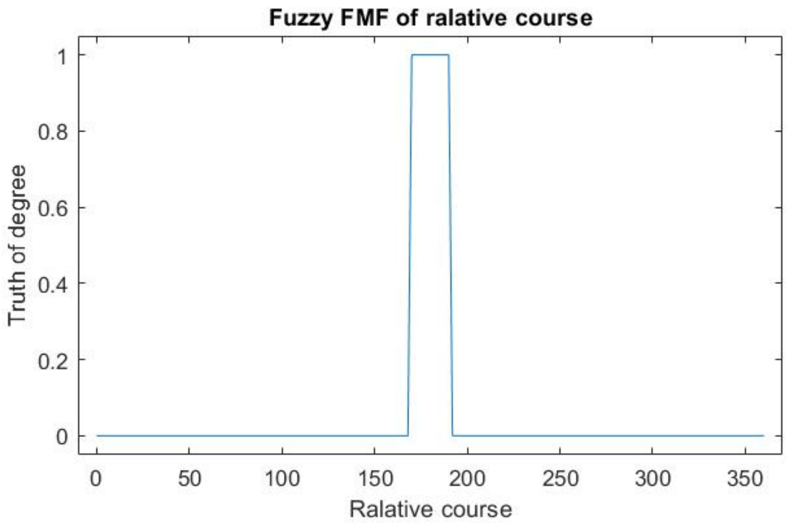


Figure 18: A example of trapezoidal FMF

Fuzzy rules

The inference process in fuzzy logic involves the utilization of fuzzy rules and intelligent reasoning. Fuzzy rules typically take the form of if-then rules incorporating AND or OR logic, which are designed for classification purposes. These rules are often derived from the experiential summaries of manual control strategies. In the context of this study, the rules are formulated by interpreting the COLREG. For instance, considering the aforementioned Rule 14, part (a), a possible fuzzy rule can be defined as follows: If OS and TS are on a head-on course, then the role of OS is governed by the GW principle, and the role of TS is also governed by the GW principle.

Defuzzifier

Defuzzification represents the final stage in a fuzzy logic system, involving the conversion of a fuzzy set into a crisp set. This involves aggregating the fuzzy sets and determining a single representative value that best represents the fuzzy output. This process commonly entails computing the weighted average of the fuzzy set, with the weights determined by the degree of membership assigned to each value within the fuzzy set. Various methods can be employed for defuzzification, including the center of gravity method, the mean of the maximum method, and the smallest of the maximum method. In this thesis, the center of gravity method is utilized, which employs the following equation:

$$COG = \frac{\sum_{i=1}^{N} A_i \times x_i}{\sum_{i=1}^{N} A_i} \tag{13}$$

Here, N represents the number of subareas, A_i denotes the area of each subarea, and x_i signifies the x-coordinate of the centroid of the corresponding area.

3.2 Case construction

The AIS data utilized in this study were extracted from land-based stations and specifically comprised the raw AIS data pertaining to the Trondheim, Oslo, and Kristiansund water areas during the years 2019 and 2020. These raw AIS data are characterized by a substantial volume, amounting to nearly 1 TB per water area per year, and exhibit significant complexity and irregularity for each individual vessel. Since the data required for following fuzzy membership training necessitates the presence of two-ship encounter situations, it becomes essential to refine the raw AIS data into distinct cases, facilitating subsequent data mining processes and the development of the fuzzy V&V system of ship collision. This section is inspired by the notable research conducted by Vassbotn (2022) on the refinement of AIS data analysis.

Ship type filter

Given that the raw AIS data encompasses information from various ship types, the initial stage of data refinement involves filtering the data to exclusively retain cargo ships and tankers. While COLREG applies to all vessels in high seas and connected waters, cargo ships and tankers typically exhibit superior compliance performance and possess more representative characteristics that are more advantageous for subsequent analysis than other ship types such as passenger ships or fishing vessels. As the raw AIS data lacks ship type information, a Python script is developed to autonomously retrieve ship types from an online database as numeric values. Specifically, the range of 70 to 79 is designated for cargo ships, while tankers are assigned values ranging from 80 to 89. The trajectories of filtered ships on a specific day in the Trondheim region are depicted in Figure 19 as an example.

Dock recognition

In this thesis, the presence of ships at dock areas and anchorage areas is deemed undesirable due to their distance from potential collision situations. To identify and exclude such ships from the AIS dataset, data instances characterized by zero speed over ground and an 'at anchor' navigation status were utilized, as depicted in Figure

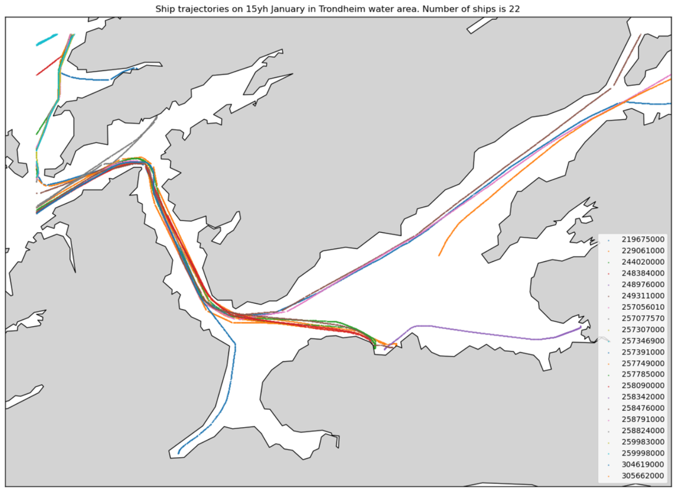


Figure 19: Trajectories of Cargo ships and tankers in Trondheim water area on 15th January 2020

20. Additionally, ships in close proximity to a dock are also considered undesired. To address this, the Density-based Spatial Clustering of Applications with Noise (DBSCAN) clustering method was employed to classify the at-dock data points into distinct classes, thereby representing different dock areas. The centroid points of these classes were subsequently designated as dock locations. By this, 16 ports are recognized, including 2 ports adjacent to a seaway. After this, the data points within a 3km radius of the dock locations were removed from the dataset. While for docks located adjacent to a seaway, a distance threshold of 0.5 km was employed. As a result, 8.43% of the data was identified as being in close proximity to a dock and subsequently eliminated.

