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Optimal Control for Torpedo Motion based on Fuzzy-PSO Advantage Technical

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Abstract
The torpedo is a nonlinear object which is very difficult to control. Via to manage the rudder angle yaw, the diving plane angle, and the fin shake reduction, the torpedo yaw horizontal, the depth vertical and roll damping of the system are controlled accurately and steadily. In this paper, the particle swarm optimization is used to correct the imprecision of architecture fuzzy parameters. The coverage width of membership function and the overlap degree influence of neighboring membership functions are considered in the method to adjust dynamically from the system errors. Thereby optimizing the control signal and enhancing the torpedo motion quality. The proposed method results in a better performance compared to the other control method such as adaptive fuzzy-neural that proved effective of the proposed controller.

Keywords: fuzzy controller, particle swarm optimization, neighboring membership functions, nonlinear object, torpedo motion

1. Introduction

The torpedo motion is a nonlinear and complicated in practical applications. The torpedo actuator system executes control commands to ensure that object sponges the reference trajectory. The accurate and steady control of torpedo is very difficult for its internal nonlinear characteristics, uncertain architecture cofficients and disturbances. A Faruq et al. (2011) present the fuzzy algorithm combined with the output gain optimization algorithm to improve the response quality as well as the weight update time of the controller [1]. C Vuilmet (2006) introduces a solution that combines a back stepping algorithm with accelerometer feedback technology to control a torpedo, sponge a preset trajectory by the navigation system [2]. This solution shows promising results on the realistic simulations, including highly time-varying ocean currents. Thereby, the environmental impact has a significant effects on the torpedo trajectory. The other study, U Adeel et al. design a sliding mode controller to aim the stable robustness of heavy-weight torpedo [3]. It is impressed that the performance of state feedback control is recovered arbitrarily fast by the proposed output feedback controller in the parametric uncertainties, and the sea current perturbation due to flow effects as well as tides. In order to improve the effective of sliding mode controller, D Qi et al. propose a hybrid fuzzy sliding mode control strategy. The fuzzy rules were adopted to estimate the disturbance terms [4]. But the fuzzy membership function that is estimated by programmer experiment are not able to provide an effective approach for nonlinear systems. The direct adaptive fuzzy-neural output feedback controller (DAFNOC) is proposed by V P Pham et al. which uses the fuzzy neural network singleton to approximate functions and calculate the control law with on-line turning weighting factors of the controller functions [5]. Simulation results show that the system is able to adapt to external disturbance and interference evaluation of control channels.

Hierarchical fuzzy structure fit out an effective method approach for torpedo nonlinear systems due to the fuzzy system ability to approximate a nonlinear composition. In this paper, the authors have been proposed fuzzy particle swarm optimization (FPSO) advantage control technical for torpedo motion optimization. Particle swarm optimization (PSO) is adopted to calibrate the structure of fuzzy controller, thereby enhancing the quality of system and optimizing the controller structure for torpedo motion. On the other hand, the proposed method

can be carried out for the other kind of autonomous underwater vehicles (AUVs) or applied in ship control.

The paper is organized as follows. Section 2 presents the torpedo mathematical model. The FPSO advantage control technical for torpedo motion optimization is proposed in section 3. Section 4 provides simulations, the results are discussed. The conclusion is given in section 5.

