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Parallel Tuning of Fuzzy Tracking Controller for Deep Submergence Rescue Vehicle using Genetic Algorithm

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Deep Submergence Rescue Vehicle (DSRV) is an underwater vehicle designed for immediate rescue operation in the incident of a submarine mishap. During this rescue operation, precise and dynamic trajectory tracking of DSRV is difficult due to poor visibility and complex marine environment caused by unstable waves, winds etc. In this work a Genetic based Fuzzy Logic Controller (GAFLC) is designed to solve the trajectory tracking control problem of DSRV in the presence of unknown time varying wave disturbances. In first step a conventional Fuzzy Logic Controller (FLC) is designed with fixed rule base and membership functions from expert's knowledge and scaling factor chosen by trial and error. In second step to enhance the trajectory tracking performance and to improve the system robustness to unstable wave disturbances the complete knowledge base of FLC is parameterized and optimized to find an optimal fuzzy controller without expert's knowledge. Genetic Algorithm (GA) is used to optimize the input and output membership functions, the rule base and the scaling factors of FLC simultaneously. Simulations are performed on four 2D reference trajectories corresponding to under water scenarios to demonstrate the effectiveness of the designed GAFLC in trajectory tracking and disturbance rejection.

[Keywords: Under water vehicle, Fuzzy logic controller, Genetic algorithm, Optimization, Trajectory tracking]

Introduction

Underwater vehicle are applied for scientific explorations, long range survey, search, rescue issues, etc[1]. DSRV is an underwater vehicle utilized for search and rescue operation, surveillance, inspection, recovery, renovation and maintenance tasks, underneath water. These vehicles are capable of moving in three dimensions and they can either float flaccid or dynamically move to the desired location and even swim at different depths [2]. To accomplish these tasks DSRV should be controlled to track a predefined trajectory when it progresses [3]. Analytically DSRV is a system with strong nonlinearity, high interaction and long delay, so controller design is a challenging task.

Kinematic and dynamic models of DSRV are highly nonlinear and coupled. Uncertainties and interactions between hydrodynamic co-efficient affect the system dynamics significantly, in addition DSRV undergoes complex multi-axis motion trajectories so it is always difficult to estimate the hydrodynamic coefficients of the vehicle[1]. Owing to the highly non linear, coupled and time-varying dynamics and uncertainties in hydrodynamics and DSRV parameters it is seldom feasible to derive an accurate mathematical model of the system. So the model based controllers such as Model predictive control[4] robust trajectory control[5] sliding mode control[6-7] Adaptive multimodal PID control [8] etc. fail to give a satisfactory control and tracking performance. So the researchers have focused their direction in designing intelligent controllers as for this design accurate model of vehicle dynamics and environmental disturbance is not mandatory.

Intelligent controllers designed for DSRV mainly come under either fuzzy or neural network or a combination of both. These include Neural controller [9], Neuro-fuzzy controller[10], self-adaptive neuro-fuzzy inference system (SANFIS)[11], conventional fuzzy controllers[12,13] fuzzy logic PID based control design[14], Single input fuzzy logic controller[15], and Single input fuzzy PID controller[16]. Neural controllers are less suited for real time operations because of its unpredictable training time. Accordingly a model free fuzzy logic controller with nonlinear structure, which is robust against parameter variation and disturbance rejection ability is more appropriate to improve the tracking performance of DSRV. However, the disadvantage of this technique is the difficulty in designing an efficient inference engine from much of the knowledge. Application of FLC still requires huge efforts in identifying the proper membership functions, fuzzy rules and scaling factor. This is predominantly true for the system like DSRV with complex dynamics. Main difficulty in the design of an FLC for DSRV is that both the inference table and the knowledge base, created by an expert's knowledge were fixed after selection, the process takes a long time and optimal control cannot be guaranteed. So instead of using human thinking in the design of FLC, the key point is to employ an evolutionary learning process to automate the fuzzy controller design this strategy involved online learning to establish suitable fuzzy control rules, thereby simplifying the procedures for designing an FLC.

Previous studies on conventional fuzzy control schemes for DSRV require expert knowledge or many cycles of trial and error to achieve desired control competence. So FLC parameters (membership function, scaling factor, rule base) tuning is still a matter of trial and error, while this approach is time-consuming and not completely reliable, an intelligent optimization algorithm may be used for selection and tuning [17].

In this paper, the procedural approach for the design of Genetic Algorithm based Fuzzy Logic Controller (GA-FLC) for DSRV is proposed in order to meet the tracking performance requirements. In first step a conventional FLC is designed for DSRV system. Subsequently, the optimal tuning of the FLC parameters, including fuzzy scaling factors, fuzzy membership function, fuzzy rules are performed based on the Genetic Algorithm (GA)

The linguistic rules framed by a human expert express the behaviour of fuzzy controller. Especially for complex control tasks such as path tracking in DSRV, construction of rule base and data base from domain expert knowledge is time consuming, tedious, unpredictable, subjective and erroneous. Major drawback of this FLC is dependence on expert knowledge, which is not always expected to be optimal or near optimal. To surmount the above difficulties this FLC design is transformed into an optimization problem and GA optimization technique is employed to search for the 14 optimal parameters of FLC.

