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Model Reference Adaptive Control based on Neural Network for Depth of an AUV

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ABSTRACT

This study proposes a Model Reference Adaptive Control (MRAC) approach based on multilayer perceptron (MLP) neural networks to control the depth of a REMUS Autonomous Underwater Vehicle (AUV) during navigation in the presence of range challenges, including hydrodynamic forces and modelling uncertainties. Therefore, Model Reference Adaptive Control (MRAC) is the appropriate controller for this task. The primary objective of this paper was to ensure adaptive control by using the hyperstability concept and applied it to the linear vertical REMUS AUV model. Furthermore, a new approach was introduced: the neural network model reference adaptive control (NNMRAC), which is a combination of the classic MRAC control with a multilayer perceptron neural network (MLPNN), resulting in enhance the performance and adaptability of the controller In addition, stability analysis of the new approach is achieved using a Lyapunov candidate function.
The effectiveness and feasibility of both adaptive control strategies on vertical AUV motion were evaluated through a comparative analysis conducted using MATLAB/Simulink. This analysis provides valuable information regarding the advantages and limitations of each approach, which can help inform decisions regarding control techniques for regulating the depth of underwater vehicles.

1. Introduction

Recently, Autonomous Underwater Vehicles (AUVs) played an important role in deployment in highly dangerous missions that have never been possible before for naval systems, such as petroleum industries for the detection of oil wells, and in the military field, particularly in intelligence gathering, surveillance, and reconnaissance.

The oceanographic solutions are mostly the guidance and control of these AUVs in the oceanic environment in the presence of many challenges[1] ,such as variations in hydrodynamic parameters and disturbances like ocean waves and currents that occur during the maneuver of an autonomous underwater vehicle (AUV). Therefore, the development of control must be adaptive and robust to address these challenges.

Many researchers concentrated their interests on the development of several proper control techniques for controlling the motion of underwater robotic vehicles, such as linear law control. In this study [2], a trajectory control of an underwater glider is proposed using an LQR optimal control to improve the glider's robustness to disturbances and uncertainties. This proposed controller is applied to the linearized glider model.

For studies that use the nonlinear control approach, a high-order sliding mode control was developed in [3] to improve controller performance by limiting the chattering phenomena. With the implementation of this HOSMC in the AUV H160 nonlinear diving model, the simulation result illustrated the effectiveness of the HOSMC compared with the classic sliding mode control.

A nonlinear state feedback H∞ control algorithm is suggested in [1] ,This controller has been developed by solving the HJI equation to control the depth and yaw angle in the diving and steering planes. In [4],a hybrid control using adaptive backstepping terminal sliding mode control for AUV trajectory tracking the stability was analyzed using Lyapunov theory. the feasibility and effectiveness of this control approach were verified using a simulation and an experimental test.

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The study conducted in [5], offline pitch angle dynamics identification was done due to the limitations of the uncertainty based on the least squares algorithm. Besides that, an online cascade tracking control was applied for the depth and pitch angle of an AUV REMUS. In[6] ,a theoretical and experimental study was proposed and applied to the path following control of an AUV, in which in the first place, a model-free adaptive control MFAC was proposed and developed, and then an event-triggered mechanism was introduced to enhance the controller performance. The paper in [7] proposed a system control called PFM (Potential Field Methods) that guarantees obstacle avoidance and navigation to detect and track cables and pipelines. Besides that, a comparative study is conducted to compare the proposed algorithm with another approach to the same mission. An experimental study is carried out in [8] Bayesian visual tracking for inspection of undersea power and telecommunications via AUV for the inspection of cables is set for more than 10,000 frames to test the cable tracking solution proposed. Authors in [9]proposed a funnel control based on terminal sliding mode control for depth and forward velocity tracking of the nonlinear AUV model ,the stability analysis of the proposed approach was achieved using Lyapunov candidate function beside that a nonlinear super twisting observer is designed to estimate the non-measurable parameters.

For the control laws that use AI, Robust diving motion control of an AUV using the adaptive neuro-fuzzy sliding mode technique is developed in [10]. The sliding mode control give a fast response time with a minimum error, and the adaptive law is used for the determination of the sliding surface coefficient. The neural network is employed in this research to estimate the nonlinear system dynamics and disturbances, and fuzzy logic is used to reduce the chattering problem caused from the sliding mode. Simulation studies in [11]proposed Deep Reinforcement Learning based on deep policy gradient for low-level Vectored Thruster AUV Control The RL input data is collected by onboard sensors. In [12], a semi-globally stable neural network was designed to control the diving motion of an AUV. The adaptation laws of the unstructured uncertainties and the update laws of the network weight are achieved via the Lyapunov-based method.

