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Obstacle Avoidance scenario of Bio-inspired Autonomous Underwater Vehicle using Fuzzy controllers

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ABSTRACT

Autonomous Underwater Vehicles (AUVs) are pre-programmable, robotic vehicles that can float, drive, or slide through the sea without operators and have real-time control, depending on their configuration. Biologically inspired AUVs (BAUVs) are a relatively new invention in the field of underwater vehicles that do away with propellers. Bio-inspired AUVs can be employed for high-speed and low-speed applications with exceptional propulsive efficiency. The navigation control mechanisms of a novel Bio-mimetic autonomous underwater vehicle were investigated in this work. In order to design a navigational system for the vehicle after avoiding obstacles, Fuzzy Logic Controller (FLC) and Neuro-Fuzzy controller approaches are utilized.

Keywords: Autonomous systems, PID control, Control applications

1. INTRODUCTION

An autonomous underwater vehicle (AUV) is a un-crewed submersible vehicle that works without requiring real-time input or control from a human operator. These are pre-programmed with mission parameters and then placed into the ocean. AUVs can be used for various commercial applications such as exploring oil and gas or locating ship and plane wrecks also used in the scientific, military, illicit drug trafficking, and commercial sectors [1]. In existing AUVs, propeller-based systems are used, which are suitable for high-speed applications. It is ineffective at low speeds and has a large turning radius. A vast number of research have been done into optimizing the propeller-based system. Bio-inspired propulsion is an alternative to a propeller system. The word bio-inspired or bio-mimetic refers to an approach that replicates nature. It can reduce the system noise and limit the noise radiation. Therefore, this study produces a biologically inspired AUV that replaces conventional propellers and can be extensively used for many applications [2].

Underwater vehicle navigation is a challenging problem in the field of robotics [14]. Path tracking or planning is a crucial function for an autonomous vehicle to navigate along the desired path. This task includes tracking previously computed paths using a path planner, a defined path by a human operator, and apprehending walls, waterways, marine gems, and other natural features in the vehicle workspace. It also involves the real-time perception of the environment to determine the robot's position and orientation concerning the desired path. For solving these navigation-related problems, many researchers have developed different techniques, including Artificial algorithms, Artificial Potential Fields, Fuzzy logic [3], Neural networks, Genetic algorithms, Ant colony optimization, etc.

The main contribution of this paper includes the design of obstacle avoidance and navigational system for the horizontal motion of the proposed Bio-inspired AUV (BAUV). A novel BAUV with a gertler geometric-shaped hull and a caudal tuna fin resembling a flapping foil tail is developed for analysis. The model of proposed biomimetic AUV system is described in Fig. 1

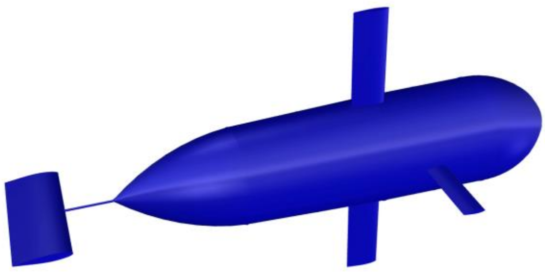

Fig 1. Proposed biomimetic AUV model

A fuzzy logic controller system has been implemented first for navigational purposes. As an extension of this work, an adaptive neuro-fuzzy controller (ANFIS) is also used for better performance.

The paper is organized into seven sections. In Section 2, the whole system model of the BAUV is presented. In section 3 navigation problem is formulated. In Section 4, the fuzzy logic controller is developed and discussed in detail, and in Section 5 Neuro-fuzzy controller (ANFIS) design is presented. Section 6 shows the simulation results and the efficiency of the proposed methods. Finally, the conclusions based on the obtained results are given in Section 7.

2. SYSTEM MODELING

2.1 Bio-inspired AUV specifications

The navigational design in this work is based on a virtual model of a Bio-inspired vehicle. Fig 2 depicts the basic proposed design of an AUV hull [4], and any additional equipment or batteries can be placed in the model mid- section if needed.

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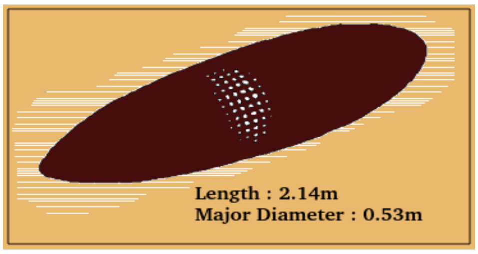

Fig. 2: Gertler shaped AUV hull

The parameters of the model are described in Table I.