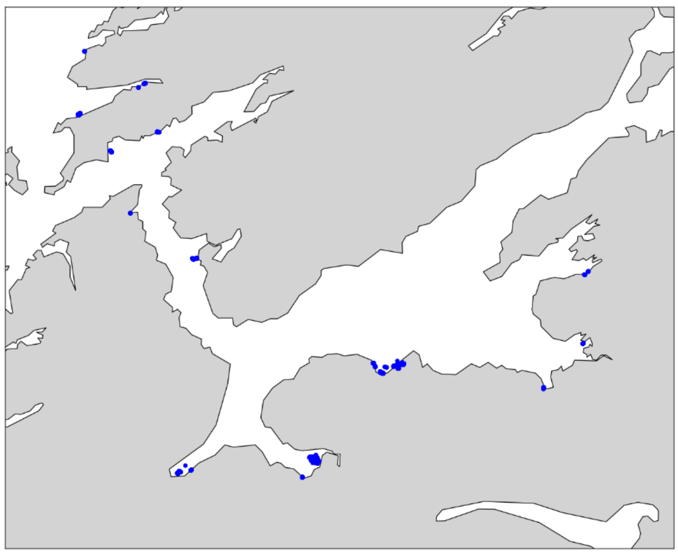


Figure 20: Data points at dock in Trondheim

Down sampling

Due to the varying transmission intervals of AIS data, typically ranging from approximately 3 to 10 seconds and dependent on ship speed and heading, the dataset may contain excessively dense data points that require removal. Such dense points commonly occur, for instance, when one returns to a straight path after a turn or prepares to dock. To address this, a simple linear approximation method is employed to estimate the location of specific data points between the preceding and subsequent data points. Data points with a difference between their actual location and estimated location of less than 10 meters are eliminated from the dataset. This process results in the removal of 26.48% of the data. To ensure the validity of the remaining dataset for collision studies, a quick validation is performed by confirming that the sog for all ships is above 1 knot, indicating the dataset's suitability for further analysis.

Estimate point

Since the AIS data is not available at any given arbitrary time with accuracy in second, it becomes necessary to estimate missing information for specific timestamps in order to facilitate subsequent computations. Assume the data needed is at timestamp t , the first step is to check t presents in the dataset or not. If not, a binary search is carried out aiming at find the closest data of the given time. Then the non-positional data (e.g., speed, SOG, COG) with the timestamp closest to t is copied over. Regarding the positional data (latitude and longitude), a linear approximation method assuming constant speed is employed using the preceding and subsequent data points. The equations for linear approximation of longitude and lagitude are as follows:

$$\hat{x}(t) = x_1 + \frac{x_2 - x_1}{t_2 - t_1} \times (t - t_1) \tag{14a}$$

$$\hat{y}(t) = y_1 + \frac{y_2 - y_1}{t_2 - t_1} \times (t - t_1) \tag{14b}$$

where $\hat{x}(t)$, $\hat{y}(t)$ are the estimated longitude and latitude at time t. t_1, and t_2 are the previous and next timestamps.

Potential COLREG case searching

To identify ship encounter cases where two ships have the potential to maneuver in accordance with COLREG, the steepest descent method is utilized. This method determines if the DCPA is within a proximity that poses a potential collision risk. The algorithm utilized in this thesis is adapted from the work of Vassbotn (2022), as illustrated in Figure 21 and 22. The underlying principle involves iterating through the data within the overlapping time interval t_{start} to t_{stop} of the two ships. During each iteration, the distance at the start time and stop time d_{start} and d_{stop} is calculated while t_{start} to t_{stop} are updated until the distance becomes smaller than a predetermined threshold d_{min} near the DCPA, or until the time step for updating is smaller than threshold Δt_{min}. In this approach, the steepest descent (or gradient) Δf is adjusted to three times the sum of the maximum speeds of ship 1 $\max(v_1(t))$ and ship 2 $\max(v_2(t))$ in order to result in a smaller time step for updating, thus leading to an enhancement of the precision. Some equations used in this method are:

$$\Delta f = (\max(v_1(t)) + \max(v_2(t))) \times 3 \tag{15a}$$

$$d_{diff} = \min(d_{start}, d_{stop}) - d_{min} \tag{15b}$$

$$\Delta t = \frac{d_{diff}}{\Delta f} \tag{15c}$$

Where Δt is the forward or backward time step of t_{start} to t_{stop} respectively. d_{min} is set as 5km, and t_{min} is set as 60 seconds.

```
Δf = max(v_1(t)) + max(v_2(t))              ▷ Theoretical steepest decent
d_start = f(t_start)                        ▷ Distance at start
d_stop = f(t_stop)                          ▷ Distance at stop
while (d_start & d_stop) > d_min do
    if t_stop − t_start ≤ Δt_min then
        return False                        ▷ Not large enough timespan
    end if
    d_diff = min(d_start, d_stop) − d_min
    Δt = d_diff / Δf
    Δt = max(Δt, Δt_min)                    ▷ Δt_min is smallest search resolution
    if d_start >= d_stop then
        t_start = t_start + Δt
        d_stop = f(t_stop)
    else
        t_stop = t_stop − Δt
        d_stop = f(t_stop)
    end if
end while
return True                                 ▷ Either d_start or d_stop is sufficiently small
```

Figure 21: Deepest decent algorithm (Vassbotn, 2022)

This algorithm is also employed to search for the DCPA in ship encounter situations, as well as the time when the ships first reach a distance of x km from each other, and when the ships exceed a distance of y km after CPA. Consequently, pairs of trajectory segments can be extracted as individual cases, where the segments span from the point when the two ships are 15 km apart, pass through CPA, and continue until the two ships are again 15 km apart.

It is important to clarify that the objective of this section is to identify potential COLREG cases, rather than definitively confirming them as such. The specific determination of a COLREG case requires the application of entry criteria, which

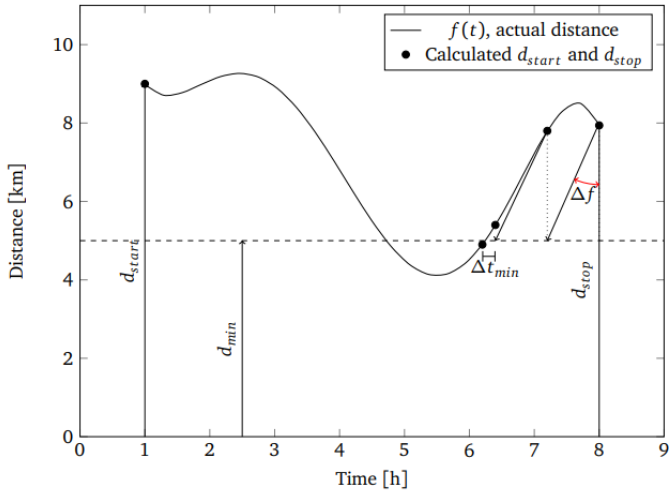


Figure 22: Deepest decent illustration (Vassbotn, 2022)

also categorizes the case according to the rules outlined in COLREG.