Based on research and a literature review, it appears that a combination of control laws and AI provides efficient trajectory tracking and control of AUV, despite the previously mentioned challenges.

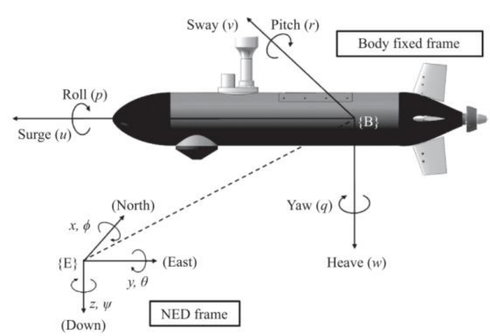
The main objective of this paper is to control the diving plane of an AUV. To achieve this, an MRAC based on hyperstability is used, which is inspired by previous research on the lateral motion of aircraft[13]. To create a closed-loop controller whose parameters can be updated to modify the system's response, the control system was further enhanced through the combination of a neural network, specifically an MLP, to improve overall performance and efficiency against noise and uncertainties .Previous research has successfully employed an RBF neural network to enhance the tracking accuracy of a quadrotor UAV when parameters are modified [14]. However, in this study, we aim to use an MLP neural network for enhanced performance.

This paper is organized as follows. Section 2 describes the mathematical modeling of the REMUS AUV in the vertical plane, which is described and linearized. In Section 3, an MRAC controller based on the hyperstability concept is proposed and developed to control the depth of the REMUS AUV. Furthermore, an MLP neural network is incorporated into the MRAC for enhancement using the neural network, and then the Lyapunov candidate function is used to analyze the stability of the new controller. The simulation results and a comparison of both approaches are presented in Section 4, and the conclusion is provided in Section 5.

2. Mathematical Modelling

The dynamics of AUV involves six-degrees-of-freedom equations of motion associated with coupled and nonlinear terms. The nonlinear terms are generally hydro- dynamic damping, added mass coefficients along with environmental disturbances. The AUV body frame with respect to NED (North-East-Down) frame is shown in Figure 1.

Figure 1: General AUV Structure with Reference Frame.



Source:[1]

The nonlinear equation of the vehicle can denote as follow [15][16]:

$$\begin{cases} \dot{\eta} = J(\eta)\,\nu \\ M\dot{\nu} + C(\nu)\,\nu + D(\nu)\,\nu + g(\eta) = \Gamma \end{cases} \quad (1)$$

Where: $\eta = [x\ y\ z\ \Phi\ \theta\ \psi\ ]^T$ indicates the vector of the position and orientation in

The NED frame $\nu = [u\ v\ w\ p\ q\ r\ ]^T$ represent the translation and rotation velocity of the vehicle in the

Body frame.

$J(\eta)$ The transformation Matrix between the body frame and NED frame, M the inertial and the added matrix, $C(\nu)$the rigid body and the added mass Coriolis and centripetal matrix, $D(\nu)$ hydrodynamic drag matrix, $g(\eta)$ restoring forces and moment vector and for Γ represent the control input vector.

The initial step to develop a pure linear depth plane model is to assumed that the forward speed u to be constant and by setting the velocityν , p , r.

The nonlinear equations of motion in vertical plane are[17]:

$$(m - Z_{\dot{w}})\dot{w} - (mx_g + Z_{\dot{q}})\dot{q} - Z_w w - (mU + Z_q)q - (W - B)\cos(\theta) - mZ_g q^2 = Z_{\delta_s}\delta_s$$
$$mZ_g\dot{u} - (mx_g + M_{\dot{w}})\dot{w} + (I_{yy} - M_{\dot{q}})\dot{q} - M_w w + (mx_g U - M_q)q \quad (2)$$
$$(x_g W - x_B B)\cos(\theta) - (Z_g W - Z_B B)\sin(\theta) = M_{\delta_s}\delta_s$$
$$\dot{z} = -u\sin(\theta) + w\cos(\theta)$$
$$\dot{\theta} = q$$

using the Maclaurin expansion of the trigonometric terms: $\sin\theta = \theta$ and $\cos\theta = 1$ and Z_g is assumed to be smaller than the other variables [18].

the linearized equation in formed as follow:

$$(m - Z_{\dot{w}})\dot{w} - (mx_g + Z_{\dot{q}})\dot{q} - Z_w w - (mU + Z_q)q = Z_{\delta_s}\delta_s,$$
$$-(mx_g + M_{\dot{w}})\dot{w} + (I_{yy} - M_{\dot{q}})\dot{q} - M_w w + (mx_g U - M_q)q - M_\theta\theta = M_{\delta_s}\delta_s \quad (3)$$
$$\dot{z} = -U\theta + w$$
$$\dot{\theta} = q$$