TABLE I: Parameters of the hull model

Parameters	Values
Moment of Inertia, I_x	8.8 Kg.m/s^2
Moment of Inertia, I_y	76.8 Kg.m/s^2
Moment of Inertia, I_z	76.8 Kg.m/s^2
Mass	320 Kg

AUV hull which features caudal fin and DC servo motors are used to actuate the system [5]. NACA63-015A foil is chosen for the vehicle and it is a low drag aerofoil. This cross section can reduce the bending stiffness of the hull in the posterior actuated segment and provide the optimum hydrodynamic shape [6]. Selected foil is shown in Fig 3.

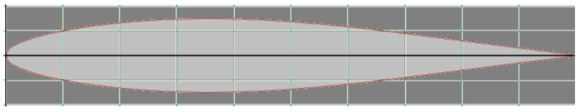

Fig. 3: NACA63-015A Aerofoil (Length 0.25m and thickness 4cm)

2.2 Tail Kinematics

Modeling of kinematic conditions of Flapping foil tail involves the investigation of geometrical aspects of motion. The tail motion consists of combination of heave and pitch, where these are the lateral and the angular motion of the fin respectively [5]. Feathering of the wing known as twist motion and it is harmonic in nature. Twist motion of the foil defined as [2];

$$\theta(t) = \theta_0 sin(\omega t + \psi) + \theta_{bias} \quad (1)$$

where: θ_0 is the twist amplitude, ψ and is the phase angle in radian. Value of ψ will be pi/2 in all experiments. There for the twist equation will be,

$$\theta(t) = \theta_0 cos(\omega t) + \theta_{bias} \quad (2)$$

The thrust forces are acts in sway and yaw components.

2.3. Vehicle Dynamics

Modeling the dynamics of the biomimetic vehicle hull using well-known theories of Fossen [7], [8]. A marine vehicle with 6 degrees of freedom (6DOF) posses independent linear and angular motions. It is typically used to determine the position and orientation of the vehicle. Surge, sway, and heave are linear motions, while roll pitch and yaw are angular motions. Earth fixed frame, and body-fixed frame are the two coordinate frames used to describe [7] or analyze vehicle motion. A moving frame that is fixed to the vehicle is known as a body-fixed frame. Low-speed marine vehicles are not affected by the motion of Earth so that the acceleration of a point on the surface of Earth can be neglected. Thus, the Earth fixed reference frameset to be inertial [8]. Designing of AUV system is completely based on the dynamic equation. The dynamic model of the vehicle on the horizontal plane is as given below:

$$M\dot{v} + C(v)v + D(v)v + g(\eta) = \tau \quad (3)$$

where, M is the inertia matrix, C(v) is Coriolis and Centripetal matrix, D(v) is the Damping matrix and τ is the input vector. The above equation is is derived from the Newton - Euler equation of a rigid body in fluid. For designing navigational system, we can consider 3DOF motions such as surge, sway and yaw velocities. These velocities are the state variables, in which surge or forward velocity is constant (u_0 = 2.57 m/s) [4]. Hence the system representation will be [8], [7],

$$\begin{bmatrix} m - Y_{\dot{v}} & 0 \\ 0 & I_z - N_{\dot{r}} \end{bmatrix} \begin{bmatrix} \dot{v} \\ \dot{r} \end{bmatrix} + \begin{bmatrix} m - Y_v & 0 \\ 0 & N_r \end{bmatrix} \begin{bmatrix} v \\ r \end{bmatrix} + \begin{bmatrix} 0 & (m - X_{\dot{u}})u_0 \\ (X_{\dot{u}} - Y_{\dot{v}})u_0 & 0 \end{bmatrix} \begin{bmatrix} \dot{v} \\ \dot{r} \end{bmatrix} = \begin{bmatrix} \tau_Y \\ \tau_N \end{bmatrix} \quad (4)$$

Let,$\tau = \begin{bmatrix} \tau_Y \\ \tau_N \end{bmatrix}$and $v = \begin{bmatrix} v \\ r \end{bmatrix}$for the system. The proposed system posses xz plane of symmetry [8], [7]. The values of hydrodynamic coefficients usually calculated by using Captive model tests. These tests are of two types namely static or straight-line test and dynamic or Planar Motion Mechanism (PMM) test, in which virtual PMM is carried out to identify the coefficients, are mentioned in the Appendix. These values are used to determine the transfer function of the proposed system.

3. PROBLEM FORMULATION

An obstacle avoidance robot is a type of autonomous mobile robot that prevents collisions from unexpected obstacles. The robot detects the impediment ahead and turns in a different direction to avoid it. A bioinspired AUV with obstacle avoiding ability is designed here with some assumptions.

A Bio-inspired AUV is confronted with several moving obstacles. Only four moving objects with the same speed are addressed in the current scenario. The AUV is designed in such a way that the vehicle detects the object and turns to a particular angular direction if the distance between the vehicle and the obstacle is less than 2m. Fig 4 depicts a typical example of the situation.