Interpolation

Due to the variations in timestamp intervals between ships, the computation of COLREG-related parameters at each timestamp, such as relative heading and critical relative heading at CPA, becomes challenging. To address this issue, a normalization of the time intervals is required, whereby the intervals are adjusted to a fixed value. In this study, a time interval of 30 seconds is chosen for normalization. By employing the methodology described in the "Estimate point" section, the remaining information in the AIS data can be derived accordingly. Two examples case of two ship encounter situation in Trondheim water area is shown as Figure 23 and Figure 24.

3.2.1 Entry and classification criteria

Until now, the possible cases of two ship encounter situation that a maneuver might exist in adherence to COLREG have been identified.However, it is imperative to further select those cases that are strictly COLREGcase more than just 'possible'. This selection process is performed through employing an entry and classification criteria algorithm based on COLREG, inspired by Hagen (2022) and Trodahl (2021). This algorithm is carried on by the calculated indicators derived from AIS data, as explicated in table 3, whereby the initial indicators represent the ship characteristics at the commencement of the encounter, specifically when the two vessels first come within a range of 10 kilometers.

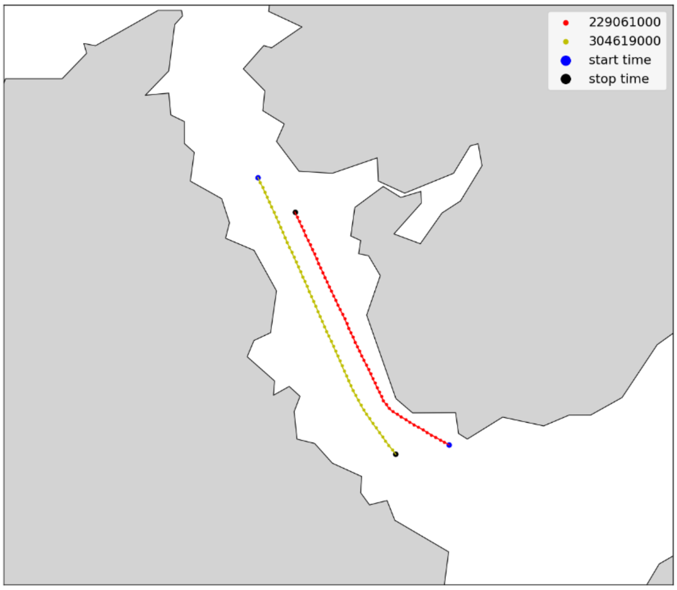


Figure 23: An example of ship encountering situation of ship 229061000 and 304619000. DCPA is 1930.52 m

Indicator	Description
r_{CPA}	range at CPA
$\bar{\beta}$	relative bearing
$\bar{\beta}_0$	initial relative bearing
$\bar{\alpha}$	relative contact angle
$\bar{\alpha}_0$	initial relative contact angle

Table 4: Explanation of indicators used in entry criteria algorithm

The specific implementation of the entry and classification criteria is executed based on the formulas outlined in Table 5. The initial step is to determine the desirability of a given case, i.e. whether there is a potential risk of collision. This assessment is conducted by comparing the range at CPA with a predetermined threshold denoted as r_{min}. Once the presence of a collision risk is confirmed, the case is subsequently classified into five distinct categories: head-on scenario, overtaking scenario where OS is required to stand on, overtaking scenario where OS is required to give way, crossing scenario where the OS is required to stand on, and crossing scenario where OS is required to give way. The thresholds utilized in this classification process are derived from COLREG and previous studies, as shown in Table 6 (Hagen, 2022) and (Trodahl, 2021).

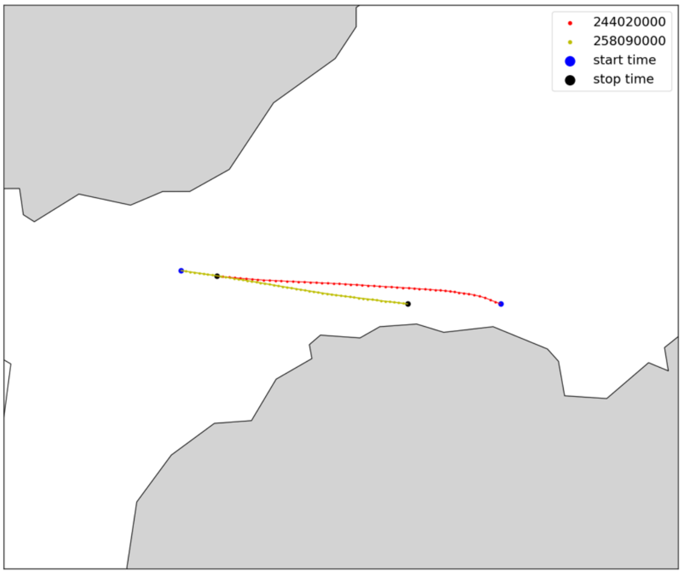


Figure 24: An example of ship encountering situation of ship 244020000 and 258090000. DCPA is 500.55 m

criteria	method
risk exists	$r_{CPA} > r_{min}$
head on	$\lvert\bar{\beta}^{180°}\rvert < \alpha^{14}_{crit}$ and $\lvert\bar{\alpha}_0^{180°}\rvert < \alpha^{14}_{crit}$
overtaking (stand-on)	$112.5° < \bar{\beta}_0 < 247.5°$ and $\lvert\bar{\alpha}_0{}^{180°}\rvert < \alpha^{13}_{crit}$
overtaking (give-way)	$112.5° < \bar{\alpha}_0 < 247.5°$ and $\lvert\bar{\beta}^{180°}_0\rvert < \alpha^{14}_{crit}$
crossing (stand-on)	$0 < \bar{\beta}_0 < 112.5°$ and $-112.5° < \bar{\alpha}^{180°} < \alpha^{15}_{crit}$
crossing (give-way)	$0 < \bar{\alpha}_0 < 112.5°$ and $-112.5° < \bar{\beta}^{180°} < \alpha^{15}_{crit}$

Table 5: Entry and classification criteria

Threshold	Value
r_{min}	$2960m$
α^{13}_{crit}	45°
α^{14}_{crit}	13°
α^{15}_{crit}	10°

Table 6: Thresholds of entry and classification criteria

3.2.2 Maneuver detection

Once the cases have been selected and categorized, attention turns to the remaining variables necessary for conducting a verification and validation process using fuzzy logic. Specifically, the focus is on assessing the extent to which a ship is complying with the COLREG when taking action. These variables pertain to the maneuvering of ships and include factors such as the time of the first maneuvers performed by OS and TS in order to avoid collision, as well as the distance between ships at the time of initial maneuvers and the magnitude of these maneuvers. To determine these crucial variables, as researched, Løvoll (2022) used a sliding window method for maneuver detection, which performs satisfactorily but is concluded to be improved for the reason of complexity of tuning and lack of controllability. In this thesis, a change point detection method is employed on each data point i utilizing derivatives, drawing inspiration from the work of Hagen (2022). This method is applied to the identified cases, commencing when the two ships enter into a COLREG scenario or reach a range of 10 kilometers to each other, terminating once the ships have passed the CPA.