2. Torpedo Models

The dynamic model of AUV [6, 7] which is presented by T I Fossen shown as in Figure 1. Torpedo motion is described by six-degree of freedom, the centre of mass coincide with the centre of gravity G_b. Physical quantities include force, torque, velocity and angular velocity of the torpedo coordinate system which are denoted by: $\tau_1 = [X, Y, Z]^T$ is an external force vector that have an effect on the torpedo; $\tau_2 = [K, M, N]^T$ is an external force vector; $\tau_1 = [U, V, W]^T$ is a linear velocity vector along the longitudinal of X_b, Y_b, Z_b coordinate axes; $\omega = [p, q, r]^T$ is the angular velocity vector of the rotating frame; $v = [u, v, w, p, q, r]^T$ is the linear velocity vector of rotating frame.
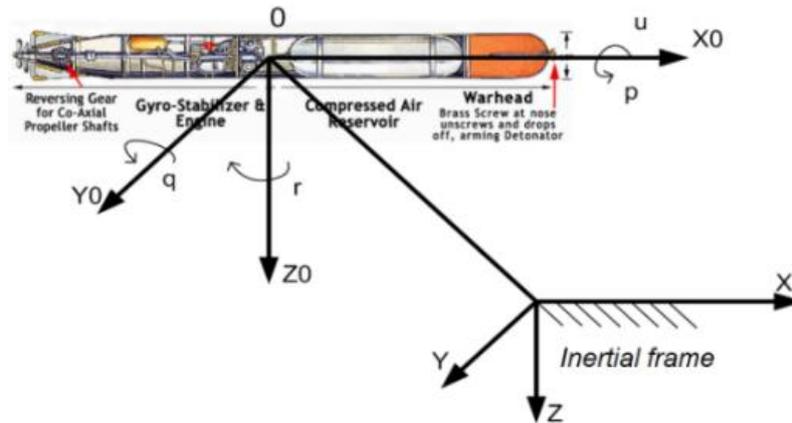
Figure 1. Inertial frame and body-fixed frame of torpedo

The positions x, y, z and φ, ∂, ψ orientation angles of torpedo are expressed by:

$$\eta = [\eta_1^T, \eta_2^T]^T \tag{1}$$

where $\eta_1 = [x, y, z]^T$ and $\eta_2 = [\varphi, \partial, \psi]^T$. For analyzing and designing of torpedo control system, it is common to study the motion of torpedo in three separately channel, i.e. horizontal, vertical and roll damping channel. The external force have an effect on torpedo are defined by

$$\tau_{RB} = M_A \dot{v} + C_A(v)v + D(v)v + L(v)v + g(\eta) + \tau \tag{2}$$

where $M_A, C_A(v)$ is the inertia matrix and the centrifugal Coriolis matrix; $D(v)$ is the matrix of hydrodynamic damping terms; $g(\eta)$ is the vector of gravity and buoyant forces; $L(v)$ is a force matrix and rudder torque parameters; $\tau = \tau_r + \tau_f$ is the control-input vector describing the efforts acting on the torpedo include the rudder, the fins and the propeller. The torpedo motion is given by

$$M_{RB} \dot{v} + C_{RB}(v)v = \tau_{RB} \tag{3}$$

where M_{RB} is the matrix of inertia; C_{RB} is the matrix of centrifugal coriolis; τ_{RB} is an external force vector which acts on the torpedo body. In the six-degree coordinate system, the torpedo motion equations are represented as follows:

$$
\begin{cases}
\dot{x} = u_0 cos\psi cos\partial + v(cos\psi sin\partial sin\varphi - sin\psi cos\varphi) + w(cos\psi sin\partial cos\varphi + sin\psi sin\varphi) \\
\dot{y} = u_0 sin\psi cos\partial + v(sin\psi sin\partial sin\varphi + cos\psi cos\varphi) + w(sin\psi sin\partial cos\varphi - cos\psi sin\varphi) \\
\dot{z} = -u_0 sin\partial + vcos\partial sin\varphi + wcos\partial cos\varphi \\
\dot{\varphi} = P + qtan\partial sin\varphi + rtan\partial cos\varphi \\
\dot{\partial} = qcos\varphi - rsin\varphi \\
\dot{\psi} = qsec\partial sin\varphi + rsec\partial cos\varphi
\end{cases}
\tag{4}
$$