Materials and Methods

DSRV modeling

DSRV modeling relies upon Newton Euler method. It can be modeled using two co-ordinate frame such as global reference frame (X Y Z) and body reference frame (X_0, Y_0, Z_0). Translational and rotational motion components in body fixed frame are modeled by six velocity components Surge (u), Sway(v), Heave (w), Roll (p), Pitch (q),Yaw (r). The velocity vector is

$$v = [u\ v\ w\ p\ q\ r]^T \quad (1)$$

Position and orientation of the vehicle using Euler angle relative to global reference frame is represented as a vector η .

$$\eta = [x\ y\ z\ \phi\ \theta\ \psi] \quad (2)$$

Euler angle transformation that maps the two co-ordinate system is

$$\dot{\eta} = J(\eta)v$$

The nonlinear vehicle dynamics is given as

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

M_{6X6} is the inertia matrix including hydrodynamics added mass, $C(v)$ is the matrix of the centripetal forces, $D(v)$ is the hydrodynamic damping matrix, $g(\eta)$ is the vector of restoring forces and moments. $B(v)$ is 6×3 control matrix. The state space model of DSRV is

$$\begin{bmatrix} \dot{w} \\ \dot{q} \\ \dot{\theta} \\ \dot{z} \end{bmatrix} = \begin{bmatrix} -0.6529 & -2.4522 & 0.0855 & 0 \\ 3.2219 & -3.1309 & -44.679 & 0 \\ 0 & 1 & 0 & 0 \\ 1 & 0 & -4.11 & 0 \end{bmatrix} \begin{bmatrix} w \\ q \\ \theta \\ z \end{bmatrix} + \begin{bmatrix} 0.4147 \\ -3.6757 \\ 0 \\ 0 \end{bmatrix} \gamma_z$$

The parameters, hydrodynamic derivatives and main dimensions are taken from [18]. Non-dimensional hydrodynamic derivatives are defined according to Prime system I [19].

Environmental disturbance

In the vicinity of complex marine environment, poor visibility and large ocean current it is difficult for DSRV to track the desired trajectory through operator manipulation. External disturbance cause the deviation (drift and/or oscillation) of the vehicle from its nominal trajectory .The environmental disturbances affecting DSRV during navigation are the waves generated by wind and ocean currents.

Wave transfer function of the wave model is given as

$$D_W(s) = \frac{k_w s}{s^2 + 2\varsigma\omega_n s + \omega_n^2} w(s) \qquad (5)$$

$$k_w = 2\varsigma\omega_n\sigma_w \qquad (6)$$

Where k_w is dependent on the sea state, ς is the relative damping ratio, ω_n is the wave frequency, σ_w is the parameter related to wave intensity, $D_W(s)$ is the yaw angle induced by waves. Fixing ς =0.1; σ_w =0.5 and ω_n =1.2 the time series of the wave model is shown in Figure 1.

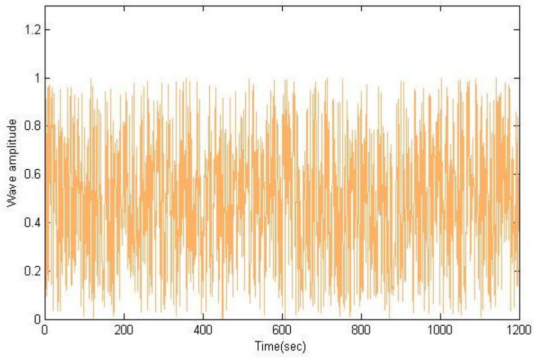


Fig 1 Time series of the wave model using the Equation (5)

Fuzzy Logic Controller

Fuzzy logic effectively approximates the behavior of complex systems. Unlike conventional logic type, fuzzy logic try to model the vague modes of human reasoning and decision making, which are essential to our ability to make rational decisions in situations of uncertainty and vagueness [20] .

In general, fuzzy control is a model-free approach; it does not rely on system model being controlled. Model-free approaches make the controller design easier, since obtaining a mathematical model of the system is sometimes a very complex task[21] .

Design of conventional FLC

In designing a conventional FLC, first decide upon the number of inputs and outputs for the controller .Then divide each universe of discourse into fitting number of fuzzy sets. Define the coverage amount of each membership function and name them. Next generate a decision table based on human intuition. Finally adjust the scaling factor by trial and error method to give high performance controller.

Fuzzification

The conventional FLC designed for path tracking in DSRV has two inputs and one output**.** The inputs are depth error $e_{dr}(t)$ and the rate of change of depth error is $\Delta e_{dr}(t)$.The output from FLC is the corresponding change of stern plane deflection $\Delta\gamma(t)$. Two input variables $e_{dr}(t)$ and $\Delta e_{dr}(t)$ are calculated as :

$$e_{dr}(t) = y_{ref}(t) - y_{dr}(t) \qquad (7)$$

$$\Delta e_{dr}(t) = \frac{e_{dr}(t) - e_{dr}(t-1)}{T} \qquad (8)$$

For fuzzification of the two inputs $e_{dr}(t)$, $\Delta e_{dr}(t)$ and the output $\Delta\gamma(t)$ five symmetrical triangular fuzzy membership functions are chosen for each variable . They are named as Negative Large (NL), Negative Small (NS), Zero (Z), Positive Small (PS), Positive Large (PL) and are shown in Figure 6 (a,c,e). Universe of discourse for the input and output membership functions varies between [-1 +1].