In the context of change point detection, two distinct types of change points can be identified: course change and speed change. Determining a speed change point is relatively straightforward, as it can be achieved by analyzing the first derivative of the ship's speed at each data point. This approach is justified by the observation that changes in ship speed often exhibit well-defined characteristics. Specifically, if the absolute value of the first derivative at a given data point exceeds a predefined threshold, that particular point is deemed to be a speed change point.

$$|\dot{U}_i| \geq \epsilon_{\dot{U}} \tag{16}$$

Course change, as a crucial indicator of a maneuver, may not be as readily discernible as a speed change. As a consequence, instead of relying solely on the first derivative, the change point detection method is employed utilizing the first to third derivatives that have been smoothed using a Gaussian filter. The equations are given by

$$\begin{aligned}
|\dot{\chi}_i| &\geq \epsilon_{\dot{\chi}} && \text{(17a)}\\
|\ddot{\chi}_i| &\leq \epsilon_{\ddot{\chi}} && \text{(17b)}\\
|\dddot{\chi}_i| &\geq \epsilon_{\dddot{\chi}} && \text{(17c)}\\
sign\ddot{\chi}_i| &\neq sign\ddot{\chi}_{i-1} && \text{(17d)}\\
sign\,\dddot{\chi}_i| &\neq sign\dot{\chi}_{i-1} && \text{(17e)}
\end{aligned}$$

where i is data point, ϵ is the preset threshold as explained in Table 7. The derivatives are computed by central finite difference with a time step $\Delta t = 60s$, as equation 18. The standard deviation of the Gaussian filter used in the analysis is set to 1.5. After this, the start point and end point of maneuver can thus be recognized when the third derivative is closest to zero. An example of the three derivatives of OS (ship 257238000) are illustrated as Figure 25, and its corresponding time series of course over ground is shown in Figure 26.

Threshold	Value	Unit
$\epsilon_{\dot{U}}$	0.8	m/s
$\epsilon_{\dot{\chi}}$	0.008	rad/s
$\epsilon_{\ddot{\chi}}$	0.01	rad/s^2
$\epsilon_{\dddot{\chi}} \times 10^4$	0.003	rad/s^3

Table 7: Thresholds of change point detection

$$\dot{\chi} = \frac{-\chi_{i-1} + \chi_{i+1}}{2 \times \Delta t} \tag{18a}$$

$$\ddot{\chi} = \frac{-\chi_{i-1} + 2 \times \chi_i + \chi_{i+1}}{(\Delta t)^2} \tag{18b}$$

$$\dddot{\chi} = \frac{-\chi_{i-2} + 2 \times \chi_{i-1} - 2 \times \chi_{i+1} + \chi_i}{2 \times (\Delta t)^3} \tag{18c}$$

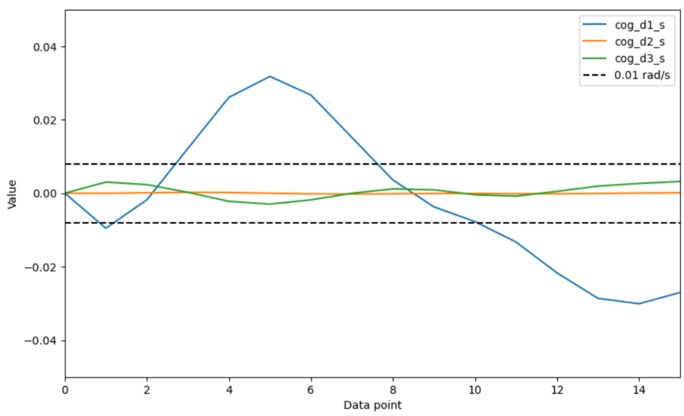


Figure 25: Change point detection

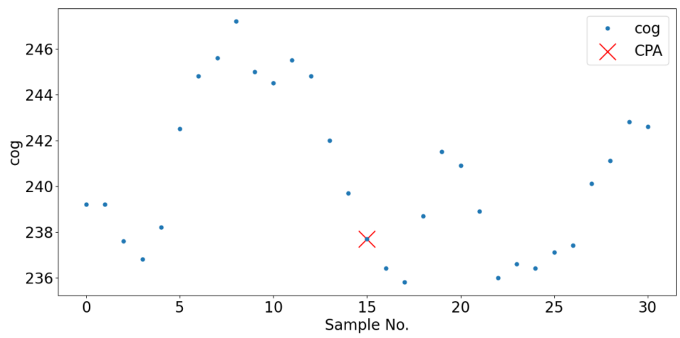


Figure 26: Time series of course

Once the change points have been identified, the total speed change and course change can be determined by subtracting the values at the stop point from the values at the start point, given by

$$\Delta U = U_{stop} - U_{start} \tag{19a}$$
$$\Delta \chi = \chi_{stop} - \chi_{start} \tag{19b}$$

In the example case of Figure 25 and Figure 26, two change points are detected, point 3 and 9. The corresponding end points of maneuver are point 7 and 15. In the first maneuver interval (3,7), course change is 8.80°, which is a turn to starboard. In the second maneuver interval (7,15), course change is −7.30°, which is a turn to port.

Moreover, it is important to emphasize that only evasive maneuvers are considered in the analysis (such as point 3 in the above example), while other maneuvers performed for purposes, for instance, navigating narrow channels in restricted water areas are excluded (such as point 7). This is performed by calculating the estimated range at CPA $\hat{r}_{cpa}$ using equation 11. A maneuver can be treated as an evasive maneuver if it causes an increase in $\hat{r}_{cpa,i}$ than $\hat{r}_{cpa,i-1}$. An example of is shown as Figure 27. The figure illustrates a head-on collision avoidance case of ship 257238000 and 257659000, where the red and yellow lines are the trajectories, blue lines are when the ships are taking a evasive maneuver. As stated above, ship 257238000 turns 8.80° to starboard, with compliance to COLREG. While ship 257659000 makes a port turn of 2.10°. After the first maneuver, it is apparent that that ship 257238000 turns back to port. This maneuver is likely executed after ensuring that there is no risk of collision and is intended to align the ship with the designated waypoints within the navigational channel. The range at CPA is 409.31m, as the red star in the figure.

3.3 Fuzzy V&V system and parameter selection

Since the objective of this thesis is to enhance the existing fuzzy V&V system by incorporating data-driven fuzzy logic, it is thus essential to provide a concise overview of the principle and methodology employed in the original fuzzy system developed by (Trodahl, 2021).