In order to control the torpedo object, it is necessary to transform the torpedo dynamics (4) to form the MIMO [8] nonlinear system with quadratic equation written as

$$
y_1 = f_1(x) + \sum_{j=1}^{1} g_{1j}(x)\, u_j + d_1;\ y_2 = f_2(x) + \sum_{j=2}^{2} g_{2j}(x)\, u_j + d_2;\ y_3
$$
$$
= f_3(x) + \sum_{j=3}^{3} g_{3j}(x)\, u_j + d_3
\tag{5}
$$

where $u = [u_1, u_2, u_3]^T \in R^3$ are the control inputs which include the rudder angle, diving plane angle and fin shake reduction. $y = [y_1, y_2, y_3]^T \in R^3$ are system outputs, including yaw horizontal, the depth vertical and roll damping. $d = [d_1, d_2, d_3]^T \in R^3$ are external disturbances, $f_k(x)$ and $g_{kj}(x)$ are smooth nonlinear functions with $k = 1 \div 3$.

3. Fuzzy-PSO Controller Design
3.1. Particle Swarm Optimization

A population consisting of particle is put into the n-dimensional search space with randomly chosen velocities and the initial location of particles [9, 10]. The population of particles is expected to have high tendency to move in high dimensional search spaces in order for detecting better solution [11]. If the certain particle finds out the better solution than the previous solution, the other will move to be near this location [12]. The process is repeated for the next position. The population size is denoted by s, each particle i $(1 \leq i \leq s)$ presents a test solution with parameters $j = 1, 2, .., n$. At the k generation, position of each particle is located by $\underline{p_i}(k)$, the current speed of particle is $v_i(k)$, and the best location is $\underline{Pb_i}(k)$. The best particle among all population is represented by $\underline{Gb}(k)$. The particles of population update the attributes then each generation [13]. Updating property will be realize according to (6) as

$$
v_{i,j}(k+1) = w(k)v_{i,j}(k) + c_1 r_1 [Pb_{i,j}(k) - p_{i,j}(k)] + c_2 r_2 [Gb_j(k) - p_{i,j}(k)]
\tag{6}
$$

where w is the inertia weight, c_1 and c_2 are acceleration coefficient, r_1 and r_2 are random constants in the range (0.1), g is the number of repetitions [14]. The inertia weights are updated according to (7) as

$$
w(g) = \frac{(iter_{max} - g)(w_{max} - w_{min})}{iter_{max}} + w_{min}
\tag{7}
$$

where $iter_{max}$ is the maximum value of multiple loop, w_{max} is respectively the largest of inertial weightsand, w_{min} are respectively the smallest of inertial weights. The new position of particle can be updated by (8) as follows:

$$
p_{i,j}(g+1) = p_{i,j}(g) + v_{i,j}(g+1)
\tag{8}
$$

the best position of each particle can be updated by

$$
Pb_{i,j}(g+1) = \begin{cases} Pb_{i,j}(g), if\ J\left(p_{i,j}(g+1)\right) \geq J\left(Pb_{i,j}(g)\right) \\ p_{i,j}(g+1), \qquad\qquad otherwise \end{cases}
\tag{9}
$$

finally, the best location for the whole group is performed by (10) as

$$Gb_j(g + 1) = arg\ min_{Pb_{i,j}} J(Pb_{i,j}(g + 1)), 1 \leq i \leq s \tag{10}$$

In order to discover the optimal parameters for fuzzy controller, each variable of the membership function for $Ke(t)$ and Kde/dt control input is attributed to a particle. So, variables are initiated randomly in the search space to aim the optimal parameter for the fuzzy controller, which defines according to the fitness function (minimizing error) [15, 16].