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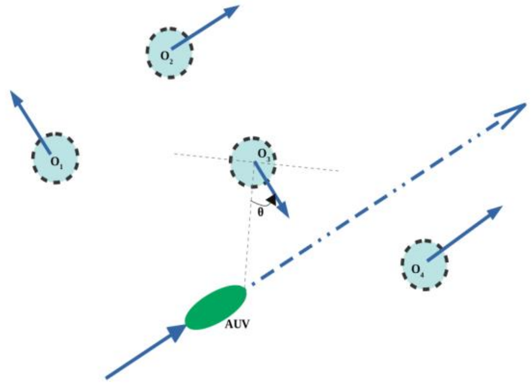

Fig. 4: Obstacle Avoiding Scenario of BAUV

4. DESIGN OF FLC

In recent years, the Fuzzy Logic Controller (FLC) has been widely used for practical applications [9]. It can be used for both linear and nonlinear systems. FLC is described by a knowledge-based system consisting of IF-THEN rules. Each of the FLC rules is characterized by an IF part called antecedent and with a Then part called consequent. If the antecedent conditions are satisfied, then the conclusions of the consequent apply [10]. An FLC consist of mainly four parts.

- Fuzzification
- Rule base
- Defuzzification
- Inference Engine

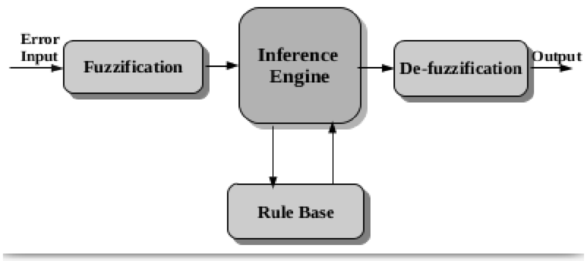

Fig. 5: A Fuzzy logic controller system

4.1 FLC Design for BAUV navigation

The developed fuzzy controller performs navigation and obstacle avoidance tasks at the same time. The first step in understanding a fuzzy controller is fuzzification, which converts inputs and outputs of any real value into member- ship grades for fuzzy control terminology [10]. The fuzzy inference engine integrates the facts gained from the rule base fuzzification and performs the fuzzy reasoning process. Depending on the uses and the type of the membership function, there are several fuzzy inference methods [11]. Proposed architecture of fuzzy inference system shown in Fig 6.

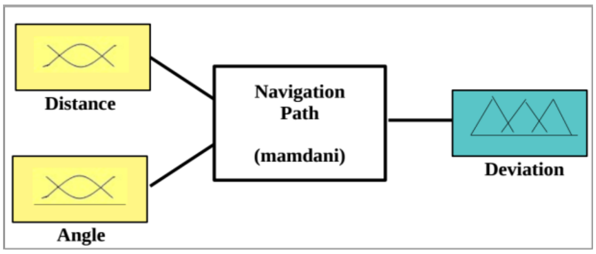

Fig. 6: Architecture of proposed Fuzzy Inference System

Considering two parameters such as.
D = [0.1, 0.2..........5]: Distance from AUV to an object
θ = [−90........+90]: Angle of motion of object with respect to an AUV
An output called Deviation will determine the value of these parameters concerning the most critical object (δ). After identifying the relevant input and output of the controller and their range of values, the Mamdani approach [10] is to select some states called "linguistic states" for each variable and express them by appropriate fuzzy sets.
1) *Linguistic states:* The first input "Distance" represented by using four Linguistic states. They are,
- VC: Very Close
- CL: Close
- VD: Very Distant
- DT: Distant

In this system, the second input and output of the fuzzy controller variables are the same. They are;
- LT: Left
- FL: Forward Left
- FD: Forward
- FR: Forward Right
- RT: Right

The Fig 7, 8, 9 shows membership function scatter gram of input and output variables.