The fuzzy V&V system, depicted in Figure 29, has been designed to assess the performance of the CAS in adherence to the COLREG. By generating a scenario of collision avoidance through simulation, parameters that indicate the performance of OS and TS can be derived accordingly. These parameters, as a combination of factors, are utilized as inputs to the system. Subsequently, the system processes these parameter combinations and produces an overall compliance score as the system's output, which serves as an assessment of the CAS's effectiveness in facilitating collision avoidance.

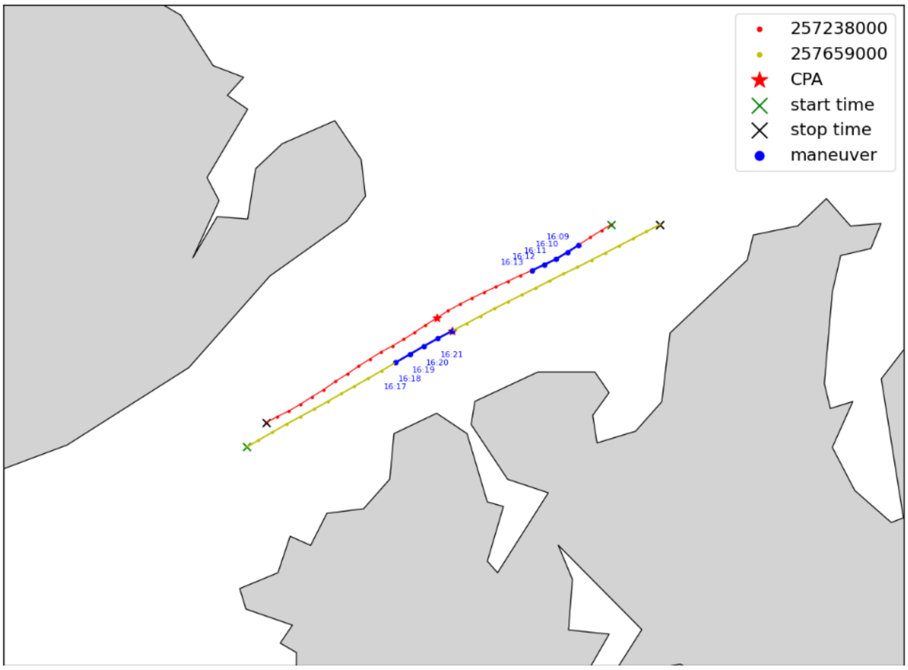


Figure 27: Example of maneuver detection

Comprising three interconnected subsystems, the V&V system fulfills evaluation of distinct rules. Firstly, subsystem A initiates the analysis by examining the initial stage of the input parameters and outputs the role of OS and TS, as SO vessel and or GW. This is conducted by inputting relative contact angle $\bar{\alpha}$, relative bearing $\bar{\beta}$ and relative course $\Delta\chi$ and setting the according FMFs, and calculating estimated DCPA which is used to reflect the risk of collision, also as a FMF. Through taking into account rules 13, 14, and 15, the types of COLREG are determined at the first step, followed by risk assessment. Finally roles of ships are determined by the if-then rules. For instance, in terms of a crossing scenario, relative bearing and relative contact angle are received by according FMFs to determine whether TS is on starboard of OS or os is on starboard of TS. By providing DCPA to its corresponding FMF as well, risk can be derived as Figure 31. Through applying these similar steps for rule 13 and rule 14, a set of summarizing FMFs of parameter $\bar{\alpha}$ can be derived, giving one fuzzy degree to each category. As illustrated in Figure 30, there are four classes in total, namely rule 14 Not Ahead, rule 13 TS Overtaking OS, and rule 15 TS on Starboard of OS and OS on Starboard of TS. By utilizing the process of defuzzification, the scenario can be categorized into the class exhibiting the highest degree of membership. At last, the result that SO is GW and TS is SO can be concluded by the fuzzy rules with logical OR between roles and logical AND of risk. as follows:

Following the assessment of vessel roles, Subsystem B evaluates the compliance of the give-way vessel. Meanwhile, Subsystem C assesses the compliance of the stand-on vessel. The overall compliance score is then obtained using a logical OR, which selects the higher score between the GW compliance and the SO compliance,