3.2. Fuzzy Controller Design based on Particle Swarm Optimization

We consider the fuzzy modulator which has a double-input, $e_x(t)$, $d_{e_x(t)}/d(t)$ and a singe-output, $u(t)$. These fuzzy sets are defined as {NB,NS,ZO,PS,PB} correspond to negative big, negative small, zero, positive small and positive big [17]. The membership function collections are similarly in Figure 2. And our fuzzy rule are using as in Table 1.
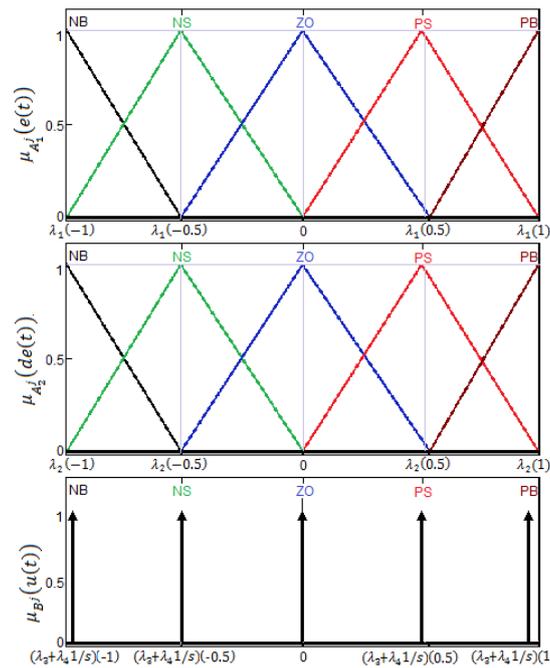
Figure 2. The membership functions are optimized by the PSO algorithm

Table 1. The Synthesis of Composition Rules

$u_h/u_s/u_r$		de/dt				
		NB	NS	ZO	PS	PB
e(t)	NB	NB_h / NB_s /NB_r	NB_h / NB_s /NB_r	NB_h / NB_s /NB_r	NS_h / NS_s /NS_r	ZO_h / ZO_s /ZO_r
	NS	NB_h / NB_s /NB_r	NB_h / NB_s /NB_r	NS_h / NS_s /NS_r	ZO_h / ZO_s /ZO_r	PS_h / PS_s /PS_r
	ZO	NB_h / NB_s /NB_r	NS_h / NS_s /NS_r	ZO_h / ZO_s /ZO_r	PS_h / PS_s /PS_r	PB_h / PB_s /PB_r
	PS	NS_h / NS_s /NS_r	ZO_h / ZO_s /ZO_r	PS_h / PS_s /PS_r	PB_h / PB_s /PB_r	PB_h / PB_s /PB_r
	PB	ZO_h / ZO_s /ZO_r	PS_h / PS_s /PS_r	PB_h / PB_s /PB_r	PB_h / PB_s /PB_r	PB_h / PB_s /PB_r

The inference mechanism of Takagi-Sugeno fuzzy method is given by

$$\mu_B(u(t)) = max_{j=1}^m [\mu_{A_1^j}(e(t)), \mu_{A_2^j}(de(t)), \mu_{B^j}(u(t))] \tag{11}$$

where $\mu_{A_1^j}(e(t))$ is the membership functions of error $e(t)$, $\mu_{A_2^j}(de(t))$ is the membership functions of error velocity de/dt. $\mu_{B^j}(u(t))$ is the membership functions of output response $u(t)$, j is the index of fuzzy set, and m is the resulting fuzzy inference [18]. In this paper, we use the Max-Prod inference rule, the singleton fuzzifier and the centre averaged defuzzifier for confirming the output response [19]. So the fuzzy output can be expressed as

$$u(t) = \frac{\sum_{i=1}^m \mu_B(u_i(t)) u_i}{\sum_{i=1}^m \mu_B(u_i(t))} \tag{12}$$

