Explainable Artificial Intelligence for Autonomous Surface Vessels by Fuzzy-Based Collision Avoidance System

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Abstract. Autonomy at sea relies on algorithms (often local) to make the decisions. One approach to create these algorithms are through the use of artificial intelligence. Numerous black-box machine learning-based algorithms are proposed for autonomous surface vessels (ASV) to make decisions like changing the speed or changing the route in order to reach the operational goal in an optimal way with respect to cost (fuel, time etc.) and safety (avoid collisions or dangerous situations). Hence, the algorithms must take into account many constraints and are influenced by several varying factors such as other vessels, weather etc. The objective of this paper is to propose a model that provides the reason behind the ASV's decision when it is on a predefined path and change speed or route. Fuzzy logic used to record the expert knowledge based on COLREGs to steer vessel and take the decision during the collision course. Data has been captured based on expert knowledge and used to train an explainable model. The explainable model predicts the reason behind the decision. The focus of the paper is on local explainability instead on global decisions. The structured abstracts of the paper is: (1) Background: Several AI-enabled algorithms has been proposed for implementing autonomy to avoid the collision. These black-box techniques provide good predictions at the same time, they fail to explain the reason behind the decision, which make the model less trustworthy; (2) Methods: Expert knowledge (COLREGs) has been captured using fuzzy rules, and applied when ASV progresses, decision has been recorded. (3) Results: The explainable model provides the reason behind the action taken by the collision avoidance system; (4) Conclusion: A model has been proposed that explains the collision avoidance system to make it transparent and trustworthy.

Keywords: autonomous surface vessels; explainable artificial intelligence; collision risk; fuzzy logic; ANFIS; COLREGs

1 Introduction

Predictions state that fully autonomous surface vehicles will be available in 2025 [1]. In the meantime, the "EMSA annual overview of yearly causalities and incidents 2021" shows that there were 2837 occurrences, 46 very serious, 38 deaths, 675 injuries, 3049 ships involved and 9 ships lost [2]. Out of which 53% were due to human action and 35% causalities were due to system or equipment failure. From these facts it could be argued that may be automatic systems could reduce errors from human (in-)actions. Likewise it could be argued that equipment must be made more robust since the two causes, humans and equipment are the main causes for the accidents. Artificial intelligence may be useful in reducing accidents from both of these causes. However, care should be taken in order to not introduce new systems that produce more accidents due to unreliable algorithms, increased system complexity etc.. This make researchers think that intelligent system must be explained and verified before they are deployed. The above mentioned statistics was from a period when world trade was heavily influenced by the COVID-19 pandemic, resulting in less traffic at sea. The situation was actually more serious in previous years [2]. "International Maritime Organization" (IMO) proposed 41 "International Regulations for Preventing Collisions at Sea" (COLREGs) in 1972. These traffic rules at sea includes qualitative measures for safe maneuvers and currently applicable for all type of vessels but the time when rules were written, ASV was just science-fiction [3].

The Norwegian Forum for Autonomous Ships (NFAS) defined the autonomous vessels, their context, and functions. They are classified as underwater or surface based on operational area, remote control or autonomous based on control mode, vessels and ship based on height and different autonomy levels based on degree of human involvement [4]. A ferry operates in a limited area and vessel operates in more diverse environment [5] .

The COLREGs rules must be adhered to while developing the path planning and collision avoidance intelligent systems for ASVs. ASVs are currently primarily deployed for use in military operations, maritime surveillance missions, and marine environmental monitoring applications [6]. Norway already started utilizing ASVs for the movement of goods and people [7, 8]. Still ASVs are facing challenges related to safety in navigation and reliability issues which need to be addressed before implementation of the intelligent collision avoidance system [1]. For example when some obstacle can not be detected by AIS, differentiate between buoy and kayak [31] etc. the algorithm may fail in performing appropriate action. Machine learning (ML) has shown impressive success in the real world in many different application areas. A number of research projects have been carried out in order to reduce collision caused by human error, one of which is risk analysis in collision scenario. There are also several fuzzy based collision risk assessment systems proposed by researchers who considered Time to Closest Point of Approach (TCPA) and Distance to Closest Point of Approach (DCPA) as risk indicators. Effective explainable AI (XAI) should provide accurate explanations, handle uncertainty, and learn from experience. This paper studies a hybrid learning technique that blends fuzzy logic's capacity to explain uncertainty with ability of artificial neural networks to learn. The outputs of decision-making model used as inputs for a neural network which provides reasoning behind decision. The suggested model describes fuzzy-based system for collision avoidance.