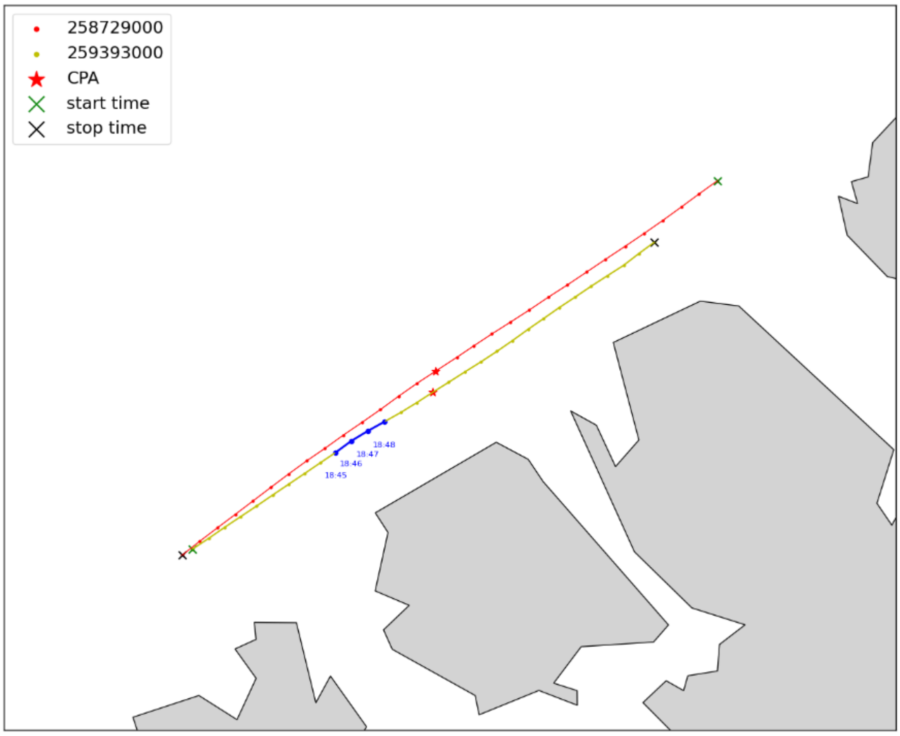


Figure 28: Another example of maneuver detection

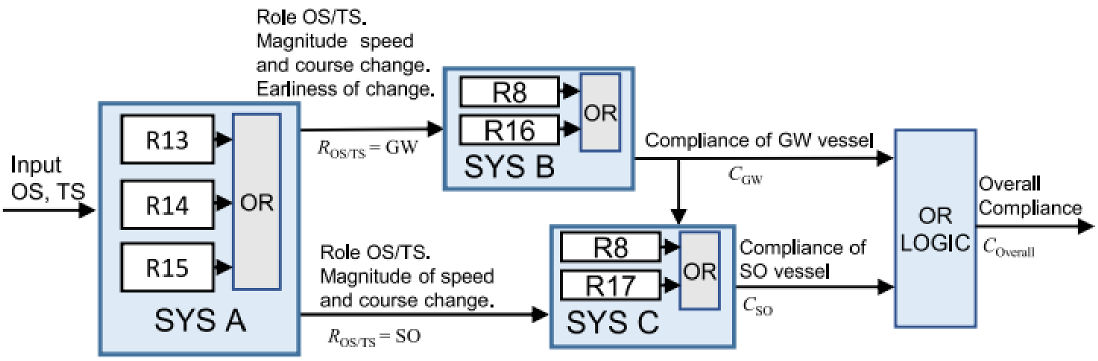


Figure 29: Fuzzy V&V system Trodahl (2021)

effectively representing the overall compliance of the CAS. In subsystems B and C, the goodness of compliance comes from rule 8 action to avoid collision, rule 16 action by GW vessel and rule 17 action by SO vessel. The specific parameters employed in this context are outlined in Table 8.

Parameter	Explanation	Vagueness of COLREG
ΔU	largest speed offset during maneuver	'readily apparent change'
$\Delta \chi$	largest course offset during maneuver	'readily apparent change'
$TCPA$	TCPA at first maneuver	'early and substantial action'
$\#SC_i$	maximum of speed and course deviations	'avoid small succession'

Table 8: Parameters used in subsystems B and C

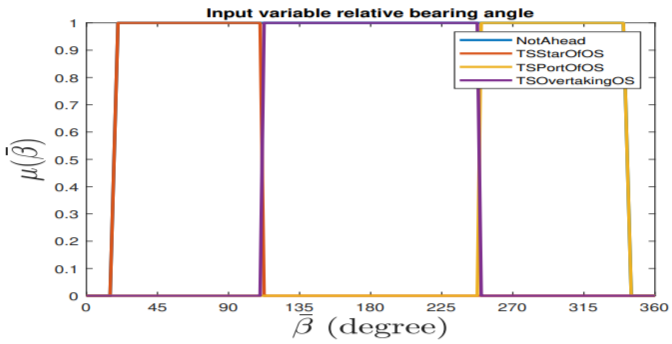


Figure 30: FMFs of relative bearing to determin role Trodahl (2021)

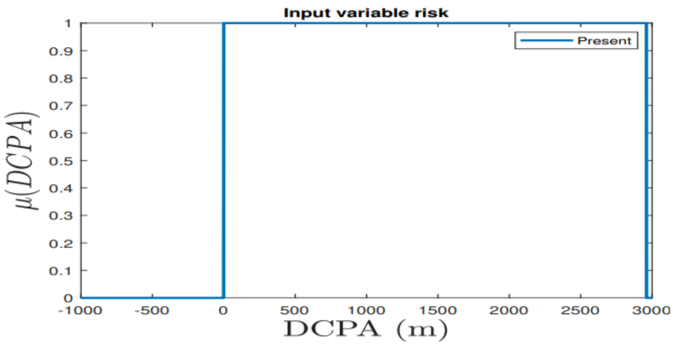


Figure 31: FMF of DCPA to determin risk Trodahl (2021)

To summarize, the parameter design for the FMFs in this fuzzy V&V system is shown as Figure 32,where there are 7 parameter designs in total. Out of all the parameters, only the ones for action for overtaking are accurate with no doubt as directly using COLREG rule. The parameters of change of course and change of speed are generated through AIS data analyzing, but are on a very early stage and need more investigation (Nguyen et al., 2023). The remaining parameters are derived from previous literature, including 'Reciprocal' and 'Risk' for determining roles in subsystem A, and 'Starboard crossing' and 'Earliness' in subsystem B.

Summary of the parameter design for FMFs.

Measures	FMF input	FMF	Method
Change of course	$\Delta\chi$	$[-4, -2, 2, 4]$	Learning from AIS data
Change of speed	ΔU	$[-2, -1.5, 1.5, 2]$	Learning from AIS data
Overtaking	$\bar{\beta}$ (for TS) and $\bar{\alpha}$ (for OS)	$[110, 112.5, 247.5, 250]$	Rule 13. Part (b)
Starboard crossing	$\bar{\beta}$ (for TS) and $\bar{\alpha}$ (for OS)	$[15, 20, 110, 112.5]$	Cho et al. (2022)
Reciprocal or Near Reciprocal	$\bar{\beta}$ (for TS) and $\bar{\alpha}$ (for OS)	$[168, 170, 190, 192]$	Cho et al. (2022)
Risk of collision	DCPA	$[0, 0, 2960, 2960]$	Vujičić et al. (2017)
Earliness of collision avoidance action	TCPA	$[360, 383, 10000, 10000]$	Vujičić et al. (2017)

Figure 32: Designed parameters for FMFs Nguyen et al. (2023); Trodahl (2021)

Through this comprehensive V&V system, the performance of the CAS is thoroughly analyzed and assessed, providing valuable insights into its compliance with COLREG and thus aiding in the design of a robust control system.

3.4 FMFs Improvement

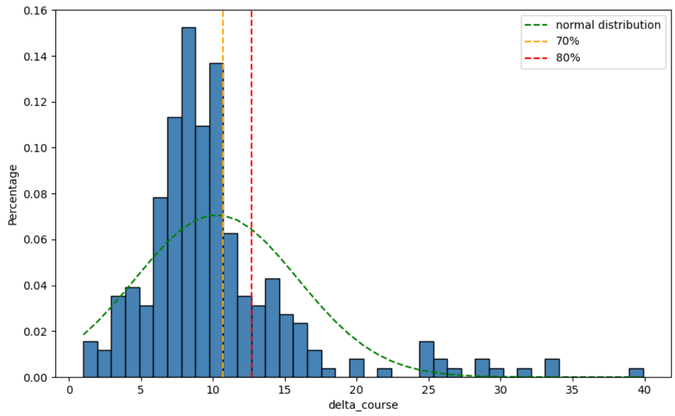
As FMFs are the most important part of a fuzzy system , but the parameters of FMFs are largely based on COLREG, previous study and expert knowledge, the existing fuzzy system may be not accurate and reliable. Building upon the motivation, the initial strategy for enhancing the fuzzy system thus becomes the improvement of the shapes and parameters of FMFs using AIS data. This involves conducting a thorough analysis of the system's parameters and providing an improvement of them through several techniques. Consequently, two ship encounter cases are extracted and constructed utilizing the AIS dataset specified in Section 3.2.