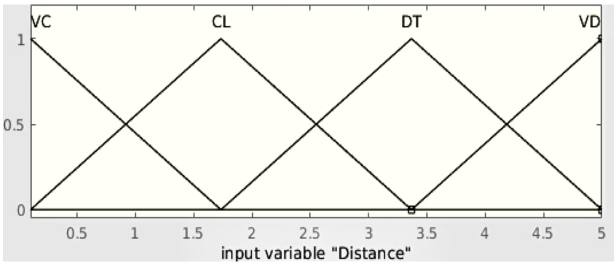

Fig. 7: Input Membership function for distance

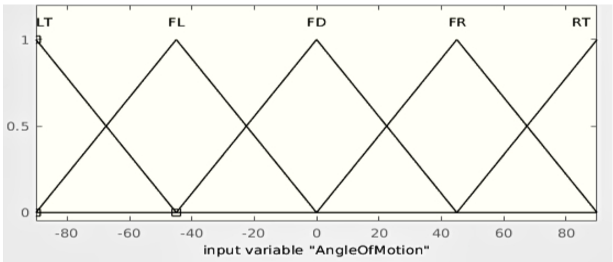

Fig. 8: Input Membership function for Angle of Motion

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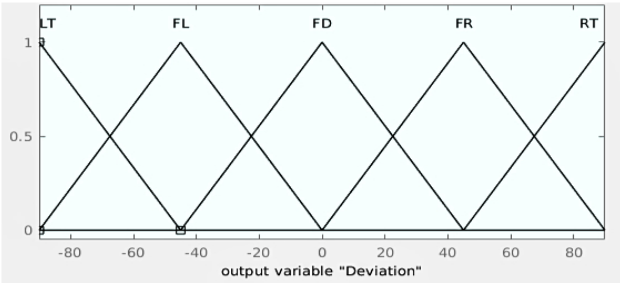

Fig. 9: Output Membership function for Deviation

Once the input, output variables, and membership functions Rule are defined, it is necessary to construct fuzzy rule bases composed of expert IF <antecedents> THEN <conclusions> rules [11]. If-Then rules are used to formulate conditional statements that are comprised of fuzzy logic. A single fuzzy If-Then rule assumes the form.

If a is X_1 Then b is Y_2, where X_1 and Y_2 are linguistic variables defined by fuzzy sets on the ranges (i.e., universe of discourse) A and B, respectively. In other words, the conditional statement can be expressed in a mathematical form [11],

• If a is X_1 Then b is Y_2

All the rules are described in Table II.

TABLE II: Fuzzy rule bases for the controller

	LT	**FL**	**FD**	**FR**	**RT**
VC	FD	FR	FL	FL	FD
CL	FD	FD	RT	FD	FD
VD	FD	FD	FR	FD	FD
DT	FD	FD	FD	FD	FD

5. NEURO-FUZZY LOGIC CONTROLLER DESIGN

A neuro-fuzzy system or fuzzy neural network is a learning machine that finds the fuzzy system parameters (i.e., fuzzy sets, fuzzy rules) by exploiting approximation techniques from neural networks. It maps inputs through input membership functions and related parameters; and then through output membership functions and associated elements to outputs, can be used to interpret the input/output map [12]. In the learning process, the parameters associated with the membership functions updates.

5.1 Neuro-Fuzzy Controller Design for BAUV Navigation

Combining Fuzzy technologies and a neural network called Adaptive neuro-fuzzy inference system (ANFIS). The ANFIS model is trained with the back-propagation gradient descent method. Adaptive Neural Fuzzy Inference System (ANFIS) is a fuzzy Sugeno model set out in the frame- work to facilitate learning and adaptation. Such a network makes fuzzy logic more systematic and less relying on expert knowledge [11]. The objective of ANFIS is to adjust the parameters of a fuzzy system by applying a learning procedure using input-output training data. A combination technique of least square algorithm and back-propagation is used for training fuzzy inference system [13]. The parameters for the neuro-fuzzy system design is given in the Table III.

TABLE III: Parameters for the neuro-fuzzy system design

Parameters	**Values**
No.of Inputs	2
No. of membership functions	45
Type of membership function for each input	Triangular
No.of Output membership functions	5
No.of training epochs	1000

1) Neuro Fuzzy AUV system Architecture: The BAUV system consists of two inputs and one output. The input layer transfers the data to the second layer, which calculates the degrees of fuzzy membership to which the input values belong to the predefined fuzzy membership functions. The third layer contains fuzzy rule nodes representing input-output fuzzy knowledge base (Takagi Sugeno coefficient) on the network controller. According to the network calculations (fuzzification, inference, defuzzification), the control action is applied to the process input that allows the system state to calculate the error with the input of the network controller. The value at the end of each rule represents the initial weight of the rule, and will be adjusted to its appropriate level at the end of training [11]. Basic architecture of ANFIS that has two inputs x and y and one output f is shown in Fig. 10.