Those equations can be expressed in state space model:

$$\begin{bmatrix} m - Z_{\dot{w}} & -(mx_g + Z_{\dot{q}}) & 0 & 0 \\ -(mx_g + M_{\dot{w}}) & I_{yy} - M_{\dot{q}} & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}\begin{bmatrix} \dot{w} \\ \dot{q} \\ \dot{z} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} Z_w & (mU + Z_q) & 0 & 0 \\ M_w & -(mx_g U - M_q) & 0 & M_\theta \\ 1 & 0 & 0 & -U \\ 0 & 1 & 0 & 0 \end{bmatrix}\begin{bmatrix} W \\ q \\ z \\ \theta \end{bmatrix} + \begin{bmatrix} Z_{\delta_s} \\ M_{\delta_s} \\ 0 \\ 0 \end{bmatrix}\delta_s \quad (4)$$

Where: w linear velocity and q angular velocity z represent the depth and is θ pitch angle and δ_s the rudder angles.

3. Controller Design

In this section the classic MRAC will be designed for the AUV vertical motion first, then it will be combined with MLP neural network ,and then the stability analysis will be demonstrate for the new NNMRAC using Lyapunov candidate function

3.1. Classic MRAC Controller

The linear plant vertical model presents by the following state space equation:

$$\dot{x} = Ax + Bu \quad (5)$$
$$y = Cx$$

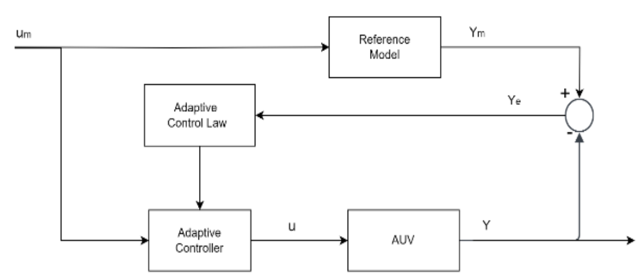
The reference model expressed by the following equation:

$$\dot{x}_m = A_m x_m + B_m u_m, \quad (6)$$
$$y_m = C_m x_m,$$

Where this system has the same state and input, output as the vertical plant model of the AUV (A_m , B_m , C_m have respectively the same dimension as A, B, C) and u_m is the reference vector [13].

The structure of direct Model Reference Adaptive Control is show in Figure 2.

Figure 2: Structure of direct MRAC for an AUV



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The error vector between the reference model and the AUV model

$$x_e = x_m - x \quad (7)$$
$$\dot{x}_e = \dot{x}_m - \dot{x}$$

Replacing (5) and (6) in (7), we obtain:

$$\dot{x}_e = A_m x_e + (A_m - A)x + B_m u_m - Bu \quad (8)$$

Using Erzerberger conditions:

$$A_m - A = BB^o(A_m - A) \quad (9)$$
$$B_m = BB^o B_m \quad (10)$$

Where: B^o is the pseudo inverse left $B^o = (B^T B)^{-1}B^T$

By substituting (9) and (10) in (8), the later will be written:

$$\dot{x}_e = A_m x_e - B\left((-B^o(A_m - A))x - B^o B_m u_m + u\right) \quad (11)$$

From (11) let:

$$\phi = \left((-B^o(A_m - A))x - B^o B_m u_m + u\right) \quad (12)$$

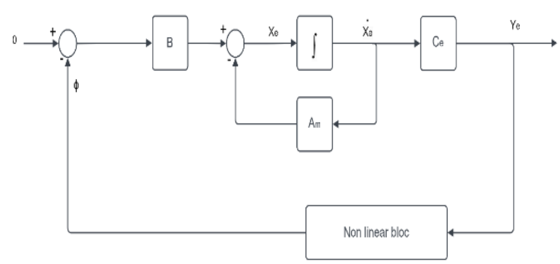
So that:

$$\dot{x}_e = A_m x_e - B\phi \quad (13)$$

$$y_e = C_e x_e$$

The corresponding non-linear closed-loop system presented in Figure.3 is used to apply the hyperstability theory and Popov's criterion (Popov 1973) to explore the absolute stability of (13).

Figure 3: Closed-loop of hyper-stable system



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ϕ is generated by a necessarily non-linear function or $y_e$this constitutes the adaptive block.

