

Multirate Depth Control of an AUV by Neural Network Model Reference Controller for Enhanced Situational Awareness

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Abstract: This paper focuses on a critical component of the situational awareness (SA), the neural control of depth flight of an autonomous underwater vehicle (AUV). Constant depth flight is a challenging but important task for AUVs to achieve high level of autonomy under adverse conditions. With the SA strategy, we proposed a multirate neural control of an AUV trajectory for a nontrivial mid-small size AUV “r2D4” stochastic model. This control strategy has been verified by simulation of diving maneuvers using software package Simulink. From the simulation results it can be seen that the chosen AUV model is stable in the presence of noises, and also can be concluded that the proposed research technique will be useful for fast SA with economy in energy of batteries can be asserted during the depth flight in real-time search-and-rescue operations.

Key-Words: Autonomous underwater vehicle, depth flight, multirate system, neurocontroller, simulation, situational awareness.

1 Introduction

Situation awareness has been formally defined as “the perception of elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future” [1]. As the term implies, situation awareness refers to awareness of the situation. Grammatically, situational awareness (SA) refers to awareness that only happens sometimes in certain situations.

SA has been recognized as a critical, yet often elusive, foundation for successful decision-making across a broad range of complex and dynamic systems, including emergency response and military command and control operations [2].

The term SA have become commonplace for the doctrine and tactics, and techniques in the U.S. Army [3]. SA is defined as “the ability to maintain a constant, clear mental picture of relevant information and the tactical situation including friendly and threat situations as well as terrain”. SA allows leaders to avoid surprise, make rapid decisions, and choose when and where to conduct engagements, and achieve decisive outcomes.

SA in the underwater battlespace is of crucial importance in contemporary underwater warfare [4]. It allows for significantly enhanced performance in torpedo defense, mine avoidance, anti-submarine

warfare and a multitude of other aspects of undersea engagement.

In [5], a two stage flight control procedure using two adaptive neural networks (NNs) for helicopter as small-scale unmanned aerial vehicle (UAV) model was proposed. The proposed control strategy has been verified by simulation of descending and landing maneuvers of helicopter using software package Simulink and demonstrated good performance for fast SA.

This paper concentrates on issues related to the area of [5], but demonstrates another field for application of these ideas, i.e., research technique using multirate control system modeling and simulation on the basis of state-space equations of motion of chosen stochastic model of an autonomous underwater vehicle (AUV) for fast SA.

The AUV provides the commander with a number of capabilities including:

- Enhanced SA.
- Target acquisition.
- Enhanced management capabilities (assessment of surface damage and visualization of blockage far and near).

Some conditions for conducting underwater reconnaissance with AUVs are as follows.

- Time is limited or information is required quickly.

- Threat conditions are known; also the risk of collisions with a rough-surfaced sea bottom is high.
- Sea bottom relief restricts approach by large-scale underwater vehicles.

A mid-small size AUV offers many advantages, including low cost, the ability to fly at constant depth levels within a narrow space and the unique diving characteristics.

The fundamental requirement for diving control is the knowledge of the depth under the sea surface, and a properly designed controller to govern the process.

Optimum values for PID (proportional-integral-derivative) controllers are derived via the simulations of an AUV “r2D4” motion based on the closed-loop vehicle dynamics [6].

The characteristics of an AUV motion depend on mode of maneuvering, forward speed, instantaneous attitude, and outside appendages such as measuring instruments. In addition, it is hard to model the system disturbances, cross-flow and the coupling effects. Due to these reasons, the NN controllers are needed to control AUV motions.

In this paper our research results in the study of depth controls of an AUV which make such SA task scenario as “go-search-find-return” possible are presented.

The contribution of the paper is twofold: to develop new schemes appropriate for SA enhancement by multirate neural control of an AUV trajectory in real-time search-and-rescue operations, and to present the results of diving maneuvers for chosen stochastic model of an AUV for fast SA in simulation form using the MATLAB/Simulink environment.

2 AUV Model

The AUV “r2D4” [6] is a mid-small size AUV designed to conduct survey of underwater hydrothermal vents. As is analogized from its name, maximum depth of operation is 4000m. This AUV is 4.4m in length, 1.08m in breadth, and 0.81m in height. It weighs 1630kg with payload. The maximum speed of given AUV is 1.544m/s.