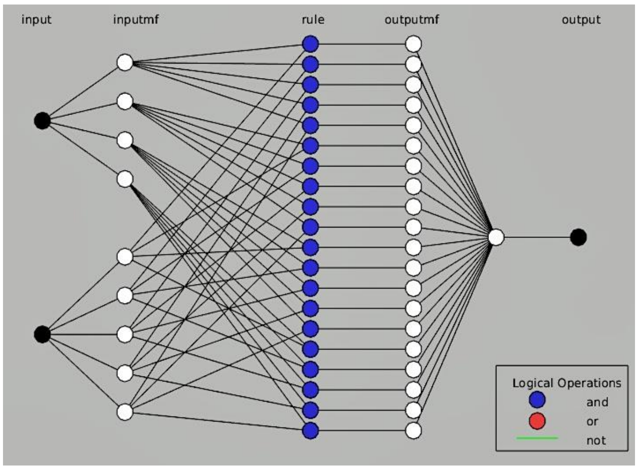

Fig. 10: Neuro-fuzzy Architecture

6. SIMULATION AND SUMMARY

An illustrative example for a Fuzzy Logic controller with Output is given below. Fuzzification is defined as converting a crisp set to a fuzzy set or a fuzzy set to a fuzzier set. Essentially, this operation translates accurate, crisp input values into linguistic variables. Defuzzification is the process of producing a quantifiable result in Crisp logic, given the fuzzy sets and corresponding degrees of membership. Consider a distance from the moving object to the AUV at any particular instant, say D = 2m and Angular direction $\theta = 27^0$. Fuzzy controller transfer output to the defuzzification system.

6.1 FLC simulation examination

Fuzzification of the inputs: Examine the Linguistic states of the system [6, 7]; the crisp input distance can be considered fuzzily in terms of two fuzzy values may call as either CL (Close) or DT (Distant) shown in Fig 11.

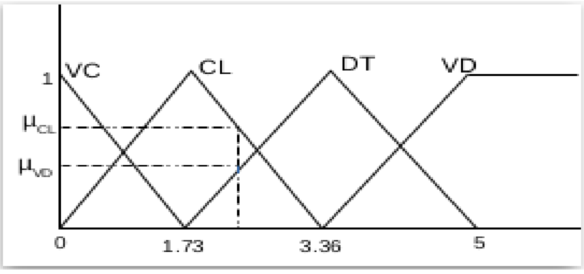

Fig. 11: Linguistic state with membership values for Distance Input

Similarly, the angular rotation input can be called as either FD (Forward) or FR (forward Right). Membership values corresponds to these crisp values can be calculated using Principles of similarity (similarity of triangle) rule, $\frac{x}{y} = \frac{a}{b}$.

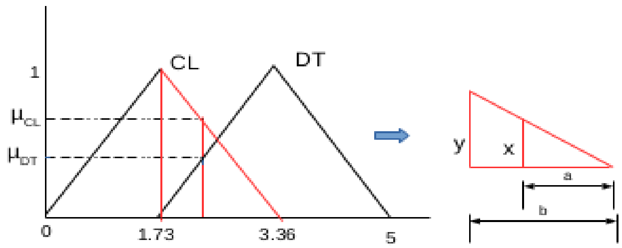

Fig. 12: Determination of Membership values

Thus, $\frac{x}{l} = \frac{3.36-2}{3.36-1.73}$, i.e, $x = 0.834 = \mu_{CL}$. Similarly, μ_{VD} can be calculated as 0.674. The same approach can be extended to compute the other input membership values also.

These values are given in the Table IV.

TABLE IV: Membership values of Linguistic function

Distance input (D=2m)	**Angular input ($\theta = 27^0$)**
$\mu_{CL} = 0.834$	$\mu_{FR} = 0.8$
$\mu_{VD} = 0.674$	$\mu_{FD} = 0.4$

Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. This mapping is based on the defined rules (obtained from Table II). The current inputs follow mainly four rules. They are;

If (Distance is CL) and (AngleOfMotion is FD) Then (Deviation is RT)
If (Distance is CL) and (AngleOfMotion is FR) Then (Deviation is FD)
If (Distance is DT) and (AngleOfMotion is FD) Then (Deviation is FR)
If (Distance is DT) and (AngleOfMotion is FR) Then (Deviation is FD)

According to mamdani approach, strength (also called α values) of the firable rules are calculated as follows.

$$\alpha(R_1) = min(\mu_{CL}, \mu_{FD})\ min(0.834, 0.4) = 0.4$$
$$\alpha(R_2) = min(\mu_{CL}, \mu_{FD}) = min(0.834, 0.4) = 0.4$$
$$\alpha(R_3) = min(\mu_{DT}, \mu_{FD}) = min(0.674, 0.4) = 0.4$$
$$\alpha(R_4) = min(\mu_{DT}, \mu_{FR}) = min(0.674, 0.8) = 0.674$$

In practice, all rules which are above certain threshold value of the rule strength are selected for the output computation here, the threshold of the α value is selected as 0.674, then final rules for the computation is taken as;

$$\alpha(R_2) = min(\mu_{CL}, \mu_{FD}) = min(0.834, 0.4) = 0.4$$
$$\alpha(R_4) = min(\mu_{DT}, \mu_{FR}) = min(0.674, 0.8) = 0.674$$

Fuzzified Outputs: The rules selected above are used to determine the fuzzified outputs. Let these rules are in the form of;

R_1: If (I_1 is A_1) and (I_2 is B_1) Then (Y is O_1)
R_2: If (I_1 is A_2) and (I_2 is B_2) Then (Y is O_2)

Let the I_1 and I_2 are the inputs for fuzzy variables I^*_1 and I^*_2. The variables μ_{A1}, μ_{A2}, μ_{B1}, μ_{B2}, μ_{O1}, and μ_{O2} are the membership values for the different fuzzy sets. Y is denoted as the output. So, the resultant output obtained from the above-mentioned rules will be the union of Y_1 and Y_2, i.e $Y = O_1 \cup Y_2$
Defuzzification of outputs: Pictorial representation of the four rule bases is shown in Fig 13.