Rule Base

Two input variables $e_{dr}(t)$, $\Delta e_{dr}(t)$ and output variable $\Delta\gamma(t)$ is used for forming the decision rule table. Rule table is composed of 25 rules which is of the form

R_1: If $e_{dr}(t)$ is NL and $\Delta e_{dr}(t)$ is NL then $\Delta\gamma(t)$ is Z

R_2: If $e_{dr}(t)$ is NL and $\Delta e_{dr}(t)$ is NS then $\Delta\gamma(t)$ is PS

Defuzzification

Defuzzification converts the fuzzy values of a FLC output into a crisp value. Defuzzification method adapted here is centre of gravity method; accordingly the change of stern plane deflection in DSRV is given as

$$\Delta\gamma = \frac{\sum_{i=1}^{n} z_i \mu(z_i)}{\sum_{i=1}^{n} \mu(z_i)} \tag{9}$$

Where n is the number of fuzzy membership function in the output side and is equal to 5. z_i is the centre of gravity of the ith fuzzy membership and $\mu(z_i)$ is the membership value of the output membership function corresponding to the ith fuzzy control rule. The fuzzy controller output can be calculated using

$$\gamma'(t) = \gamma(t-1) + G_u \Delta\gamma(t) \tag{10}$$

Design of GAFLC

In designing GAFLC the constituents of the fuzzy logic controller such as scaling factors, membership functions and rule bases are to be optimized simultaneously by genetic algorithm to provide an optimal solution. A schematic of GA based Fuzzy Logic Controller for DSRV is shown in Figure 2**.** In this work, real coded GA is preferred to reduce the processing time and to avoid the necessity of considering bits to represent the decision variables. GA cannot directly act upon the parameters of FLC,for this reason the members of scaling factors, membership functions and rule base are parameterized and expressed together into a genetic code called chromosome . Chromosome string used in GAFLC is shown in Figure 2.This incorporates a total of 14 members (R_1,R_2,R_3,R_4,R_5,a,b,c,d,e,f,GE,GEC,GU) i.e. first 5 members from Rule base , second 6 from Membership function and the last 3 from scaling factor.

Genetic algorithm

Genetic algorithm was introduced by Holland[22].GA is a probabilistic adaptive search optimization method based on the natural biological evaluation. GA is successful in solving optimization problems with non-convex, non-continuous and non-differentiable objective function.GA operates on individuals in a population, each individuals is a encoded string called chromosome. These chromosomes contain the decision variables. GA performs a parallel exploration of the parameter space using genetic operators to manipulate a set of encoded chromosome. Basically, GA goes through three main stages: selection, crossover and mutation[23]. Application of these three operations permits the creation of new individuals which may be superior to their parents. This algorithm is repeated for a number of generations and finally stopped when the optimum solution is reached or when the stopping criteria is satisfied.

Tuning of membership function plays a major role for improving the performance of fuzzy logic controller compared to scaling factor. Triangular membership function symmetrical to the Y-axis is used in this study. GA optimizes centre point x_p of the input and output membership functions. Center point x_p of the triangular membership functions are calculated as

$$\left(\frac{i}{k}\right)^{x_p} k = \left(\frac{m-1}{2}\right) \tag{11-12}$$

Where *m* represents the number of membership function and *i=1, 2, 3.....k*. In the structure of chromosome, x_p is has two parts, x_{p1} and x_{p2}. x_{p1} is set in the range [0.2, 1] and x_{p2} can take either -1 or +1. Thus, x_p is calculated as $x_p = x_{p1}^{\,x_{p2}}$.