Consider the stochastic model using linear model of AUV “r2D4” [6] in terms of a state variable representation as follows:

$$\dot{x}_1 = A_1 x_1 + B_1 u_1 + v_1 \quad (1)$$

$$y_1 = C_1 x_1 + w_1 \quad (2)$$

$$\dot{x}_2 = A_2 x_2 + B_2 u_2 + v_2 \quad (3)$$

$$y_2 = C_2 x_2 + w_2 \quad (4)$$

where

$$u_1 = (n_m \ n_{\gamma_f} \ n_{\gamma_r} \ \delta_{e_l} \ \delta_{e_r})^T, u_2 = (\delta_{p_r} \ \delta_{e_r} \ \delta_{e_l})^T,$$

$$x_1 = (u \ \omega \ q \ \theta)^T, x_2 = (\gamma \ p \ r \ \phi)^T,$$

$u(m/s), \gamma(m/s), \omega(m/s)$ are surge, sway and heave velocities;

$p(radn/s), q(radn/s), r(radn/s)$ are angular velocities of roll, pitch and yaw motions;

$n_m(rps), n_{\gamma_f}(rps), n_{\gamma_r}(rps)$ are numbers of revolutions per second of main, fore-vertical and rear-vertical thrusters;

$\delta_{p_r}(radn), \delta_{e_r}(radn), \delta_{e_l}(radn)$ are deflection angles of main thruster, right and left elevators;

$\phi(radn), \theta(radn)$ are roll and pitch displacements;

$$A_1 = \begin{bmatrix} -0.1465 & 0.0263 & 0 & -0.0006 \\ 0.0683 & -1.3658 & 3.8905 & 0.1900 \\ -0.0062 & -0.0132 & -1.2340 & -0.0832 \\ 0 & 0 & 1 & 0 \end{bmatrix},$$

$$B_1 = \begin{bmatrix} 0.0491 & 0 & 0 & 0 & 0 \\ 0 & 0.0112 & 0.0006 & 0.0679 & 0.0679 \\ 0 & -0.0029 & 0.0018 & -0.0979 & -0.0979 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix},$$

$$A_2 = \begin{bmatrix} -0.5266 & -0.0024 & -0.8046 & -0.0052 \\ -3.5308 & -4.7897 & 8.0281 & -10.5544 \\ -0.1472 & -0.0332 & -0.4068 & -0.0722 \\ 0 & 1 & 0 & 0 \end{bmatrix},$$

$$B_2 = \begin{bmatrix} -0.0335 & -0.0011 & 0.0011 \\ 0.0244 & -2.1704 & 2.1704 \\ 0.0486 & -0.0149 & 0.0149 \\ 0 & 0 & 0 \end{bmatrix}, C_1 = C_2 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}.$$

In [7], the derivative of yaw displacement ψ of AUVs could be expressed as

$$\dot{\psi} = (q \sin(\phi) + r \cos(\phi)) / \cos(\theta) \quad (5)$$

Then, we have

$$\psi(\tau) = \int_0^{\tau} \dot{\psi}(t) dt + \psi(0) \quad (6)$$

3 Multirate Subsystems

Consider the stochastic continuous-time control system described by the state and output equations

$$\dot{x}(\tau) = Ax(\tau) + Bu(\tau) + v(\tau) \quad (7)$$

$$y(\tau) = Cx(\tau) + w(\tau) \quad (8)$$

where

$x(\tau) \in R^n, u(\tau) \in R^m, y(\tau) \in R^p, v(\tau) \in R^n, w(\tau) \in R^p$ are the state, control input, output, noise of excitation of state and noise of measurement vectors, respectively.

In [8] it is offered the approach to design of decomposed multirate stochastic linear systems, which consist of naturally grouped entrance and target signals that are caused by their characteristic frequencies.