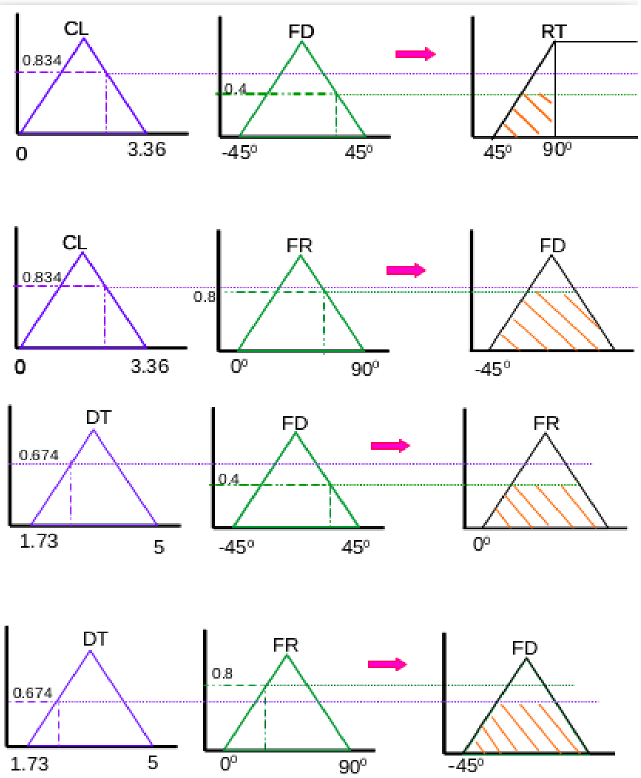

Fig. 13: Pictorial representation of Rule base Fuzzy output computation

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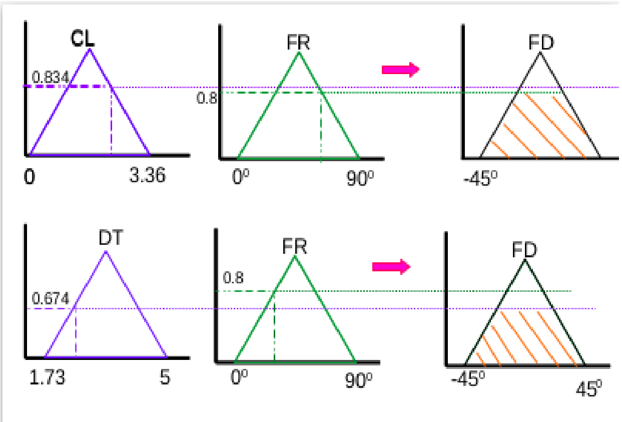
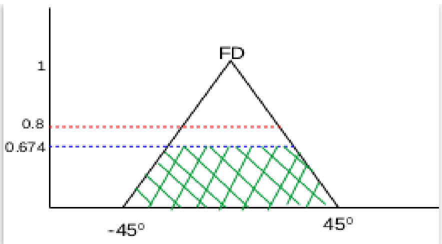
Defuzzification is the final step of process, in which fuzzy output is translated into a single crisp value. Fig 14a illustrates the computation of crisp output using selected value threshold rule strengths. Resultant output will be the union of two rule strength output which is shown in Fig 14b.



(a)



(b)

Fig. 14: Representation of rule base and resultant Fuzzy output

From the combined fuzzified output for two fired rules, we get the crisp output using Center of Sum method (COS). Therefore, the AUV should deviate by 20.8^0 towards the right with respect to the line of joining to the move of direction to avoid co alition from the obstacle O_3 shown in Fig. 15.