2 Literature Review

Several models has been proposed for collision avoidance in different research articles. Most of autonomous navigation decision support systems are categorise as 1. Mathematical models and computations 2. Soft computing and 3. Hybrid navigation systems [9].

Vagale et al. reviewed in their paper [1] the state of the research in the field of path planning and collision avoidance of ASVs with emphasis on the importance of autonomy and safety. Safety can be validated by humans if a machine learning-based collision avoidance system capable of explaining the reason behind the decision. The authors also reviewed 45 path planning and collision avoidance algorithms [10] for autonomous surface vehicles using these criteria: compliance with COLREGs, environmental disturbances, planning type, obstacle type, environment type, type of action to avoid collision, testing, traffic category, predictability of environment, planning time, control horizon, number of obstacles, vessel kinematics, type of vessel, safe zone. The authors also mentioned TCPA and DCPA as collision risk assessment (CRA) criteria and discussed the interpretation of the algorithm as limitation of several algorithms. Further they proposed an approach [11] for the use of maritime navigation training simulators to understand the algorithms. In addition the authors suggested that there are benefits from broadcasting the reasoning behind the action taken by an autonomous vessel to other seafarers.

Ohn and Namgung extended type-1 fuzzy inference system [12] for near collision into a fuzzy inference system based on interval type-2 fuzzy logic. They considered TCPA and DCPA for calculation of collision risk indicator (CRI) which helps navigator to make decision well in advance.

Perera et al. divided the collision region into low risk, medium risk and high risk with respect to orientation of own vessel and target vessel to assess the collision risk in their work [13]. They considered a case when target vessel which is also "Give way" vessel do not take any action to avoid collision so "Stand on" vessel need to take action. Decisions in said critical conditions are formulated using fuzzy logic because, COLREGs do not suggest action in this case.

Yancai and Park proposed extra vulnerability factors [14] for collision risk solving system such as wind, tidal, accident prone area, traffic congestion, operator fatigue, fishing boats operating area apart from TCPA and DCPA especially for non-SOLAS ships such as coastal operating ships and fishing vessels. Fuzzy system was used to implement the system.

Ahn et al. applied fuzzy inference system, neural network and multilayered perceptron (MLP) to collision avoidance system[15]. The neuro-fuzzy system was found more realistic and diverse parameters considered to train the neural network.

Brandsæter and Glad used data-driven trained model to demonstrate [16] how training data affect the decision of machine learning model. Shapley values explain the feature importance in a decision.

Namgung defined the actions [17] for collision avoidance based on CRI levels.To take action ship domain overlapping, DCPA, TCPA and CRI considered. Author also proposed fuzzy inference rule based on ANFIS learning.

Fıskın et al. studied 180 research articles [18] in which techniques, models and methods for ship collision avoidance path planning problem were proposed. Fuzzy logic is the most frequently solution method for the pertaining area.

Several fuzzy rule based collision risk model proposed for autonomous vehicles and this work is extension of the previous research in the sense that it explain the prediction of the model. This research suggests utilizing fuzzy logic to avoid collisions before explaining decisions. Using a similar method, ASV scenario and decision simulations are executed.

3 Explainable Artificial Intelligence

Explainable AI is a set of tools and methods to understand AI and ML models, their predictions and decisions to make them trustworthy and helps to find a space for improvement, optimize and fine tune before deployment.

As shown in figure 1 [19] there are variety of explainable methods that focus on model design, internal representation, decision made by model etc.