In order to design the optimal fuzzy controller, the PSO algorithm is applied to discover optimal parameters for the controller. The process of optimizing parameters consists of three parts: membership functions correspond to $e(t)$ fuzzy sets, membership functions correspond to $de(t)$ fuzzy sets and membership functions correspond to the output fuzzy sets. Thereby, the process of optimizing parameters is described as

$$\tau = PSO[\lambda_1 \mu_{A_1^j}(e(t)), \lambda_2 \mu_{A_2^j}(de(t)), (\lambda_3 + \lambda_4 1/s)\mu_{B^j}(u(t))] \tag{13}$$

where $\lambda = [\lambda_1, \lambda_2, \lambda_3, \lambda_4]$ is the parameter adjusting vector which is determined by the PSO. The different characteristics of fitness function affect how easy or difficult the problem is offered for a PSO algorithm [20]. The most commonly used fitness function is minimizing the errors, which is between the output and input signal for the torpedo object. The optimized structure of controller shows in Figure 3. The fitness function is chosen according to the ITAE criteria [21, 22] as follows:

$$ITAE = \int_0^\infty t\,|e(t)|dt \tag{14}$$

There are three different fuzzy controllers which are designed for the torpedo motion. The first fuzzy structure is defined by the object characteristic knowledge. The second based on the PSO algorithms which aim at the optimal range of membership functions. Finally, the optimal fuzzy controller (FPSO) is designed by the parameters of second fuzzy. The PSO parameters used for simulation are presented in Table 2.

Table 2. PSO Parameters for Torpedo Simulation

Particles of population	10	Ke and Kde	[0.01 0.05]
Loops	30	e1, de1 and u1	[-1 -0.5]
w_{max}	0.6	e2, de2 and u2	[-1 0]
w_{min}	0.1	e3, de3 and u3	[-0.5 +0.5]
c1 = c2	1.5	e4, de4 and u4	[0 +1]
Min-offset	200	e5, de5 and u5	[+0.5 +1]
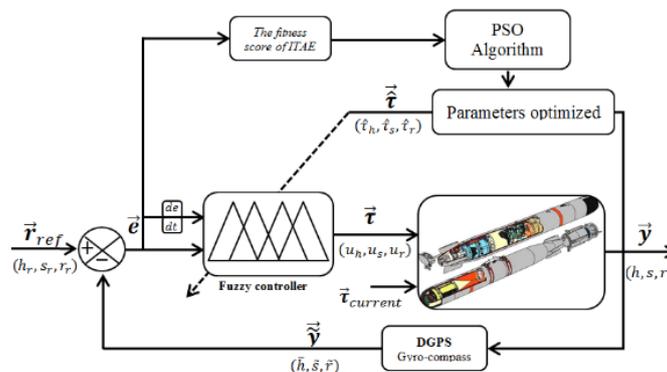
Figure 3. PSO algorithms for torpedo motion optimization
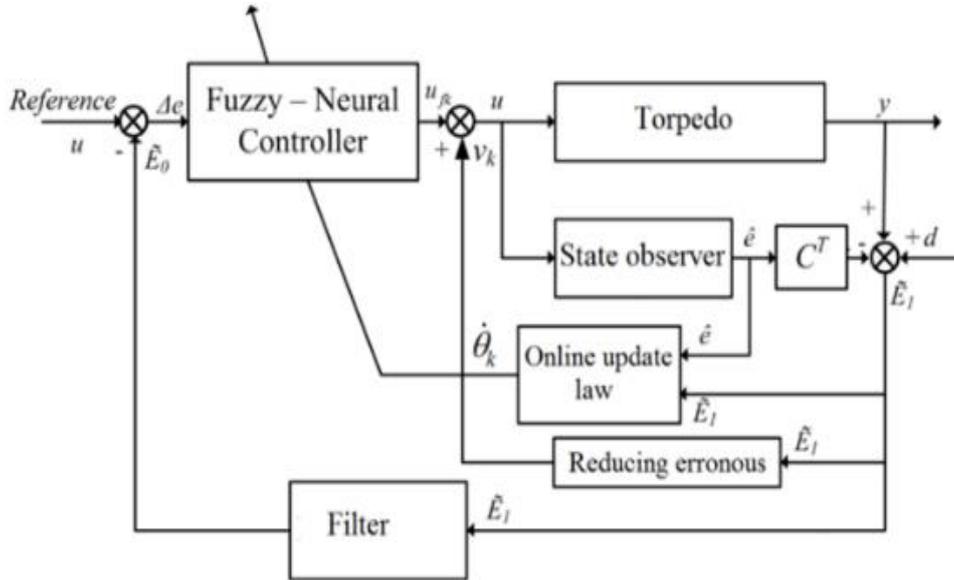
Figure 4. Adaptive fuzzy-neural for torpedo control system