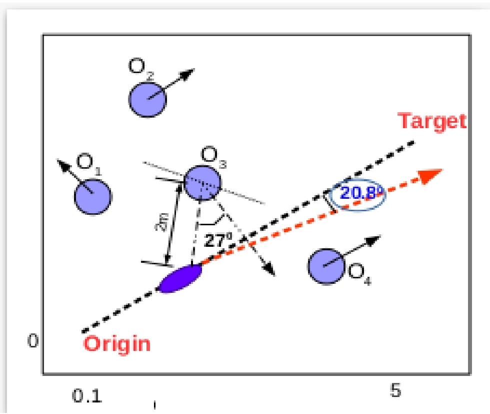


Fig. 15: Resultant AUV path with obstacles environment

1) Neuro FLC examination: Neural network used with Takagi-Sugano fuzzy model needs some mathematical treatment. It should be stored in the form of mathematical representation, that is a big challenge for the designer. Here the Output is expressed in the function of input parameters, i.e; O = f (I_1 , I_2) = f (D, θ), where I_1 and I_2 are the two inputs, which are D and θ explained in the explanatory example section. Membership function distribution is same as that of Fuzzy logic Mamdani system [Fig. 6, Fig. 7, Fig. 8]. According to the Takagi Sugano model of FLC,

$$y^i = a_i I_1 + b_i I_2 + c_i \tag{5}$$

where i = 1, 2, ..., 20 and a_i , b_i , c_i are the coefficients. These coefficients can be determined by Least Square Error technique and also use some sort of nature inspired optimization tool like Genetic algorithm. Same linguistic variables and rule bases [Table II] of Mamdani system is taken here also. The fired rules should be taken according to the input. They are;

If (Distance is CL) and (AngleOfMotion is FD) then $y^8 = a_8 I_1 + b_8 I_2 + c_8$
If (Distance is CL) and (AngleOfMotion is FR) then $y^9 = a_9 I_1 + b_9 I_2 + c_9$
If (Distance is DT) and (AngleOfMotion is FL) then $y^{18} = a_{18} I_1 + b_{18} I_2 + c_{18}$
If (Distance is DT) and (AngleOfMotion is FR) then $y^{19} = a_{19} I_1 + b_{19} I_2 + c_{19}$

Fig 16 represents the ANFIS system rule surface viewer.

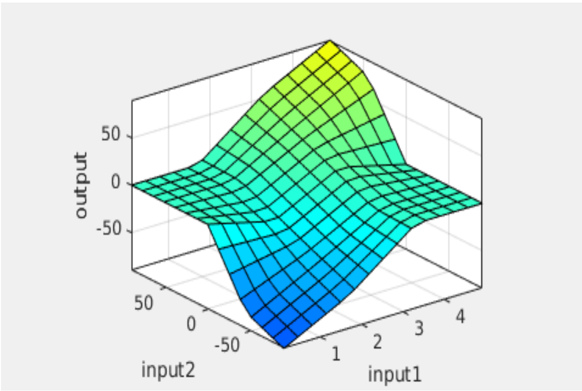


Fig. 16: ANFIS system rule surface viewer

The final output O is calculated as the product of normalized firing strength and output of the corresponding fired rule y^i. The weight calculation in between second and third layer, i.e membership function layer and rule layer [Fig. 9] is given as;

- $R_8 = \mu_{CL} \times \mu_{FD} = 0.834 \times 0.4 = 0.3336$
- $R_9 = \mu_{CL} \times \mu_{FR} = 0.834 \times 0.8 = 0.6672$
- $R_{18} = \mu_{DT} \times \mu_{FD} = 0.674 \times 0.4 = 0.2696$
- $R_{19} = \mu_{DT} \times \mu_{FR} = 0.674 \times 0.8 = 0.5392$

Hidden layer is existing in between third (rule layer) and fourth (membership output layer) layers, and hidden nodes are $\bar{W}_1, \bar{W}_2, \ldots, \bar{W}_{20}$ for 20 rules. Thus, the calculation is;

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$\bar{W_1} = \frac{R_1}{R_1+R_2+......+R_{20}}$, …. ,$\bar{W}_{20} = \frac{R_{20}}{R_1+R_2+......+R_{20}}$. Here calculating normalized firing strength of each rule (required rules);

- $\bar{W_8} = \frac{R_8}{R_8+R_9+R_{18}+R_{19}} = \frac{0.3332}{1.8096} = 0.1843$
- $\bar{W_9} = \frac{R_9}{R_8+R_9+R_{18}+R_{19}} = \frac{0.6672}{1.8096} = 0.3687$
- $\bar{W}_{18} = \frac{R_{18}}{R_8+R_9+R_{18}+R_{19}} = \frac{0.2696}{1.8096} = 0.1489$
- $\bar{W}_{19} = \frac{R_{19}}{R_8+R_9+R_{18}+R_{19}} = \frac{0.5392}{1.8096} = 0.2979$

From all the above calculations, the over all output is obtained as; $\bar{W_8}y^8 + \bar{W_9}y^9 + \bar{W}_{18}y^{18} + \bar{W}_{19}y^{19} = 15.5^0$. That is the BAUV should deviate by 15.5^0 towards the right with respect to the line of joining to the move of direction to avoid collision from the obstacle O_3 shown in Fig. 17.