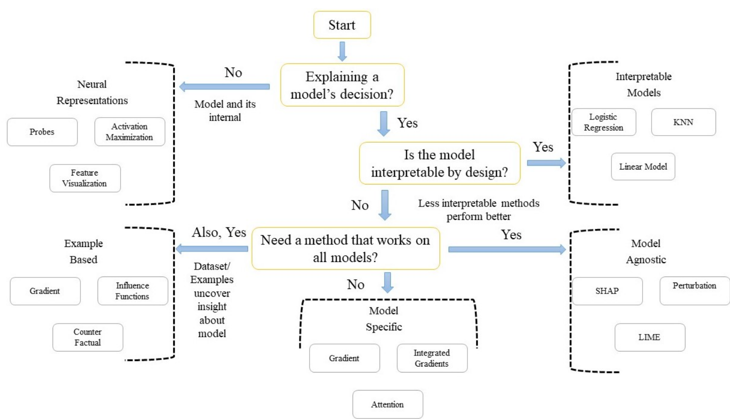


Fig. 1. An overview of explainable artificial intelligence .

Simple models are self explanatory by design and first category belongs to this group. Lot of problems can be better solved by models which are more complex and not interpretable by design such as computer vision and natural language processing. Model agnostic XAI methods works on all models. Examples are Shapley additive explanation, which gives additive information how each feature push the prediction. Next category is model specific method, in which gradient saliency method related to neural network. Another group explain based upon dataset. Adversarial attack the model fails or other examples are there when data make a model fail. Few model looks into model's internals such as activation probes used in NLP, and how neuron detect edges, textures, patterns etc [19].

Explainability can be useful for collision avoidance situation in an ASVs. When an ASV is on its perception-action mapping as shown in figure 2, explainability ensure the action taken by ASV is safe as it is avoiding collision,

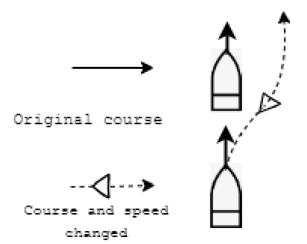


Fig. 2. A graphical illustration of an ASV on its perception-action mapping that is safe, explainable, and regulatory compliant during overtaking situation.

according to regulations as it is following COLREGs and explaining the reason behind the decision taken by ASV.

4 Materials and Methods

4.1 Fuzzy Inference System

Experts rely on experience and expertise. It expresses knowledge via vague, imprecise, non-numerical terminology. Lotfi Zadeh proposed fuzzy logic or fuzzy set theory [20] in 1965 to describe expert knowledge. A fuzzy set assigns a membership degree, [0,1], to universe elements. Fuzzy logic grades propositions. The standard set of truth-values (degrees) is [0,1], where 0 means "completely false," 1 means "entirely truthful," and the other values relate to partial truth, or intermediate degrees of truth. Fuzzy logic converts human-stated heuristic control rules into an automatic strategy. A fuzzy subset of discourse U is characterized by a membership function $\mu : U \rightarrow (0,1))$ that assigns each element u of U a number $\mu(u)$ in the interval (0, 1) representing u's membership in A. The fuzzy set A of universe $X = x_1, x_2, x_3, ...x_n$ is denoted by a function [21]:

$$\boldsymbol{\mu_A(x) : X \rightarrow [0,1]} \tag{1}$$

Where
$\mu_A(x) = 1$ if x fully belongs to A;
$\mu_A(x) = 0$ if x does not belongs to A;
$\mu_A(x) =$ greater than 0 and less than 1 if x partly belongs to A.

By using theory of fuzzy sets, fuzzy inference systems (FIS) has been defined. In this paper Mamdani and Sugeno FISs has been used.

4.1.1 Mamdani Fuzzy Inference System Mamdani FIS [21] process consist of four steps: 1. Fuzzification of input 2. Rule evaluation 3. Aggregation and 4. Defuzzfication.In this paper Mamdani FIS has been used to record the expert knowledge which has been used to drive the ferry and record the decisions in the form of outputs of the FIS (Course deviation and speed change).

4.1.2 Sugeno Fuzzy Inference System A mathematical model to build a fuzzy inference system was proposed by Sugeno in 1985 [22].This model uses function of input variable to map with output.The Sugeno method is computationally efficient and integrates well with optimization and adaptive techniques, making it particularly useful in dynamic nonlinear systems. As a result, the system is an excellent choice for developing a hybrid system that can both explain autonomous decisions and learn from them.