3.3. Adaptive fuzzy-neural controller design

The advanced adaptive method for torpedo control system (shown as in Figure 4) presented by V P Pham [5], the state observer given as:

$$\begin{aligned} \hat{e} &= A_0\hat{e} - BK_c^T\hat{e} + K_0(E_1 - \hat{E}_1) \\ \hat{E}_1 &= C^T\hat{e} \end{aligned} \tag{15}$$

where $K_0 = diag[K_0, K_0, K_0] \in R^{6x3}$ is the gain vector of state observer. Observer error is defined by: $\tilde{e} = e - \hat{e}$ and $\tilde{E}_1 = y + d - \hat{E}_1$. The fuzzy-neural output is combined u_{fk} and v, that reduces disturbance and error for torpedo model. Control signal is express by (16) as

$$u = u_{fk} + v \tag{16}$$

where $u_{fk} = [u_{fk}, u_{fk}, u_{fk}]^T \in R^3$, $v = [v_1, v_2, v_3]^T \in R^3$. In order to design a Takagi-Sugeno fuzzy logic with a compact rule base, the rule notation form within B_k^i is a binary variable that determines the consequence of the rule given as

$$R_i : \text{If } \hat{e}_1 \text{ is } A_{k1}^i \ldots\ldots\text{and } \hat{e}_n \text{ is } A_{kn}^i \text{ then } u_{fk} \text{ is } B_k^i.$$

where $A_{k1}^i, A_{k2}^i, \ldots A_{kn}^i$ and B_k^i are fuzzy sets. By using the Max-Prod inference rule, the singleton fuzzifier and the centre averaged defuzzifier [23]. The fuzzy output can be expressed as bellows:

$$u_{fk} = \frac{\sum_{i=1}^{h} \theta_k^{-i} \left[\prod_{j=1}^{n} \mu_{A_{kj}^i}(\hat{e}_j)\right]}{\sum_{i=1}^{h}[\prod_{j=1}^{n} \mu_{A_{kj}^i}(\hat{e}_j)]} = \theta_k^T \varphi_k(\hat{e}) \tag{17}$$

For $\mu_{A_{kj}^i}(\hat{e}_j)$ is the membership function, h is the total number of the If-Then rules, θ_k^{-i} is the point at which $\mu_{B_k^i}(\theta_k^{-i}) = 1$, $\varphi_k(\hat{e}) = [\varphi_k^1, \varphi_k^2, \ldots, \varphi_k^h]^T \in R^h$ fuzzy vector [24] with φ_k^i is defined as

$$\varphi_k^i(\hat{e}) = \frac{\prod_{j=1}^{n} \mu_{A_{kj}^i}(\hat{e}_j)]}{\sum_{i=1}^{h}[\prod_{j=1}^{n} \mu_{A_{kj}^i}(\hat{e}_j)]} \text{ (where } i = 1 \div h) \tag{18}$$

The online update law is given by

$$\dot{\theta}_k = \begin{cases} \gamma_k \tilde{E}_{1k} \emptyset_k(\hat{e}) \, if \, \|\theta_k\| < m_{\theta_k} \\ or \, (\|\theta_k\| = m_{\theta_k} \, and \, \tilde{E}_{1k} \theta_k^T \emptyset_k \geq 0 \\ P_r \left(\gamma_k \tilde{E}_{1k} \emptyset(\hat{e}) \right) if \, \|\theta_k\| = m_{\theta_k} \\ \qquad and \, \tilde{E}_{1k} \theta_k^T \emptyset_k < 0 \end{cases} \tag{19}$$