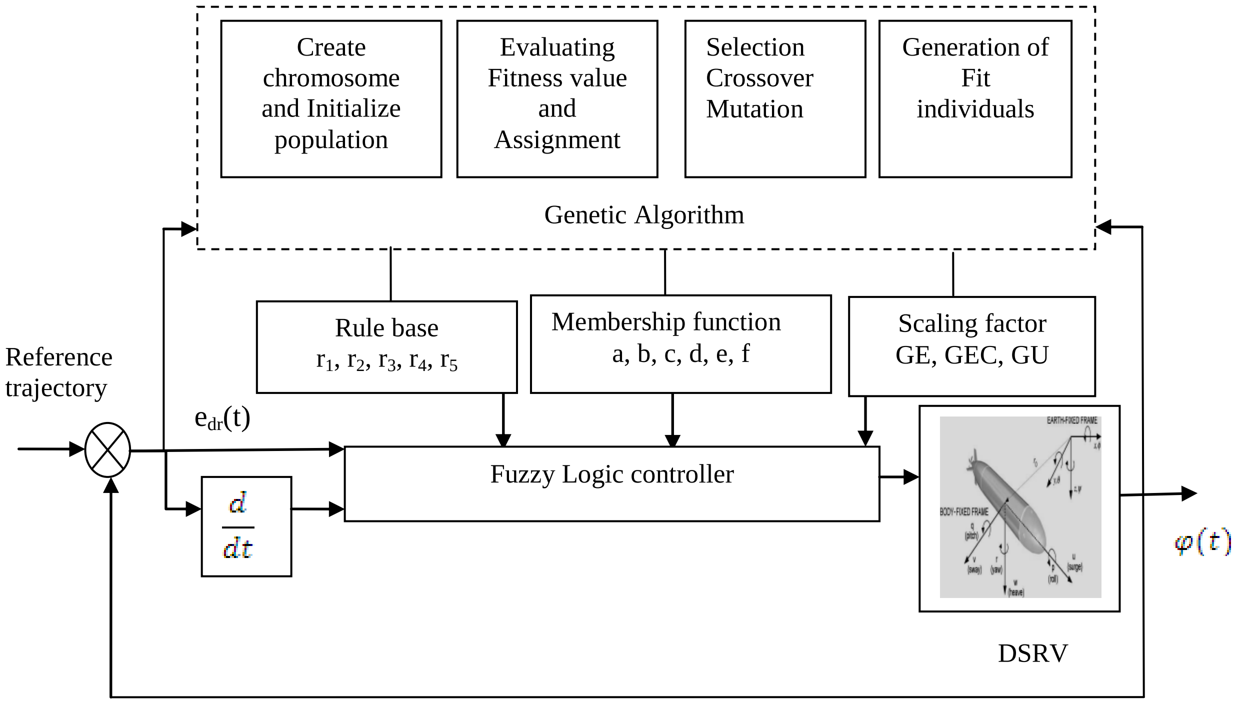


Fig. 2- GA based Fuzzy Logic Controller for DSRV

R_1	R_2	R_3	R_4	R_5	a	b	c	d	e	f	GE	GEC	GU
Membership function					Rule base						Scaling factor		

Fig 3 Appearance of a chromosome in GA population

Scaling factors have a big impact on the controller performance as they map the input and output variables onto the universe of discourse over which the fuzzy sets are defined. Three scaling factor used for the optimization of fuzzy logic controller includes input scaling factor (GE, GEC) and an output scaling factor (GU).Search range for the optimization of GE, GEC is [0.0001 to 1] and is [0 to -1000] for GU.

In this study, the rule base is composed of a total of 25 rules (5 X 5).Here the rule weights are optimized using GA and as there are as much as 25 parameters to be optimized, difficulty level in optimization increases. To minimize the number of parameters to be optimized the following procedure is followed.

In the rule base plane shown in Figure 3 intersection of dashed line with rule boxes indicate the same rule. Now the rule base parameters to be optimized is reduced to 9 i.e. R_1, R_2, R_3, R_4, R_5, R_6, R_7, R_8 and R_9. Since the rule base is symmetrical about its diagonal axis it can be considered as $R_1 = R_9$; $R_2=R_8$; $R_3= R_7$ and $R_4 = R_6$, now the parameters are reduced to five i.e R_1, R_2, R_3, R_4 and R_5.Decimal numbers between -3 and +3 are used to encode the fuzzy rules into genetic form accordingly each decimal number indicates a single fuzzy rule. These decimal numbers are optimized using GA.

e \ e		NS	Z	PS	PL
NL	Z	PS	PL	PL	PL
NS	NS	Z	PS	PL	PL
Z	NL	NS	Z	PS	PL
PS	NL	NL	NS	Z	PS
PL	NL	NL	NL	NS	Z

R_1 R_2 R_3 R_4 R_5 R_6 R_7 R_8 R_9

Fig 4 Generation of Fuzzy rule base

The performance index or fitness function is necessary for the optimal settings of the fuzzy logic controller. Performance index is a quantitative measure that evaluates the degree of fitness of each individual chromosome. In optimization processes this fitness function is defined according to the system requirement. Since in trajectory tracking of DSRV the main goal is to minimize the error between the reference trajectory y_d and the actual trajectory y the performance measure considered for minimization is Integral Time Absolute Error (ITAE)

$$F = \int_0^t t|e(t)|dt \qquad (13)$$

Where t is the time and e is the difference between the reference trajectory y_d and the actual trajectory y.

In GA-FLC designed for DSRV, 14 variables of the fuzzy controller are to be optimized using GA. Initially a random population of 20 chromosomes is generated. The chromosomes are sorted based on the fitness value evaluated through equation (13). As the selection rate is fixed as 50%, in each generation only 10 of the chromosomes are selected from the sorted population to become potential parents. The ten discarded chromosomes are replaced by off springs generated through uniform crossover from the potential parents using rank order selection. Now in each generation GA operations such as selection; crossover and mutation are performed on the population. This operation is repeated until 50th generation. The parameters used for GAFLC designed for DSRV is listed in Table-1

Result and discussion

Efficiency of the designed GAFLC scheme for trajectory tracking in DSRV could be explained by simulation. Four scenarios with different desired trajectories are considered. It is assumed that all trajectories considered have constant velocity.

Simulation of Reference depth trajectories

(i) *Reference trajectory-1 (y_{d1})* **:** Simulated for a short period of 500 secs with varying depths as indicated in equation (14) and this reference depth trajectory is shown in Figure 5(a)

Table 1 Parameters used in GA-FLC designed for DSRV

Parameters	Values
Population size	20
Maximum generation	50
Mutation rate	0.2
Selection rate	0.5
Chromosome length	14
Crossover type	uniform
Selection method	Rank order selection
Multi objective performance index	$F = \int_0^t \lvert e \rvert t dt$

$$y_{d1} = \begin{cases} 50 & 0 \le t \le 100 \\ 20 & 100 \le t \le 150 \\ 30 & 150 \le t \le 250 \\ 50 & 250 \le t \le 300 \\ 20 & 300 \le t \le 400 \\ 50 & 400 \le t \le 500 \end{cases} \tag{14}$$

(ii) *Reference trajectory -2 (y_{d2})*: Randomly chosen trajectory for a period of 1200 sec as illustrated in Figure 5(b).