The system is hyper-stable if A_m, B, C_e is a hyper stable block [19]:

$$C_e A_m + A_m^T C_e = -Q, \quad Q > 0 \tag{14}$$

Moreover, Popov’s criterion is satisfied:

$$\int_{t0}^{t1} y_e\,(t)\phi(t)^T dt \geq -\gamma^2 \tag{15}$$

The adaptive controller is proposed as:

$$u = K_x x + K_u u_m \tag{16}$$

Replacing the equation (16) and (12) in Popov’s inequality (15):

$$\int_{t0}^{t1} \left[\left((K_x - B^o(A_m - A)\,)x + (K_u\, - B^o B_m)u_m\,\right)\right]^T y_e(t)dt \geq -\gamma^2 \tag{17}$$

The solution that met the hyperstability requirement for K_x and K_u is:

$$\left(K_x - B^o(A_m - A)\right)^T = \alpha(x{y_e}^T)^{2N+1} \tag{18}$$

$$\left(K_u - B^o B_m\right)^T = \beta(u_m\, {y_e}^T)^{2N+1} \tag{19}$$

Where: α and β are two strictly matrices, if $N = 0$ then K_x and K_u will be as follow:

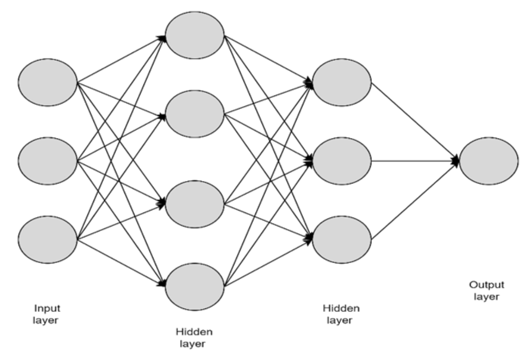
$$K_x = B^o(A_m - A) + \alpha^T x^T\, y_e \tag{20}$$

$$K_u = B^o B_m + \beta^T {u_m}^T\; y_e \tag{21}$$

3.2. MLP Neural Network

MLP NN is consists of an input layer, a hidden layer, and an output layer. Each layer has numbers of neurons and each neuron in each layer is connected to every neuron of the subsequent layer. The structure of MLP is show in Figure4.

Figure 4: MLP neural network structure



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The network input vector x The output of the output last hidden (l) neurons as follow[20]:

$$z_k^l = h^l\left(w_k^l\, z^{l-1}(x) + b_k^l\right) \tag{22}$$

Where l represent the number of network layers w is the weight matrix, b is bias vector ,and h is the activation function it can be a sigmoid function (logsig) , a hyperbolic tangent activation function (tanh),or linear function (purelin).

The output of the controller is presented by the following equation:

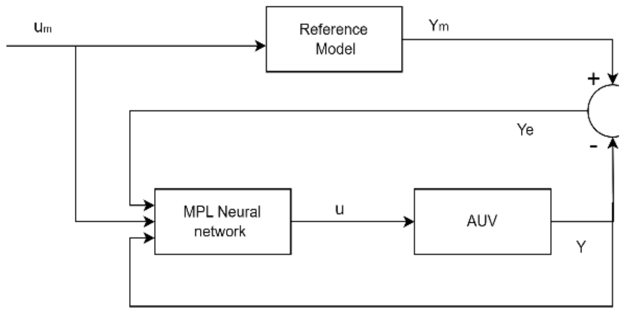
$$u(x,h) = \sum_{k=1}^{l+1} w_k^{l+1}\, z_k^l + b_k^{l+1} \tag{23}$$

The neural network used in this paper has 3 input $x = [y, ye, u_m]$ the output of AUV, the error between the output of the reference model and the output of AUV, The reference signal. [21]for the output represent the control signal (rudder angle).

Levenberg Marquardt algorithm was used for the training of the network, the preps of training is to minimize the sum of square error energy function is $E = \frac{1}{2}[y_m - y]^2$ [22].

The structure of the MRAC controller combined with MLP neural network show in Figure 6:

Figure 6: Block diagram of MRAC combined with MLP NN.



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3.3 Stability Analysis of MLP Neural Network MRAC

In this subsection, stability analysis will be done for the case with MLP neural network is employed to control the AUV depth, using Lyapunov function.