Setting $q(\tau) = Tx(\tau)$, where T is a nonsingular $n \times n$ matrix, we see that (7)-(8) are transformed into the equations

$$\dot{q}(\tau) = J_c q(\tau) + \tilde{B}u(\tau) + Tv(\tau) \quad (9)$$

$$y(\tau) = \tilde{C}q(\tau) + w(\tau) \quad (10)$$

where

$$J_c = TAT^{-1}, \tilde{B} = TB, \tilde{C} = CT^{-1}.$$

The equations (9)-(10) may be written in terms of submatrices as

$$\dot{z}_1(\tau) = A_1 z_1(\tau) + B_1 u(\tau) + T_1 v(\tau) \quad (11)$$

$$\dot{z}_2(\tau) = A_2 z_2(\tau) + B_2 u(\tau) + T_2 v(\tau) \quad (12)$$

$$\dot{z}_3(\tau) = A_3 z_3(\tau) + B_3 u(\tau) + T_3 v(\tau) \quad (13)$$

$$y(\tau) = C_1 z_1(\tau) + C_2 z_2(\tau) + C_3 z_3(\tau) + w(\tau) \quad (14)$$

where

small eigenvalues of a matrix $A_1 : |\lambda(A_1)| < \gamma_{s_{\max}}$,

intermediate eigenvalues of a matrix

$$A_2 : \gamma_{i_{\min}} < |\lambda(A_2)| < \gamma_{i_{\max}},$$

large eigenvalues of a matrix $A_3 : |\lambda(A_3)| > \gamma_{f_{\min}}$,

$$J_c = \begin{bmatrix} A_1 & 0 & 0 \\ 0 & A_2 & 0 \\ 0 & 0 & A_3 \end{bmatrix}, \tilde{B} = \begin{bmatrix} B_1 \\ B_2 \\ B_3 \end{bmatrix}, \tilde{C} = [C_1 \ C_2 \ C_3],$$

$$T = \begin{bmatrix} T_1 \\ T_2 \\ T_3 \end{bmatrix}, q(\tau) = \begin{bmatrix} z_1(\tau) \\ z_2(\tau) \\ z_3(\tau) \end{bmatrix}.$$

Definition 1: A function with a large derivative which is quickly decreasing is said to be the “fast” function; a function with a small derivative which is slowly decreasing is said to be the “slow” function. A function is said to be the “intermediate” function if the derivative of this function is intermediate between small and large values.

Consider the first time interval $0 < \tau_f \leq \tau_{fi}$. Applying a method of the Euler to (11), (12) and

assuming that $z_1(0) = 0$ and $z_2(0) = 0$, we find

$$z_1(\tau_f) \approx \tau_f B_1 u(\tau_f) + \tau_f T_1 v(\tau_f),$$

$$z_2(\tau_f) \approx \tau_f B_2 u(\tau_f) + \tau_f T_2 v(\tau_f). \quad (15)$$

Using (13)-(15), we obtain the state equations for a “fast” subsystem

$$\dot{z}_f(\tau_f) = A_f z_f(\tau_f) + B_f u_f(\tau_f) + T_f v_f(\tau_f) \quad (16)$$

$$y_f(\tau_f) = C_f z_f(\tau_f) + D_f u_f(\tau_f) + w_f(\tau_f) \quad (17)$$

where

$$A_f = A_3, B_f = B_3, T_f = T_3, C_f = C_3,$$

$$D_f = \tau_f (C_1 B_1 + C_2 B_2), V_f = \tau_f (C_1 T_1 + C_2 T_2),$$

$$z_f(\tau_f) = z_3(\tau_f), u_f(\tau_f) = u(\tau_f), v_f(\tau_f) = v(\tau_f),$$

$$y_f(\tau_f) = y(\tau_f), w_f(\tau_f) = w(\tau_f) + V_f v(\tau_f).$$

Consider the second time interval $\tau_{fi} < \tau_i \leq \tau_{is}$. According to the Definition 1, a variable z_3 can be considered as a “fast” function, achieving on this interval a steady meaning. Inserting $\dot{z}_3(\tau_i) \approx 0$ in (13) gives

$$z_3(\tau_i) \approx -A_3^{-1} B_3 u(\tau_i) - A_3^{-1} T_3 v(\tau_i) \quad (18)$$

Using the implicit formula of the Euler for (11) and assuming that $z_1(0) = 0$ leads to

$$z_1(\tau_i) \approx \tau_i (I - \tau_i A_1)^{-1} B_1 u(\tau_i) + \tau_i (I - \tau_i A_1)^{-1} T_1 v(\tau_i) \quad (19)$$