(iii) *Disturbance added trajectory- 3 (y_{d3})* : Environmental disturbances corresponding to unstable winds, waves and ocean currents are considered to be time varying disturbances and are added as wave force disturbance to a trajectory similar to depth trajectory -1 over a period of 1200 sec and is shown in Figure 5(c)

(iv) *Reference Trajectory- 4 (y_{d4}) :* In a trajectory similar to depth trajectory-1 for a period of 1200 secs wave force disturbances are considered intermittently over the period of 400 sec to 500 sec and 1000sec to1100 sec only. This trajectory is illustrated in Figure 5(d).

Design of FLC and GA-FLC for DSRV

A conventional fuzzy logic controller as described in section 3.1 is designed for trajectory tracking in DSRV with fixed membership function and fixed rule base and the scaling factors chosen by trial and error. Now the designed conventional FLC is optimized using GA to give GA-FLC for trajectory tracking in DSRV system. Membership functions for the error input, change in error input and the stern plane deflection output before and after optimization using GA is shown in Figure-6(a-b), 6(c-d) and 6(e-f) respectively. It is clearly illustrated that the optimization process, optimizes centre point x_p of the input and output membership functions corresponding to ‘NS’,’Z’ and ‘PS’ suitably.

It is also seen from Figure 7 that the optimization procedure restructures the rule base sufficiently according to the requirement. After optimization all the lower diagonal elements in the rule base have been transformed into upper diagonal elements and vice versa. Nonlinear control surface plots between the two inputs and the output stern plane deflection before and after optimization is shown in Figure 8 .

In addition instead of using trial and error method for choosing the scaling factor an optimal tuning is adapted. Scaling factors for the onventional FLC,which are decided based on trial and error method are GE = 0.0001, GEC = 0.0009 and GU = -1000, respectively. The scaling factors of GAFLC after optimization procedure are approximately GE' = 0.0041, GEC' =0.0004 and GU' = -850