4.2 ANFIS : Adaptive-Network-Based Fuzzy Inference System

ANFIS is a hybrid inference system to map input with output based on input-output data pairs and human knowledge having learning capability [23]. ANFIS is normally represented by a six-layer feedforward neural network as shown in figure 3 [24]. Layer 1 (Input layer) neurons simply pass external crisp inputs

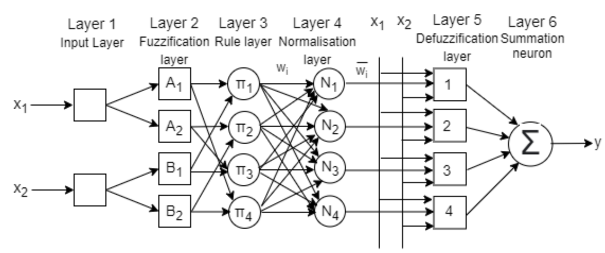


Fig. 3. Structure of Adaptive-Network-Based Fuzzy Inference System .

to layer 2. Layer 2 (Fuzzification layer) uses membership functions in order to obtain fuzzy clusters from input values x_i and linguistic labels (fuzzy-set) A_i and B_i. Layer 3 (Rule layer) generate the firing strength wi by using membership values computed in fuzzification layer. Layer 4 (Normalization layer) calculates the normalized firing strength $\overline{w_i}$ as ratio of the firing strength of the ith rule to the total of all firing strengths. Layer 5 (defuzzification layer) calculates the weighted consequent value of a given rule. Layer 6 (Summation layer) sum the output obtained from defuzzification to get the actual output.

4.3 Methodology

The overall steps followed for the simulation of proposed model are as mentioned in table 1.

Table 1. Steps for ASV decision explanation model

Data Generation and Explanation Paradigm	
1	Define collision avoidance FIS (CA FIS): Define and integrate fuzzy sets, membership functions and rules for inputs (TCPA and DCPA) and outputs (Speed change and route change).
2	Simulation setup: Define path and collision scenario for ASVs. (For this paper 2 ASVs and overtaking scenario has bee discussed).
3	Situational awareness: Calculate DCPA and TCPA.
4	Activate FIS: Take decision to avoid collision when distance to CPA fall below a threshold to generate training data for explainable model.
5	Train and tune the explainable model: A sugeno type reverse FIS has been trained and tuned to explain the decisions of CA FIS.
6	Test the model: Repeat steps 2-4 to generate the test data and test the model.

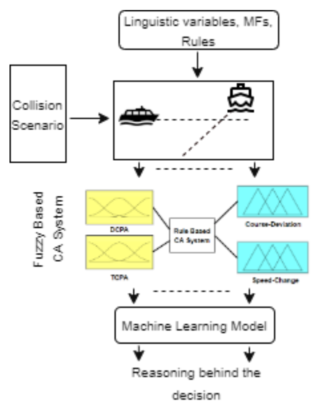


Fig. 4. Proposed Model.

Fuzzy based decision model as shown in figure 4 has been used to make the decisions about course deviation and speed change.The decisions of the model are explained using a reverse Sugeno FIS.

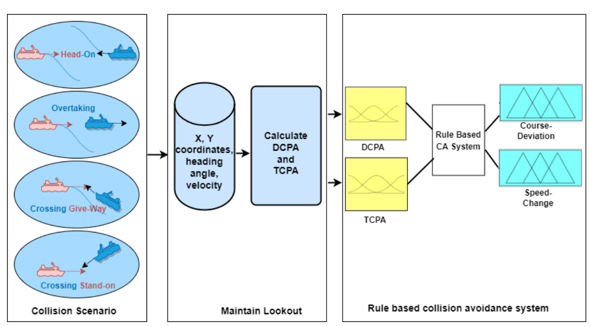


Fig. 5. Data Generation Model.

The proposed explanation approach has two major steps: (1) ASV makes decisions based on expert knowledge. (2) An Explainable model answer "Why a decision was taken?"

Two input parameters and two decisions are selected for decision making model as shown in figure 4. The inputs are:

1. Distance to Closest Point of Approach (DCPA): When the present heading angle and speed are maintained, the closest point specifies the position where the own ship and the target ship will be nearest. [25]. If target vessel is approaching from starboard or stern side the CPA is positive while negative CPA means from port or bow side [26].