As shown stated in the last section, there are 7 parameter designs in total. The overtaking design, reciprocal design and risk design are quite clear so no need to be improved. To ensure simplicity and validate the effectiveness of the proposed methodologies, a comprehensive analysis is conducted on 452 encounter cases and only the 266 head-on cases are analyzed.

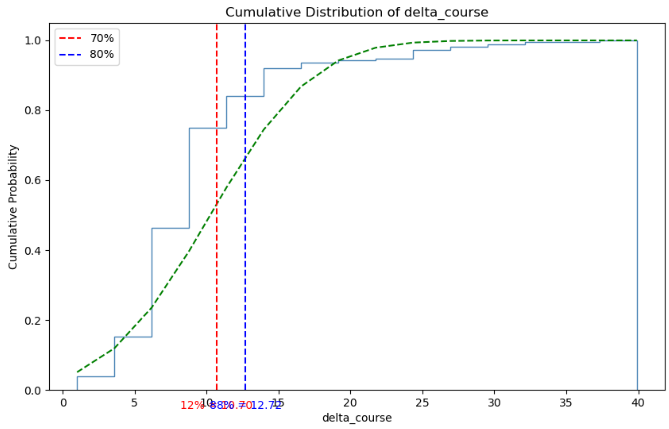
3.4.1 Histogram

Inspired by Yadav and Yadav (2015)'s study, it has been demonstrated that utilizing histogram-derived parameters can lead to a more accurate and realistic fuzzy system. In his research, triangular FMFs were generated by selecting the point with the highest value in the histogram as the center point of the triangle, and the closest local minimum point as the positions of the remaining two vertices. However, this approach is not suitable for determining ship collision avoidance parameters. As the original FMFs were set as trapezoidal shapes as stated in the above section, the values of the trapezoidal vertices can be generated using the percentages obtained from a normal distribution.

The determination of course change in each scenario involves aggregating the course alterations resulting from starboard maneuvers. Turns to port are not desired as are not compliant maneuvers according to COLREG. Similarly, the speed change is calculated by summing the speed alterations of all speed maneuvers. The histograms and normal distributions depicting these changes are presented in Figure 33 and Figure 34, respectively. Based on the distribution of course changes, the fuzzy set denoted as 'Insufficient' is associated with parameters derived from 70% and 80% of the distribution, corresponding to 10.70° and 12.72°. Consequently, the updated FMFs can be represented using the modified parameters [-12.72, -10.70, 10.70, 12.72], as opposed to the original parameters [-4, -2, 2, 4]. Analysis of the histogram also indicates that a significant proportion of vessels did not exhibit noticeable course alterations. Concerning speed changes, it is evident that 97% of vessels did not experience substantial speed modifications, with 85% maintaining constant speeds or making minimal changes below 0.3 m/s. This observation suggests that course changes outweigh speed changes in terms of maneuver preference



(a) Histogram and normal distribution curve of course change



(b) Cumulative distribution of course change

Figure 33: Course change

among vessels. Accordingly, the original FMF parameters for speed change, [-2, -1.5, 1.5, 2], remain unchanged.

In terms of 'earliness of collision avoidance maneuver' in COLREG rule 16, TCPA is used for the evaluation of compliance. TCPA is computed as the estimated time to CPA when the ship first deviates from original course or speed, and the normal distribution is given as Figure 35. From this, $2.5\% = 361s$ and $4.5\% = 401s$ are utilized, and the improved FMF parameters are [361,401,1500,1500], compared to the original [360,383,1000,1000] derived by expert knowledge.

Regarding the range at CPA, its histogram is presented in Figure **??**. However, this variable lacks relevance in the design of risk assessment, which instead relies on DCPA to determine the presence of collision risk. Therefore, the original parameters of the FMFs for the evaluating risk remain unchanged as [0, 0, 2960, 2960].

In addition, a joint distribution plot depicting the relationship between course

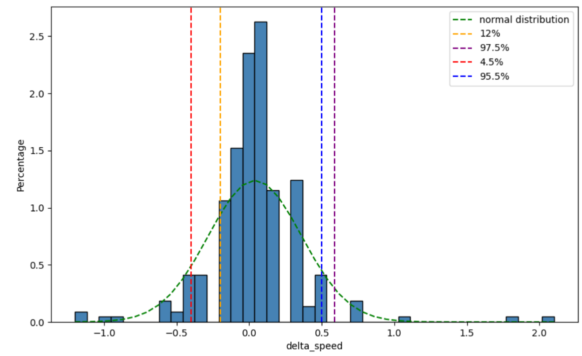


Figure 34: Histogram and normal distribution curve of speed change

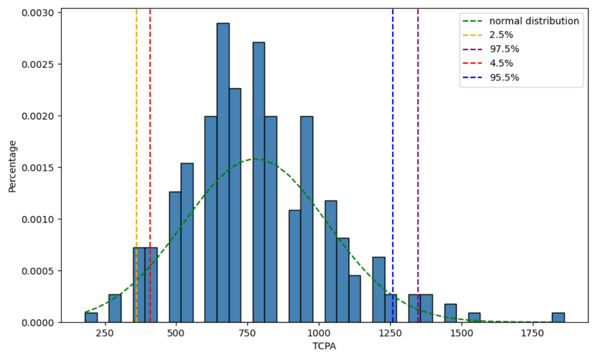


Figure 35: Histogram of TCPA

change and TCPA is generated to assess their correlation, as Figure 37. Observing the plot, it can be concluded that no significant correlation is evident. Contrary to expectations, no negative correlation is observed, implying that a ship would not make minor course alterations when time is realy, or not make large course alterations when time is late.

3.4.2 Shapes of FMFs

The previous subsection of the study focuses on updating the parameters of the FMFs for speed change, course change, and TCPA. In order to further enhance the fuzzy V&V system, the trapezoidal shape of the FMFs can be improved. Specifically, the FMFs for course change, speed change, and TCPA are modified to adopt the generalized bell, generalized bell, and sigmoidal shapes, respectively. The corresponding parameter values for the improved TCPA are [12.7, 11, 0], [2, 11, 0], and [0.25, 381].