with $\gamma_k > 0$ is the design adaptive parameter. If $\|\theta_k\| < m_{\theta_k}$ and $\|\tilde{\theta}_k\| < 2m_{\theta_k}$, the (19) will be rewritten as follows:

$$P_r \left(\gamma_k \tilde{E}_{1k} \emptyset(\hat{e}) \right) = \gamma_k \tilde{E}_{1k} \emptyset_k(\hat{e}) - \gamma_k \frac{\tilde{E}_{1k} \theta_k^T \emptyset_k(\hat{e})}{\|\theta_k\|^2} \theta_k \tag{20}$$

where $\emptyset_k$ is updated by the update law (19), then the reducing erroneous (v_k and α_k) is a positive parameter [25] which is expressed by (21) as

$$v_k = \begin{cases} \rho_k \, if \, \tilde{E}_{1k} \geq 0 \, and \, |\tilde{E}_{1k}| > \alpha_k \\ -\rho_k \, if \, \tilde{E}_{1k} < 0 \, and \, |\tilde{E}_{1k}| > \alpha_k \\ \rho_k \tilde{E}_{1k}/\alpha_k \qquad if \quad |\tilde{E}_{1k}| > \alpha_k \end{cases} \tag{21}$$

The adaptive fuzzy-neural control (AFN): The torpedo dynamics are expressed by (5). The feedback gains are chosen as follows:
a) $K_{0h}^T = [45 \, 60]; K_{ch}^T = [66 \, 4]; \ K_{0s}^T = [26 \, 290]; K_{cs}^T = [640 \, 360]; \ K_{0r}^T = [130 \, 240]; K_{cr}^T = [240 \, 130];$
b) Reducing erronous parameters are selected as: $\rho_h = 0.4, \rho_s = 0.5pi, \ \rho_r = 10, \ \alpha_h = 0.001, \ \alpha_s = 0.1$ and $\alpha_r = 0.01$.
c) The coefficients of adaptive law are given by: $\gamma_h = 100pi, \gamma_s = 25pi$ and $\gamma_r = 2$.
d) Current velocity: $v_c = 0.2 \, m/s$, rotation frequence of current: $w_c = 0.2 \, m/s$.

4. Results and discussion

The presented torpedo control system is carried out by proposed FPSO advanced control technique in section 2. The results of simulation process is described in Figure 5. At the time 0s and 40s, the torpedo moves from 0m depth to 12 m depth and 24 m depth, the roll motion of torpedo is fluctuated by current impact. Applying FPSO algorithm to control the torpedo motion, the torpedo response (yaw horizontal) has good dynamic and static performance in different initial conditions of entering sea. The optimal control signal makes the rudder angle yaw, and the fin shake reduction to be accurately. As a result, it helps the torpedo quickly follow the desired trajectory. At the time 100s, the torpedo horizontal switch from 45 degree to -45 degree, the torpedo depth vertical and roll damping are significantly affected. As expected, the results show that the proposed method outperforms technical on its effectiveness and efficiency. The torpedo motion in 3D space (described in Figure 6 and Figure 7) expressed the stable characteristic of system when the depth object switches over distance, corresponding change in yaw horizontal. The result of propose controller has strong adaptability and achieves better control performance for all cases. In the other hand, the response of diving plane angle plays slowing down process, but it seems appropriate the physical nature of torpedo.
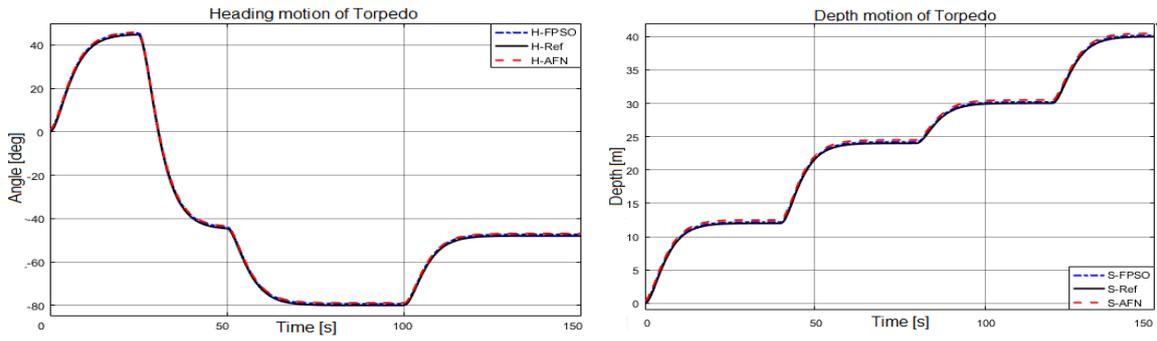
a. Yaw horizontal   b. Depth vertical
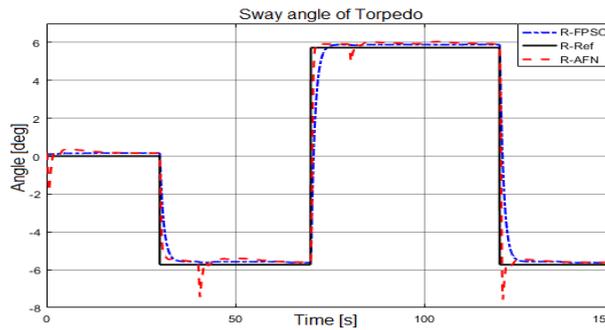
c. Roll damping