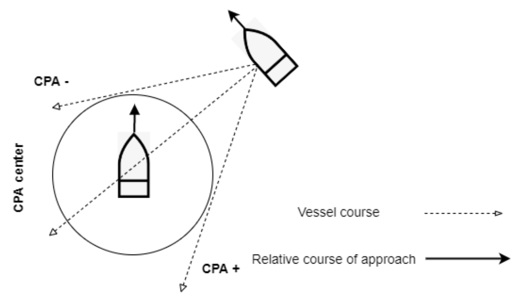


Fig. 6. Position of CPA for different course of approach.

The distance between the own ship and the target ship at CPA is DCPA [27]. DCPA has been calucalted as follows [28]:

$$\boldsymbol{DCPA = R_T sin(\varphi_R - \alpha_T - \pi)} \tag{2}$$

where

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

and x_O, x_T,y_O and y_T are coordinates of own ship and target ship.φ_R and α_T are heading of relative speed and true bearing of other ship.

2. Time to Closest Point of Approach (TCPA): The time it takes for a ship to reach CPA from its current position is called time to CPA (TCPA) [27].For simulation purpose TCPA has been calculated as below [28]:

$$\boldsymbol{TCPA = R_T cos(\varphi_R - \alpha_T - \pi)/v_R} \tag{4}$$

where v_R is relative speed.
In simulation, FIS has been activated when distance between own ship and target ship reach upon a threshold value which is named as action point in [3, 29, 30].

and decisions are:

1. Course-Deviation: COLREG rule 8 states that:
"Any change in course and/or speed to avoid a collision must be big enough to be seen by another vessel either visually or with radar. Small changes should be avoided. [3]."

Based on interpretation of the rule the course alternation should be noticeable. In the decision model 3 fuzzy sets are defined to justify the rule.

2. Speed-Reduction: When course deviation is not sufficient to avoid collision,vessel must decrease its speed. This is in case when there is no enough sea-room or need more time to analyze the situation. 3 fuzzy sets are defined for speed reduction.

4.3.1 Problem formulation and define linguistic variable The first step is to specify the problem and create a Mamdani model. The problem statement is to avoid the collision by considering the closest point of approach, action point, relative bearing, speed of own vessel. The outputs are route change and speed change. Followings are the linguistic variables:

1. Input 1 (DCPA): Very Close, Close, Far and Very far;
2. Input 2 (TCPA): Very less, Less, Long and Very Long;
3. Output 1 (Route Change): Short, Middle and Large
4. Output 2 (Speed Change): Small, Medium and Full

The overall structure of the Mamdani FIS is shown in right most part of figure 5.

4.3.2 Identify fuzzy sets Fuzzy set is a combination of (U,m) where U is a set and m is membership function. Triangular function have 3 parameters [a,b,c] where a represent left vertex, b represents center and c is right vertex. Trapezoidal shape have four parameters [d,e,f,g] and each represent a vertex respectively. Gaussian combination membership function (gauss2mf) computes fuzzy membership values using a combination of two Gaussian membership functions.

Figure 7 shows the fuzzy sets and membership functions for input and output variables.

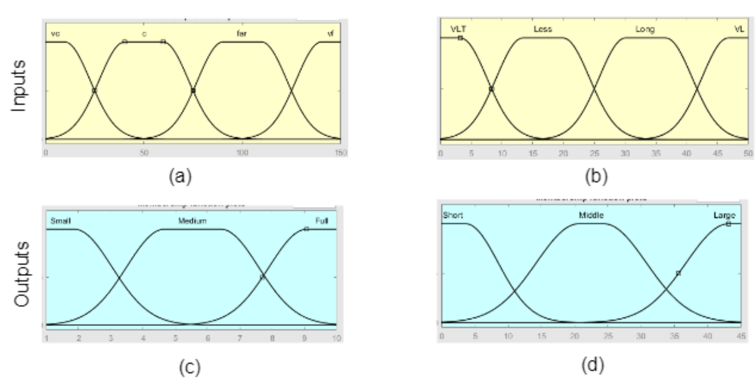


Fig. 7. Inputs: (a) DCPA (b) TCPA Outputs:(c) Speed change (d) Course change membership functions.