Compared to the trapezoidal TCPA, the use of generalized bell and sigmoidal TCPA offers smoother transitions between different membership degrees, contrasting with the abrupt transitions observed in trapezoidal TCPA. This smoothness can contrib-

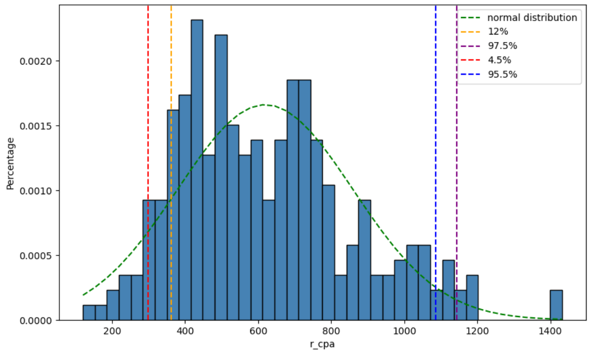


Figure 36: Histogram of range at CPA

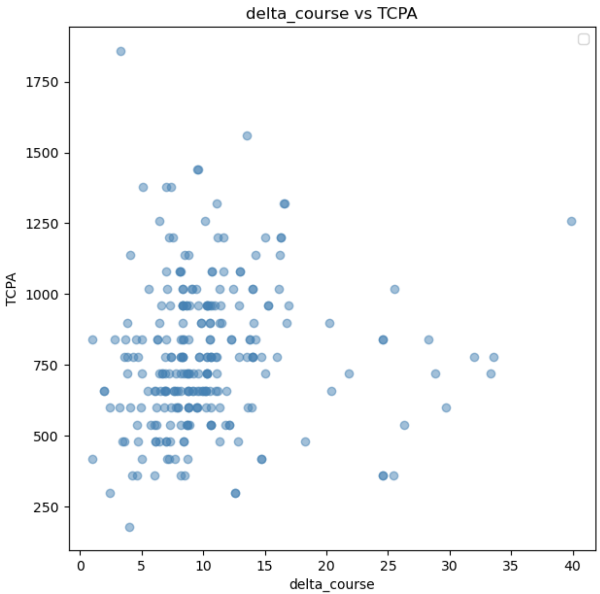
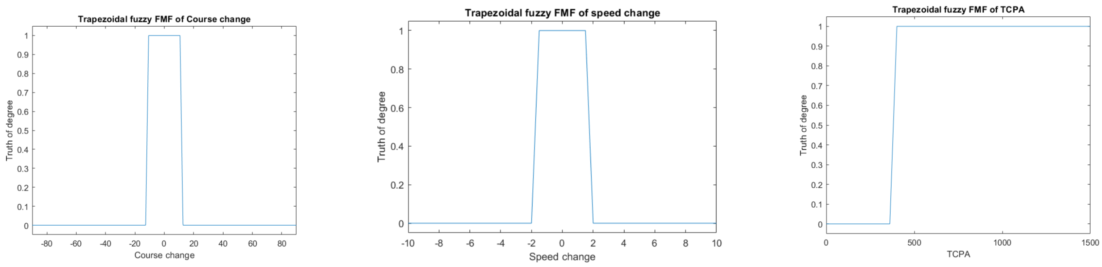


Figure 37: Correlation between course change and TCPA

ute to better continuity and smoother inference processes. Although the difference of the shapes is not large, it is reasonable to expect that with improved continuity and smoothness, the membership degrees become more realistic, especially for ships that near the abrupt values. Consequently, the improved fuzzy V&V system, particularly in the context of CAS for autonomous ships, can achieve higher accuracy, thus aiding the decision-making process for design. The original and improved FMFs are depicted in Figure 38 and 39.

3.5 FNN

In the preceding section, various techniques were employed to enhance the realism and accuracy of the FMFs in evaluating collision avoidance scenarios. However,

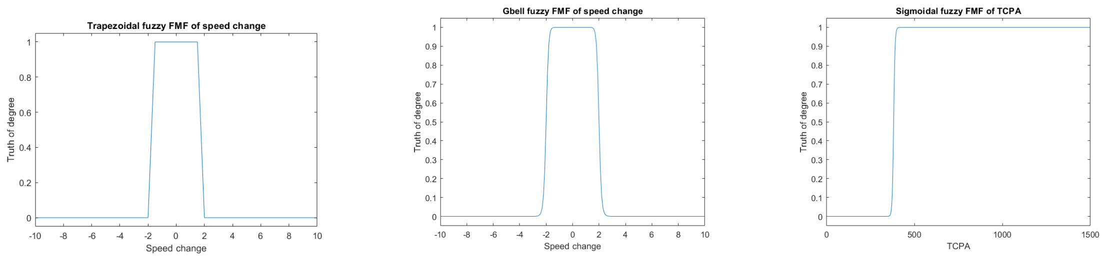


(a) Trapezoidal FMF of course change

(b) Trapezoidal FMF of speed change

(c) Trapezoidal FMF of TCPA

Figure 38: Original FMFs



(a) Gbell FMF of course change

(b) Gbell FMF of speed change

(c) sigmoidal FMF of TCPA

Figure 39: Improved FMFs

these modifications were limited to a single component of the overall system, thus it is still cumbersome and time-consuming to employ the system in actual. To address this limitation, it is feasible to transform this fuzzy V&V system into a "black box" implementation utilizing a FNN. This conversion would simplify the system and streamline its usage, offering a more efficient and user-friendly approach thus promoting the design process of CAS.

Specifically, the initial step involves preparing the training and test data. For the 266 head-on collision cases, the improved fuzzy V&V system is employed to evaluate each case, resulting in a corresponding overall score. The seven parameters of the cases, including relative bearing, relative contact angle, course change, speed change, DCPA, and TCPA, are computed and treated as a set of inputs. The output corresponds to the overall compliance score. The main structure of the FNN utilized in this study follows the framework proposed by Lin et al. (2006) in the literature review section of data-driven fuzzy logic. The FNN consists of five layers, with seven input nodes and one output node. In the second layer, which represents the fuzzification process, each node functions as a FMF utilizing the improved FMFs generated in subsection 3.4.2.

4 Conclusion

The predominant approach in formal V&V methods for CAS in autonomous vessels involves the utilization of a fuzzy logic system, which heavily relies on expert knowledge to determine the membership functions and fuzzy rules. However, the subjectivity inherent in expert opinions may introduce accuracy issues. This thesis seeks to address this challenge by focusing on training a fuzzy neural network model using real Automatic Identification System (AIS) data to represent the formal fuzzy system, thereby enhancing the system's accuracy and performance.

The data-driven approach involves several time-consuming steps in the preprocessing of raw AIS data. These steps encompass ship type extraction, dock recognition, downsampling, searching for potential COLREG cases, point interpolation, and maneuvering detection. These preprocessing tasks are crucial in preparing the data for subsequent analysis.

Initially, the essential parameters in the head-on scenario are identified and selected from a dataset consisting of 266 real scenarios. Subsequently, histograms and distribution plots are generated to gain insights into the characteristics of these parameters. Furthermore, efforts are made to improve the shape of the FMF based on the obtained data and insights from the histogram and distribution analysis.

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