Figure 5. To compare the simulation responses of Torpedo control system in case of using proposed FPSO controller (blue) with AFN controller (red) (continue)
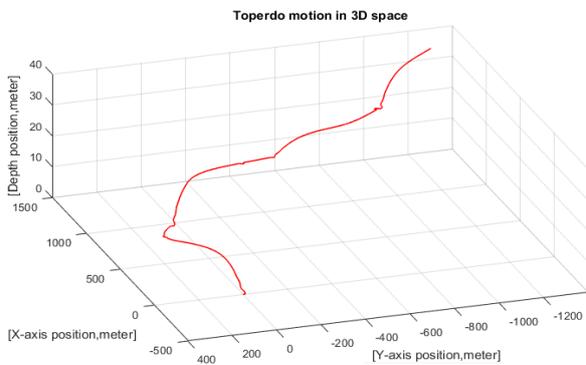
Figure 6. Torpedo motion in 3D space with adaptive fuzzy-neural control
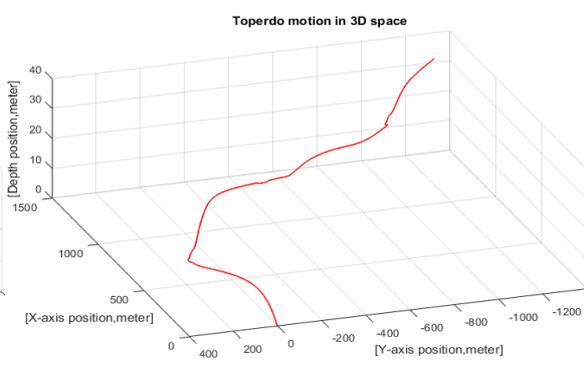
Figure 7. Torpedo motion in 3D space with proposed FPSO control

5. Conclusions

In this paper, the proposed FPSO controller has been developed for the torpedo motion. Our proposed control scheme improves the torpedo motion quality, while guaranteeing the parameters of fuzzy controller in the optimal case. Calibrating control structure of fuzzy system was intuitive to perform. Its optimal to variations in its displacement and the changing conditions. Besides, simulation results and simulation comparisons on a torpedo model have confirmed the effectiveness of the proposed control scheme and its robustness against nonlinear characteristic. However, the restriction of studies only explore the factors that cause erroneous is current. In the future work, this study can be extended by examining the other influences such as seawater viscosity to improve the optimizing accuracy of controller structure.

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