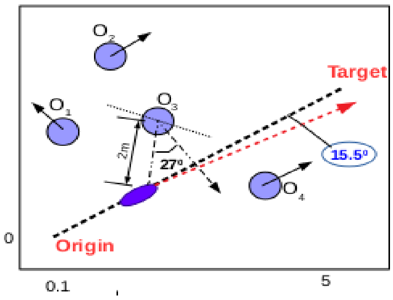
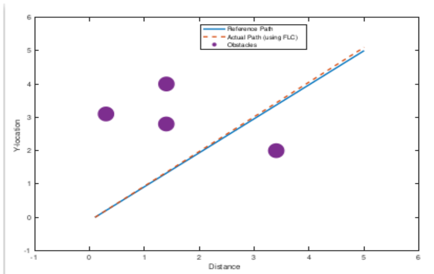
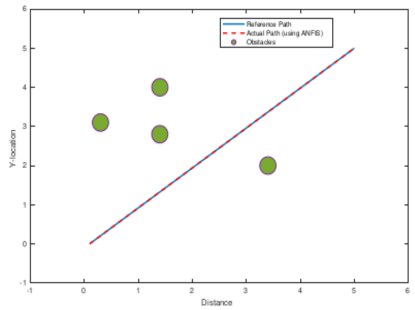


Fig. 17: Resultant AUV path with obstacles environment

Fig 18a depicts the path obtained using fuzzy logic controller simulation setup, which is close to the reference path. But the path procured by the BAUV using a neuro- fuzzy controller, which is more adjacent to the reference path shown in Fig 18b.



(a) Path following of AUV using FLC



(b) Path following of AUV using ANFIS

2) Comparison of the ANFIS result with Fuzzy Logic Controller: The comparison study of two logic are mainly based on the obtained trajectory and training error. Fig 19 depicts simulation results for trajectories at the obstacles environment. The blue line shows the desired trajectory, red and green lines are the actual trajectories using ANFIS and fuzzy logic controller.

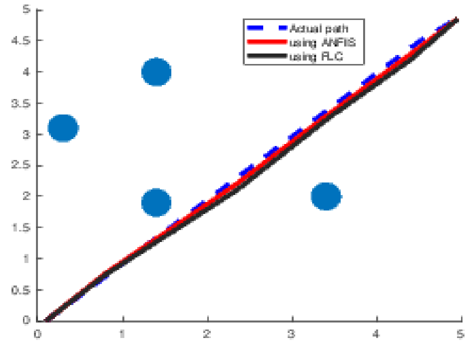


Fig 19. Comparison of resultant trajectories at the obstacle environment

The Table V illustrates the comparison of fuzzy logic controller and neuro-fuzzy controller in terms of error from the actual trajectory and overshoot of the response.

TABLE V: Comparison of parameters

	FLC	**ANFIS**
Error (%)	6.6570	2.7051
Overshoot (%)	2.8301	1.6075

In order to show the performance of the results obtained by ANFIS system, pictorial representation of the training error is given below in Fig 20. Therefore, it can be concluded that the ANFIS controller have a good potential to effect fast response to obstacles and reduce errors.

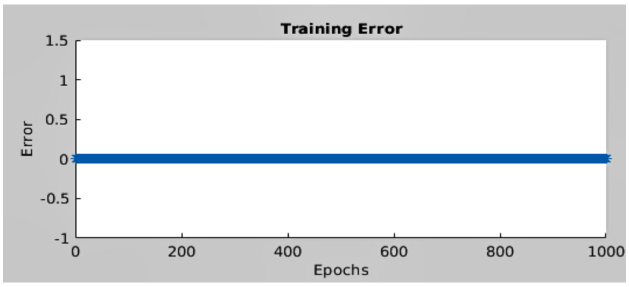


Fig. 20: Training error plot for ANFIS output

7. CONCLUSION

The problem of obstacle avoidance in navigation of BAUV has been solved by developing an advanced fuzzy logic Fig. 20: Training error plot for ANFIS inference system. In this study, for the verification, novelty, and reliability of the proposed method, we had simulated the algorithm in the fuzzy logic toolbox of MATLAB R2018a. For the comparison purpose, an Adaptive Neuro-Fuzzy type controller is also designed. The ANFIS architecture has shown good performance in modeling the navigation of the AUV. The best feature of ANFIS is that it pre-processes all data into several membership functions before mapping data into an adaptive neuro structure. This pre-processing feature allows ANFIS to converge faster and better. Through comparisons with the Fuzzy logic Controller, it is found that the proposed system is a powerful tool for controlling robotic navigational systems. As for future work, we can do the multiple AUVs using the advanced constructed fuzzy logic and genetic algorithms to tune the membership function of the fuzzy inputs.

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