The MRAC MLP neural network can be write as [23]:

$$u = w^T h(x) + \varepsilon(x) \qquad (24)$$

Where: $\varepsilon(x)$ is the neural network learning error

The error dynamic in the MLPMRAC is represent as follow

$$\dot{x}_e = A_m x_e - B\, w^T h(x) - B\varepsilon(x) \qquad (25)$$

Where:

$\tilde{w}$ Is the weight derivation $\tilde{w}(t) = w - w^*$

Theorem:

Consider that the learning law is given as:

$$\dot{w}(t) = -\Gamma\, h(x) x_e^T PB \qquad (26))$$

Where:

Γ Diagonal positive definite matrices $\Gamma > 0$ and $\Gamma = diag(\Gamma_i)$

P Is the positive define solution excite to the Lyapunov equation

$$PA_m + A_m^T P = -Q \quad Q > 0$$

Proof:

Let the Lyapunov candidate function [24]

$$V(x_e, \tilde{w}) = \tfrac{1}{2} x_e^T P x_e + \tfrac{1}{2}(\tilde{w}^T \Gamma^{-1} \tilde{w}) \qquad (27)$$

Where: the Γ diagonal positive definite matrices define above, to prof that the s stable it necessary to satisfied the Lyapunov stability condition theorem by the derivation of V along the system solution.
The Lyapunov candidate function can be upper bounded by [25]

$$\tfrac{1}{2}\underline{\lambda}(P)\|x_e\|^2 + \tfrac{1}{2}\underline{\lambda}(\Gamma^{-1})\|\tilde{w}\|^2 \le V(x_e, \tilde{w}) \le \tfrac{1}{2}\bar{\lambda}(P)\|x_e\|^2 + \tfrac{1}{2}\bar{\lambda}(\Gamma^{-1})\|\tilde{w}\|^2 (28)$$

The $\underline{\lambda}$ and $\bar{\lambda}$ is the minimum and maximum Eigen value operator
The time derivation of V along the error dynamic

$$\dot{V}(x_e, \tilde{w}) = \tfrac{1}{2} x_e^T P \dot{x}_e + \tfrac{1}{2}(\tilde{w}^T \Gamma^{-1} \tilde{w}) \qquad (29)$$

Substituting (25) into (29) the derivation of Lyapunov candidate function is:

$$\dot{V}(x_e, \tilde{w}) = -x_e^T P A_m x_e - x_e^T PB\tilde{w}^T h(x) - x_e^T PB\varepsilon(x) + \tilde{w}^T \Gamma^{-1} \dot{\tilde{w}}$$

$$\dot{V}(x_e, \tilde{w}) = -\tfrac{1}{2} x_e^T Q x_e - tr(\tilde{w}^T h(x) x_e^T PB) - x_e^T PB\varepsilon(x) + \tilde{w}^T \Gamma^{-1} \dot{\tilde{w}} \qquad (30)$$

Using the weight learning law (26), the above equation will be as follows

$$\dot{V}(x_e, \tilde{w}) = -\tfrac{1}{2} x_e^T Q x_e - tr(\tilde{w}^T\, h(x) x_e^T PB) - x_e^T PB\varepsilon(x) + tr(\tilde{w}^T h(x) x_e^T PB)$$

$$\dot{V}(x_e, \tilde{w}) = -\tfrac{1}{2} x_e^T Q x_e - x_e^T PB\varepsilon(x) \qquad (31)$$

The derivation of the Lyapunov can be upper bounded by:

$$\dot{V}(x_e, \tilde{w}) \le -\tfrac{1}{2}\lambda_{min}(Q)\,\|x_e\|^2 - x_e^T\|PB\|\|\varepsilon(x)\| \ (32)$$

Let $d_1 = \|PB\|$, and The $sup\|\varepsilon(x)\| \le \bar{\varepsilon}$.
Using the bound variable in above expression the Lyapunov derivation is write as follow:

$$\dot{V}(x_e, \tilde{w}) \le -\tfrac{1}{2}\lambda_{min}(Q)\,\|x_e\|^2 - \|x_e\| d_1 \bar{\varepsilon} \qquad (33)$$

The set ξ outside in which $\dot{V}(x_e, \tilde{w}) \le 0$ [25]

$$\xi = \left\{\|x_e\| \ge \frac{d_2}{\lambda_{min}(Q)}\right\} \qquad (34)$$

Let $d_2 = 2d_1\bar{\varepsilon}$

The outside set ξ defines the range which the Lyapunov condition assure the stability ,it signifies that as long as the error $\|x_e\|$ is large enough then the term $\frac{d_2}{\lambda_{min}(Q)}$, then the dynamics error and the neural network weight $\tilde{w}$ guaranteed the stability.