4.3.3 Build fuzzy rules Four membership functions in input 1 and input 2 each, give total 16 fuzzy rules. All membership functions for inputs and outputs are shown in table 2.

Table 2. Fuzzy Rules

Input					Output	
IF	DCPA	AND	TCPA	THEN	Course Deviation	Speed Change
	Very close		Very less Time		Short	Small
	Close		Less time		Middle	Medium
	Far		Long time		Large	Full
	Very far		Very long time			

4.3.4 Combine Fuzzy inference and build expert system Fuzzy inference combines fuzzy rules with fuzzy operator "AND" to include fuzzy sets, fuzzy rules, and membership functions. "AND" returns the minimum of the two membership functions. For example rule firing strength will be $\mu_{Action} = min\left[\mu_{speedchange}, \mu_{coursechange}\right] = min\left[0.6, 0.5\right] = 0.4$ if speed change is medium and course change is short with strength of 0.6 and 0.4 respectively.

4.3.5 Analyse and fine tune The input-output relationship can be examined from the system's surface view, as shown in figure 8.

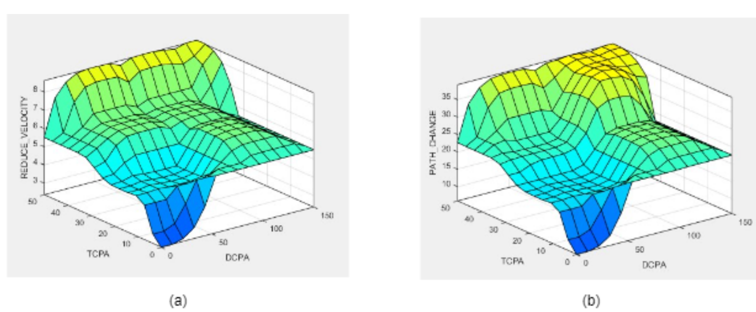


Fig. 8. Surface views of tuned systems (a) Reduce Velocity (b) Path Change.

In order to simulate ASV collision scenario, utilizing the rules obtained from this Mamdani FIS, a MATLAB program was written.

4.4 ASV scenario

A simulation environment for overtaking collisions as shown in figure 2 has been developed to assess the accuracy and robustness of the proposed model's explanation. In a circumstance of overtaking, two ASVs navigate using x and y coordinates. Under some conditions, the ASV would be required to alter its speed or course.

5 Rule base explanation by ANFIS

Sugeno FIS generates a single-output. Figure 9 shows the structure of ANFIS model with 9 rules.

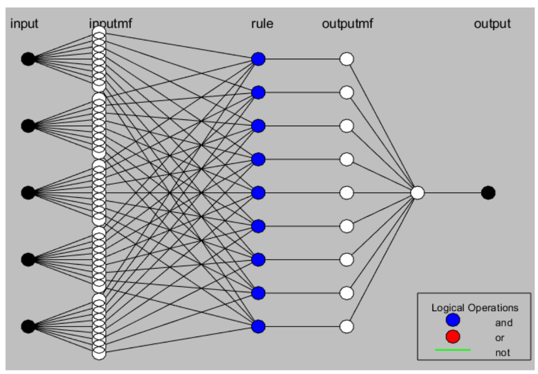


Fig. 9. ANFIS model structure.

6 Development tools and performance criteria

The suggested architecture requires a development tool. Fuzzy Logic Toolbox (FLT) [33] was developed using MathWorks' MATLAB. This graphical application creates and evaluates fuzzy systems. FIS, rule, membership function, fuzzy inference, and output surface editors are included. The FIS editor shows information about FIS. The membership function editor displays and edits input and output variable membership functions. The user can automatically generate rule statements by clicking and selecting one item in each input variable box, one item in each output box, and one connection item in the rule editor. The rule viewer shows the entire fuzzy inference process. Use the ANFIS editor GUI menu bar to load a FIS training initiation, save the trained FIS, and open a Sugeno system to analyze the model [34].