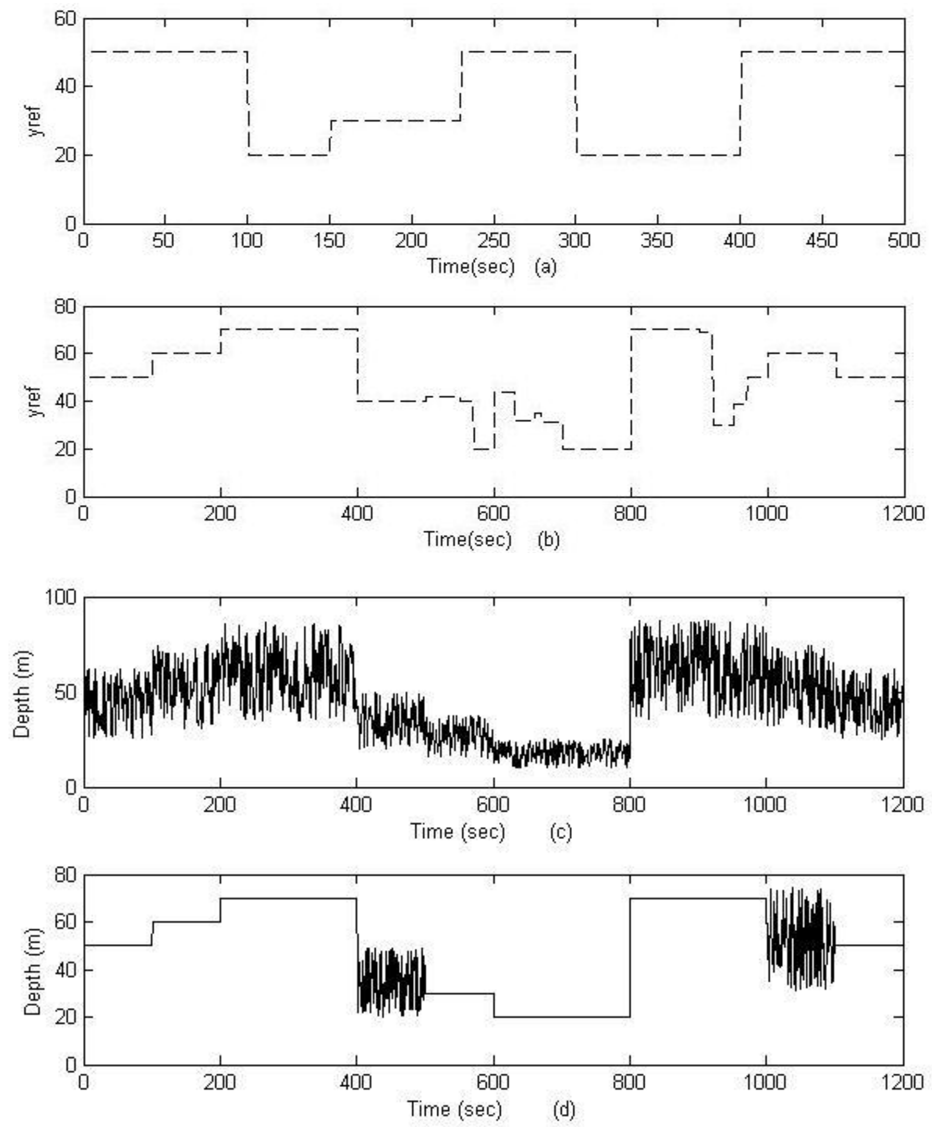
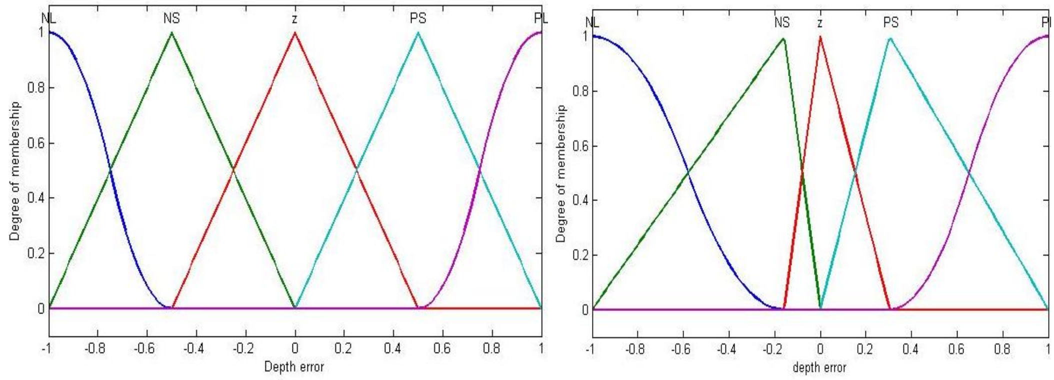
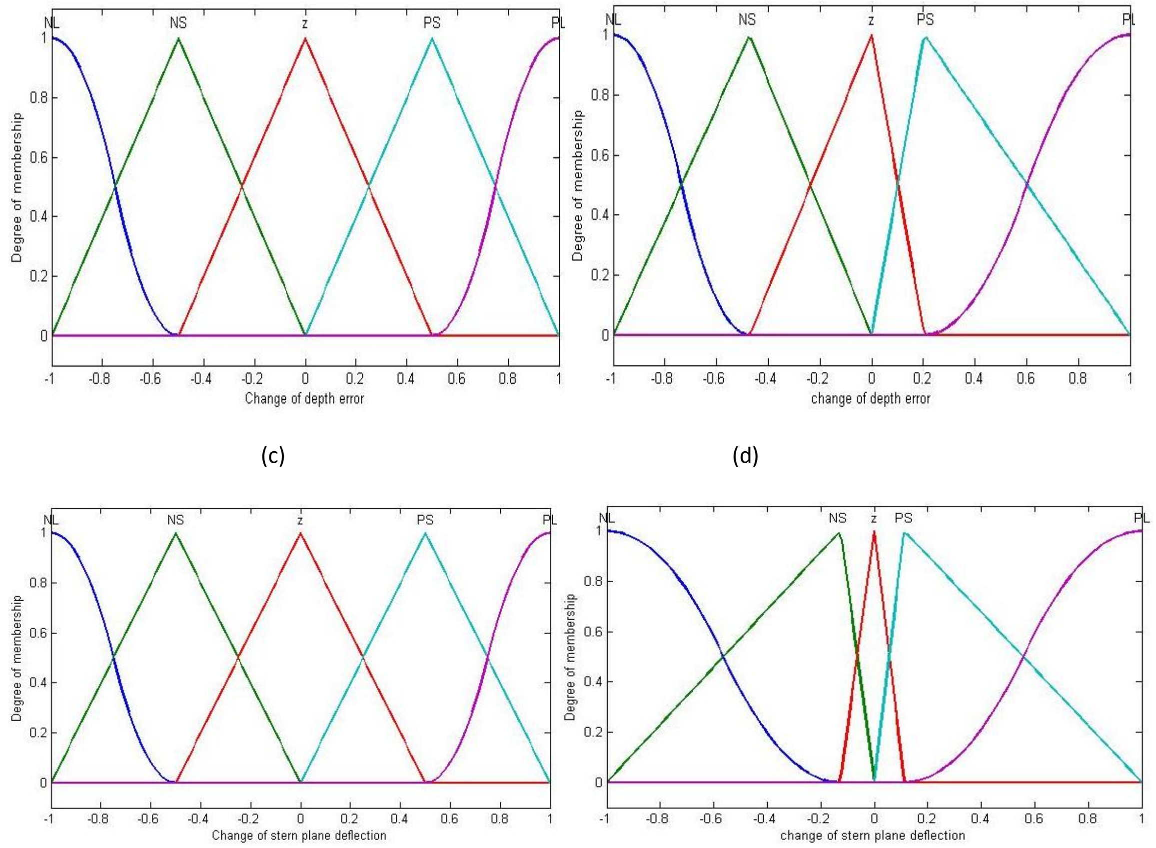


Fig. 5 Reference trajectories used in simulation (a) y_{d1} -Reference trajectory-1 *(b)* y_{d2}- Reference trajectory -2 (c) y_{d3}- Wave disturbance added trajectory- 3 (full period of movement) (d) y_{d4}-Intermittently added wave disturbance trajectory- 4