4. Simulation and Results

The reference model of the AUV is choosing according to specific objectives were 2.46% overshoot and 1.68 second rise time

By using those parameters, the matrices of the reference model chowing by the following state space representation:

$$\dot{x}_m = A_m x_m + B_m u_m$$

Will equal to:

$$A_m = \begin{bmatrix} -0.097 & -0.0059 & 0.16 & -0.98 \\ -0.93 & -2.15 & -1.13 & 0.13 \\ 0 & 1 & 0 & 0 \\ 20.21 & -300.36 & -1.24 & -300.75 \end{bmatrix} B_m = \begin{bmatrix} 0.001 \\ 2.06 \\ 0 \\ 0.9714 \end{bmatrix}$$

The reference signal u_m is as step signal whose amplitude is 2

The REMUS AUV parameters are illustrated in Table 1 [17].

Table 1: REMUS AUV parameters

PARAMETER	VALUE/UNITES
m	30 [Kg]
$Z_{\dot{w}}$	-0.93 [Kg/s]
x_g	0 [m]
$Z_{\dot{q}}$	-1.93 [Kg.m]
$M_{\dot{w}}$	-1.93 [Kg.m]
I_{yy}	3.45 [Kg.m^2]
$M_{\dot{q}}$	-4.88 [Kg.m^2]
Z_w	-66.6 [Kg/s]
Z_q	-9.67 [Kg.m/s]
M_w	30.7 [Kg.m/s]
M_q	-6.87 [Kg.m^2/s]
M_θ	-5.77 [Kg.m^2/s^2]
$Z_{\delta s}$	-34.6 [Kg.m^2/s^2]
$M_{\delta s}$	-50.6 [Kg.m^2/s^2]
U	1.54[m/s]

Source : [17]

The following part shows and demonstrates the result of classic MRAC using hyperstability critic and MRAC enhanced with MLP neural network to control the depth of AUV REMUS.

Figure 7 shows the simulation result for depth tracking the output of the reference model using classic MRAC and MRAC combined with MLP NN.

From the signal, the depth stabilized in the required value in 6 s in both controllers but it appears that the classic MRAC has a small overflow compared with the MRACMLP controller that provided efficient tracking of the reference signal with high accuracy and speed.

Indeed, the control surface of the MRAC controller is unsaturated until 6 s, which means that the depth is stabilized, according to the Figure 8.

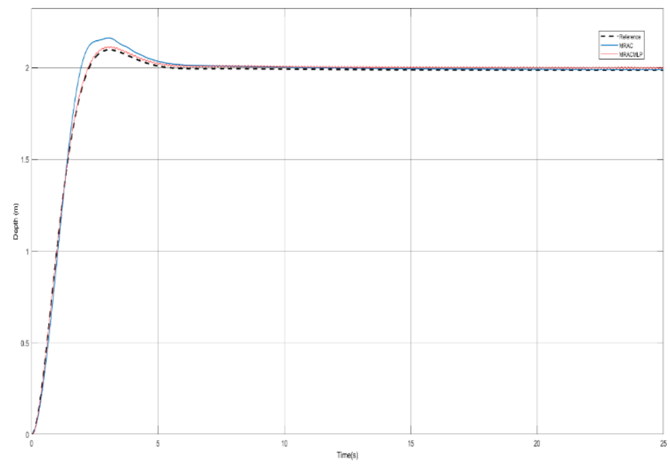
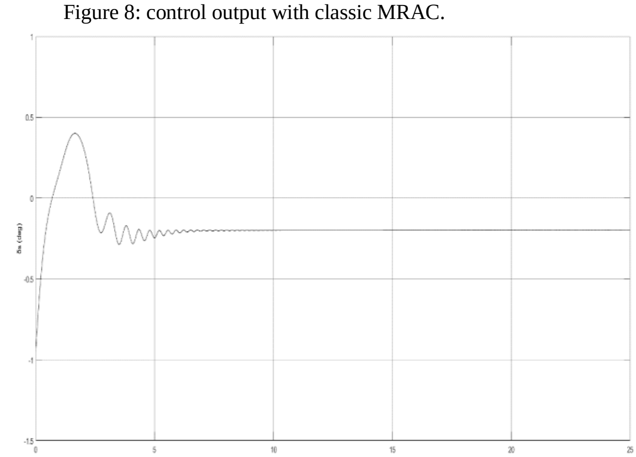


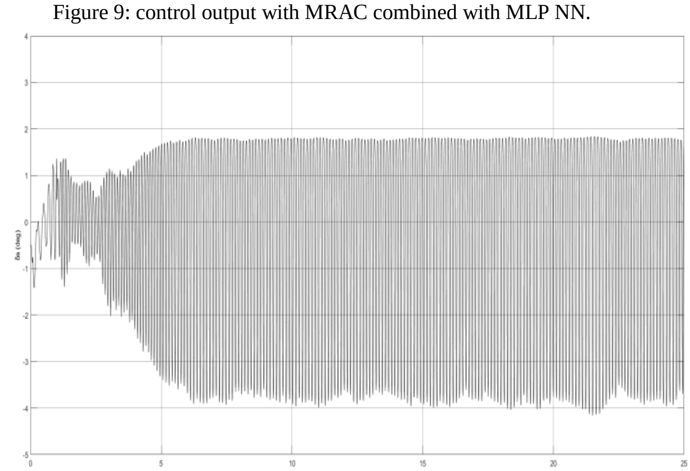
Figure 7 Depth control with classic MRAC and MRACMLP

Figure 8: control output with classic MRAC.