The root mean square error (RMSE) has been used to test the performance criterion [35]:

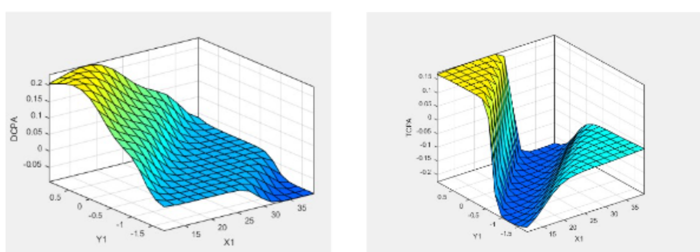
$$\boldsymbol{RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Actual_i - Predicted_i)^2}} \tag{5}$$

Accuracy is another performance metric. For accuracy, an RMSE threshold value and simple percentage calculation are used [35]:

$$\boldsymbol{AccuracyPercentage} = \frac{\boldsymbol{Threshold - RMSE}}{\boldsymbol{Threshold}} \times \mathbf{100\%} \tag{6}$$

7 Results and discussion

The results in this section are shown by comparing the RMSE values of the actual and predicted values from ANFIS models developed for explaination of the collision avoidance. Data has been split for training and testing. The findings suggest that ANFIS can be utilized in a variety of settings to help autonomous systems evolve useful explanation features. The subclustering parameters used to generate a Sugeno model are modified in the findings. The models' performance is then evaluated to see how much the RMSE changes as the subclustering parameters change. The ANFIS model has the restriction for single output. So we have generated two separate XAI models for DCPA and TCPA as shown in figure 10. In both cases only the portion of data considered for training and testing when fuzzy based CAS activated in simulation. The data has been divided for training and testing.

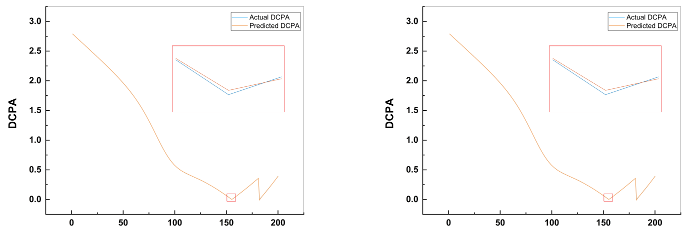


(a) (b)

Fig. 10. Surface views of XAI Models (a) DCPA (b) TCPA.

7.1 ANFIS Model 1: DCPA as output

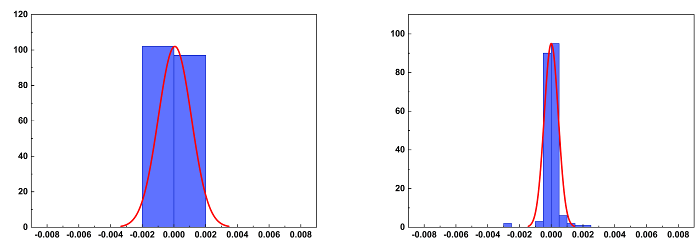
This model has five inputs and single output (DCPA). Each Suegeno FIS output number specifies the DCPA value that led ASV to change course or speed at that time, place, and heading direction. The structure of DCPA ANFIS XAI model is shown in figure 10 (a). Actual and predicted DCPA values showing good results as shown in figure 11.



(a) **(b)**

Fig. 11. Actual vs Predicted DCPA (a) Training (b) Testing.

Mostly testing errors for DCPA XAI model are in the range of between -0.002 to 0.002 as shown in figure 12.



(a) **(b)**

Fig. 12. Error Histogram during testing (a) DCPA (b) TCPA.

Left side of figure 13 shows training and testing RMSE for DCPA XAI model. If the acceptable threshold RMSE criterion for this study is 0.04, then equation 6 shows $\approx 97\%$ accuracy.

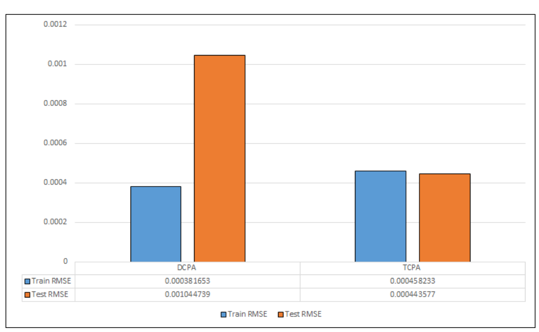


Fig. 13. Root mean square error.