(a) (b)



(c) (d)

(e) (f)

Fig.6 Membership functions for FLC (Before optimization) and GA-FLC (after optimization (a,b) for depth error; (c,d) for depth error change; (e,f) for change in stern plane deflection

e' \ e	NL	NS	Z	PS	PL
NL	Z	PS	PL	PL	PL
NS	NS	Z	PS	PL	PL
Z	NL	NS	Z	PS	PL
PS	NL	NL	NS	Z	PS
PL	NL	NL	NL	NS	Z

e' \ e	NL	NS	Z	PS	PL
NL	Z	PS	PL	PL	PL
NS	NS	Z	PS	PL	PL
Z	NL	NS	Z	PS	PL
PS	NL	NL	NS	Z	PS
PL	NL	NL	NL	NS	Z

Fig.7 Rule base for error, rate of error and control output (a) FLC -Before optimization (b) GAFLC –After optimization

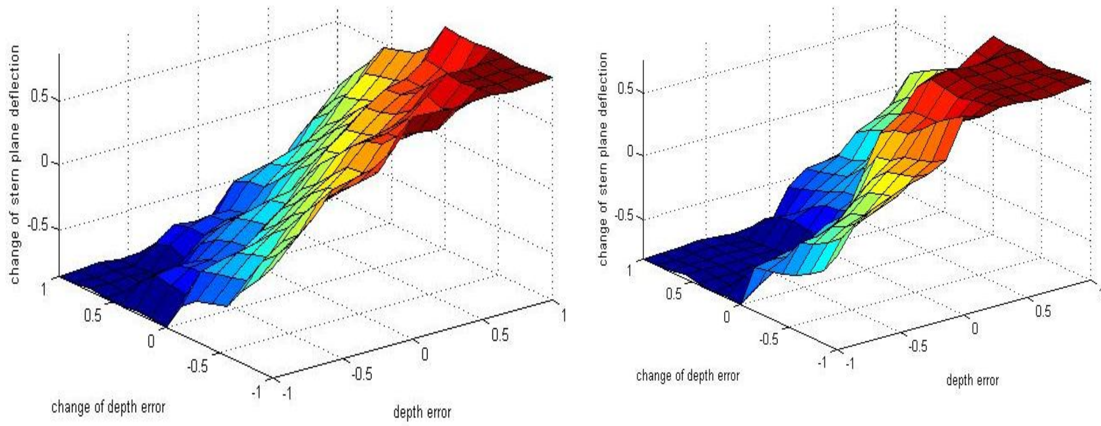


Fig.8 Surface plot for rule base (a) FLC -Before optimization) (b) GA-FLC -After optimization

Tracking response of DSRV

Tracking the reference trajectory-1 with constant velocity is shown in Figure 9(a).It is noticed that the tracking error in DSRV has reduced considerably with GAFLC compared to conventional FLC. It is also noted that on occurrence of positional variations in reference trajectory at time instants of 100 th secs, 150th secs, 250th secs, 300th secs and 400th secs DSRV controlled through GAFLC shows superior dynamic response compared to conventional FLC.

Reference trajectory-2 is a randomly chosen one and it extends for a period of 1200 secs. It is noticed in Figure 9(b) that using GAFLC reduces the tracking error considerably and pushes the tracking error to converge towards the neighbourhood of zero. In this trajectory severe positional variations are noticed around 600th secs and 1000th secs. In this scenario also GAFLC shows a good dynamic response compared to conventional FLC.Time axis for reference trajectory-1 y_{d1} is set as 500 sec and y_{d2} is set to be 1200 sec to illustrate the tracking performance for short and long duration rescue operation .

In reference trajectory-3 time varying disturbances due to wave forces are considered. Even in the presence of unknown time varying disturbances the tracking accuracy of GAFLC is acceptable. Though the magnitude of wave disturbance is more in some parts of the trajectory, GAFLC exhibits a good steady state and transient state performance throughout its trajectory tracking. It is illustrated through Figure9(c)

During rescue operation phase the ocean may be unstable for a particular duration and rest of the period it may be stable. This scenario is simulated through the desired trajectory-4 and shown in Figure9(d). Unknown wave disturbances are introduced intermittently from 400 sec to 500sec and from 1000sec to1100sec. Tracking accuracy of GAFLC is for superior than FLC in both stable and unstable ocean states.

Tracking performance of FLC and GAFLC

Trajectory tracking accuracy of conventional FLC and GAFLC are determined by the performance measures ITAE and tabulated in Table 2. Minimum the values for ITAE more will be the tracking accuracy. Calculations reveal that GAFLC has more tracking accuracy compared to conventional FLC