The Figure 9 below shows control output of depth tracking using the reference model with MLP as the replacement for the adaptive control law and adaptive controller.

Figure 9: control output with MRAC combined with MLP NN.



This next part, a noise signal was added in the both classic MRAC and MRAC combined with MLP NN to evaluate them against the noise.

The noise signal is given as sin function whose amplitude is 3.5 degree and frequency 0.4 rad/s.

Figure 10: Depth control with classic MRAC and MRACMLP in noise presence.

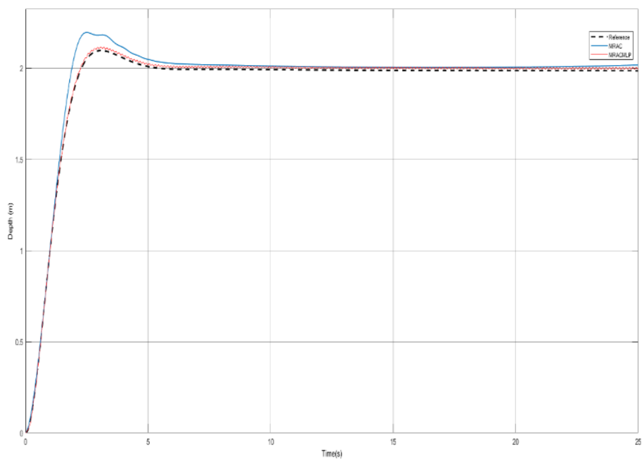


Figure 11: control output with classic MRAC in noise presence.

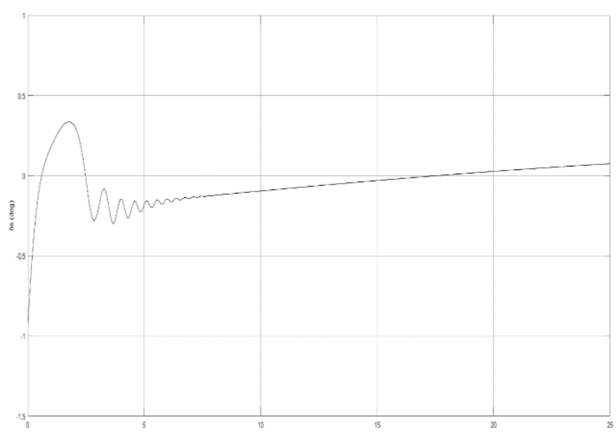
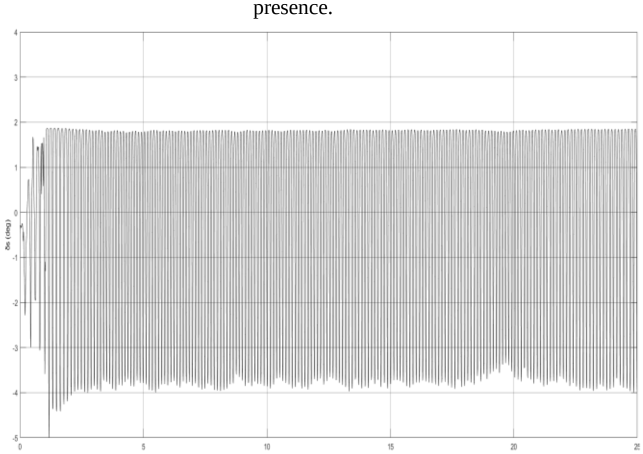


Figure 12 control output with MRAC combined with MLPNN in noise presence.



The Figure 10 above illustrates the consequences of adding a noise signal to the MRAC controller based on hyperstability approach and MRAC enhanced with MLP NN. It can be observed that there is a divergence between the tracking of the actual depth and the reference in the classic MRAC compared with the controller without adding noise. It notices that the MRAC combined with

MLP NN has favorable result compared to the classic MRAC controller against uncertainties.

From Figure 11 and 12 the output controller, we may observe that the control surface is unsaturated in classic MRAC, contrary to the proposed MRAC approach control surface is roughly saturated which means that the depth is stabilized.