For DCPA, an example to explain what caused the ASV to change route or change speed is given. Figure 14 shows a rule view window for Sugeno model that has DCPA as output.

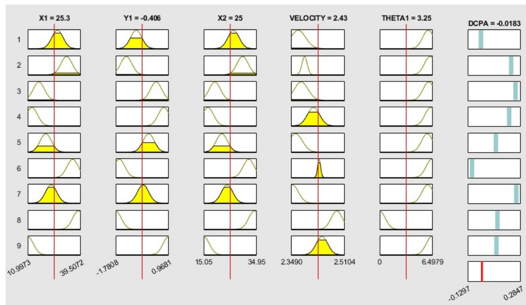


Fig. 14. Rule Viewer of XAI for DCPA.

7.2 ANFIS Model 2: TCPA as output

As DCPA XAI model, this model also has five inputs and single output (TCPA). Each value specifies the TCPA value responisble for change course or speed at respective situation. The structure of TCPA ANFIS XAI model is shown in figure 10 (b). Actual and predicted TCPA values showing good results as shown in figure 15. Mostly testing errors for DCPA XAI model are in the range of between -0.001 to 0.001 as shown in figure 12.

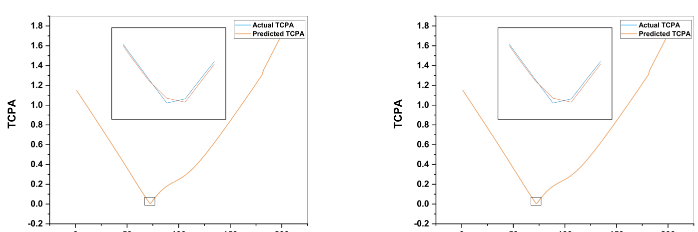


Fig. 15. Actual vs Predicted TCPA (a) Training (b) Testing.

For TCPA, an example to explain what caused the ASV to change route or change speed is given. Figure 16 shows a rule view window for Sugeno model that has TCPA as output. Right side of figure 13 shows training and testing RMSE for TCPA XAI model. If the acceptable threshold RMSE criterion for this study is 0.04, then equation 6 shows ≈ 98% accuracy.

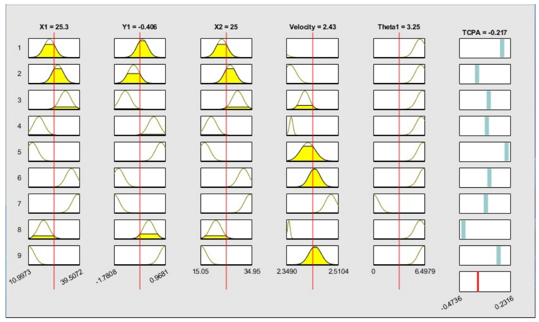


Fig. 16. Rule Viewer of XAI for TCPA.

8 Conclusion and future scope

The purpose of this study is to look into a method for developing an explanation for ASV's fuzzy based decisions. An overtaking collision scenario has been considered in order to explain the decisions taken by ASVs. Then, based on the ASV's actions when met with a collision scenario, data has been recorded and a clear and accurate explanation is given by a reverse explanation model. Mamdani FIS is used to create a simulation environment that incorporates fuzzy rules. The overtaking collision scenario is setup in MATLAB. The ASV steers and follows the fuzzy rules during a collision scenario. During the overtaking scenario testing RMSE was found 0.00104 and 0.00044 for DCPA and TCPA respectively.

Explainability of autonomous system decisions is a matter of growing importance these days. Autonomous vehicles are getting increasingly common in today's era. The job of establishing trust between humans and technology is critical. More collision scenarios, more fuzzy rules in collision avoidance system can be included as future study to test explanation of any fuzzy based collision avoidance system. As a result, the method proposed in this research makes the ASV's decisions more transparent, intelligible, and reliable. The simulated environment can be used to generate simulated data for research purpose. It can be tested using real time data and rule can be fine tuned to for smooth course deviation. The model can be applied to explain the smoothness of trajectory generated by a path planning algorithm.

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