$$ITAE = \int_{0}^{t} t|e(t)|dt \tag{15}$$

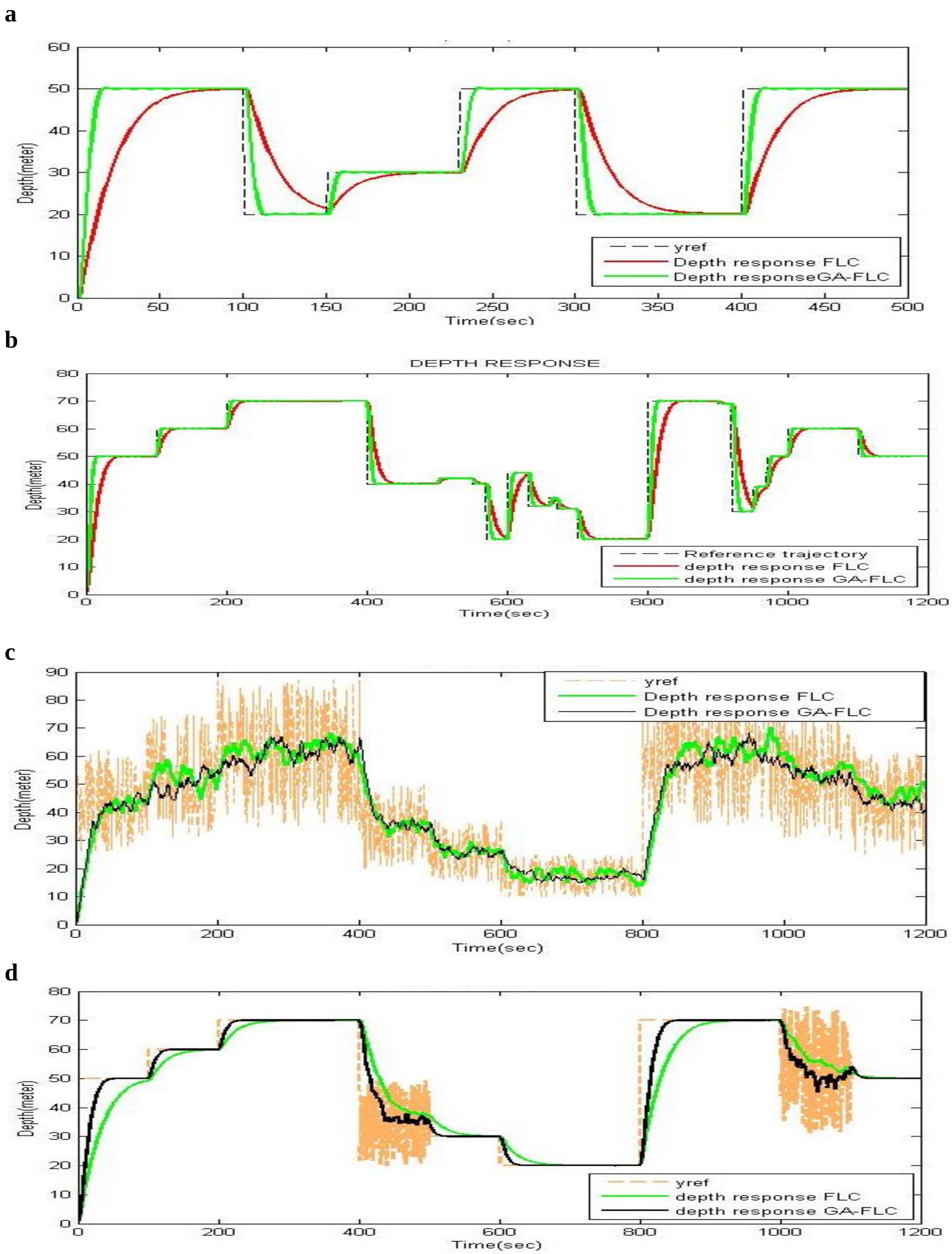


Fig.9 Trajectory tracking of DSRV through FLC and GA-FLC (a) y_{d1} -Reference trajectory-1 *(b)* y_{d2}- Reference trajectory -2 (c) y_{d3}-Wave disturbance added trajectory- 3 (full period of movement) (d) y_{d4}-Intermittently added wave disturbance trajectory- 4 (Wave disturbance introduced from 400 sec to 500sec and 1000sec to1100sec)

Table 2 . Performance comparison of FLC and GA-FLC for DSRV

Reference trajectory	ITAE	
	FLC	GA-FLC
y_{d1} -Reference trajectory-1	4.2	0.01
y_{d2}-Reference trajectory -2	4.87	0.06
y_{d3}-Wave disturbance added trajectory- 3	7.46	0.02
y_{d4}-Intermittently added wave disturbance trajectory- 4	5.823	0.061

Conclusion

In this work an approach for the design of GA based fuzzy tracking controller is proposed to meet the tracking performance of DSRV in the presence of environmental disturbances . Firstly a conventional FLC is designed with fixed rule base and membership functions from expert's knowledge and scaling factor chosen by trial and error. In the second step optimal tuning of FLC parameters are carried out simultaneously using GA. Four reference trajectories corresponding to complex marine environment is generated and the tracking and dynamic performance is studied. For Reference trajectory-1 (y_{d1}) and Reference trajectory -2 (y_{d2}), ITAE measure is minimum for DSRV controlled through GAFLC guaranteeing high accuracy tracking control. In the case of Disturbance added trajectory- 3 (y_{d3}) and Reference Trajectory- 4 (y_{d4}) also closed loop system with GAFLC is superior in tracking ability compared to conventional FLC ensuring robustness against environmental disturbance for the system. Designed GAFLC also provides high accuracy control for both short and long duration rescue operations. In addition it also gives a very good dynamic response which accelerates the rescue operation.

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