As part of the effectiveness analysis for both MRAC and MRAC combined with MLPNN controllers against parameter uncertainties, it is suggested to increase the hydrodynamic parameters by 30% of their value. The Figure below illustrate the reaction of the classic MRAC and the MRAC combined with MLPNN.

Figure 13: Depth control with classic MRAC and MRACMLP With uncertainties

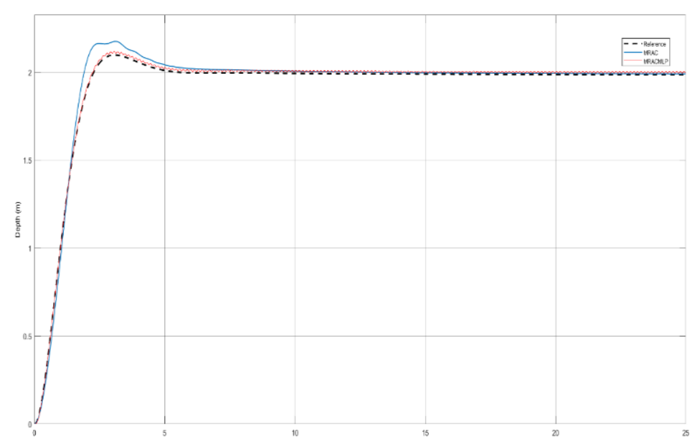


Figure 14 control output with classic MRAC with uncertainties.

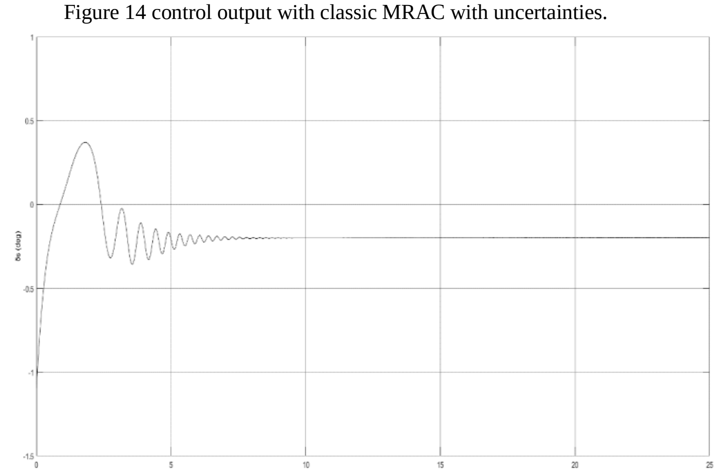


Figure 15 control output with MRAC combined with MLP NN with uncertainties.

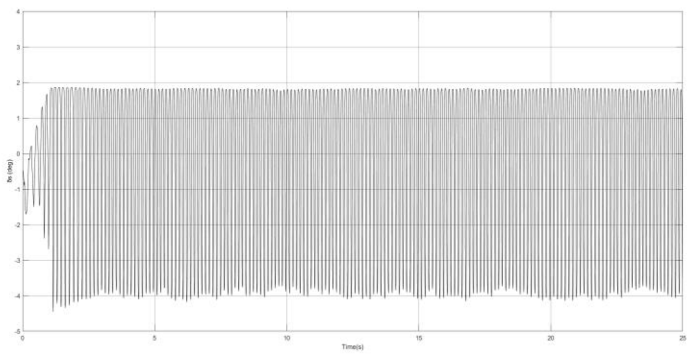


Figure 13 illustrates that the MRAC combined with MLPNN provide an efficient reference tracking compared with the classic MRAC in the presence of parameter uncertainties; beside that the classic MRAC provide an increase in overshot than MRAC without uncertainties.

It’s observed from Figure.14 that the control output of the classic MRAC hasn’t change compared with Figure.8, that’s mean that the uncertainties hasn’t any reject on the control input.

Conclusions

The general idea in this paper focuses on proposing a reference model controller for depth tracking of an AUV REMUS. Initially, the approach involved, use MRAC based on the hyperstability concept in a linear vertical AUV model. However, in order to improve the performance and address uncertainties and noise, the adaptive control law and the adaptive controller were substituted with an MLP neural network, Then the stability analysis for the new control approach it been demonstrated using Lyapunov candidate function , the neural network training is performed using MATLAB.

Through simulations, it has been demonstrated that this enhanced MRAC controller, incorporating an MLP NN, is more suitable for handling uncertainties and noise. This expansion highlights the significance of using an MLP NN in enhancing the control system for depth tracking of the AUV REMUS.

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