Combining (12), (14), (18) and (19), we find that an “intermediate” subsystem is given by

$$\dot{z}_i(\tau_i) = A_i z_i(\tau_i) + B_i u_i(\tau_i) + T_i v_i(\tau_i) \quad (20)$$

$$y_i(\tau_i) = C_i z_i(\tau_i) + D_i u_i(\tau_i) + w_i(\tau_i) \quad (21)$$

where

$$A_i = A_2, B_i = B_2, T_i = T_2, C_i = C_2,$$

$$D_i = \tau_i C_1 (I - \tau_i A_1)^{-1} B_1 - C_3 A_3^{-1} B_3,$$

$$V_i = \tau_i C_1 (I - \tau_i A_1)^{-1} T_1 - C_3 A_3^{-1} T_3,$$

$$z_i(\tau_i) = z_2(\tau_i), u_i(\tau_i) = u(\tau_i), v_i(\tau_i) = v(\tau_i),$$

$$y_i(\tau_i) = y(\tau_i), w_i(\tau_i) = w(\tau_i) + V_i v(\tau_i).$$

Consider the last time interval $\tau_s > \tau_{is}$. According to the Definition 1 it is possible to consider variables z_2 and z_3 as the “intermediate” functions achieving on this interval the steady meanings. Then, from (12) and (13), we have

$$z_2(\tau_s) \approx -A_2^{-1}B_2u(\tau_s) - A_2^{-1}T_2v(\tau_s),$$

$$z_3(\tau_s) \approx -A_3^{-1}B_3u(\tau_s) - A_3^{-1}T_3v(\tau_s) \quad (22)$$

Further, from (11), (14) and (22), we find that the state equations for a “slow” subsystem may be written as

$$\dot{z}_s(\tau_s) = A_s z_s(\tau_s) + B_s u_s(\tau_s) + T_s v_s(\tau_s) \quad (23)$$

$$y_s(\tau_s) = C_s z_s(\tau_s) + D_s u_s(\tau_s) + w_s(\tau_s) \quad (24)$$

where

$$A_s = A_1, B_s = B_1, T_s = T_1, C_s = C_1,$$

$$D_s = -C_2 A_2^{-1} B_2 - C_3 A_3^{-1} B_3, V_s = -C_2 A_2^{-1} T_2 - C_3 A_3^{-1} T_3,$$

$$z_s(\tau_s) = z_1(\tau_s), u_s(\tau_s) = u(\tau_s), v_s(\tau_s) = v(\tau_s).$$

$$j_{21} = \sin(\psi)\cos(\theta),$$

$$j_{22} = \cos(\psi)\cos(\phi) + \sin(\phi)\sin(\theta)\sin(\psi),$$

$$j_{23} = -\cos(\psi)\sin(\phi) + \sin(\theta)\sin(\psi)\cos(\phi),$$

$$j_{31} = -\sin(\phi), j_{32} = \cos(\theta)\sin(\phi), j_{33} = \cos(\theta)\cos(\phi).$$

Then, we have

$$x(\tau) = \int_0^\tau \dot{x}(t)dt, y(\tau) = \int_0^\tau \dot{y}(t)dt, z(\tau) = \int_0^\tau \dot{z}(t)dt, \quad (26)$$

where

$$x(0) = 0, y(0) = 0, z(0) = 0.$$

From (1)-(6), (25)-(26) we can see that the attitude vector $(x \ y \ z)^T$ for given model of an AUV can be computed.

4 AUV Attitude

The derivative of attitude vector $(x \ y \ z)^T$ for center of mass of an AUV can be described in a common way through next expression as indicated in [7]

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{z} \end{bmatrix} = \begin{bmatrix} j_{11} & j_{12} & j_{13} \\ j_{21} & j_{22} & j_{23} \\ j_{31} & j_{32} & j_{33} \end{bmatrix} \begin{bmatrix} u \\ v \\ w \end{bmatrix}, \quad (25)$$

where

$$j_{11} = \cos(\psi)\cos(\theta),$$

$$j_{12} = -\sin(\psi)\cos(\phi) + \cos(\psi)\sin(\theta)\sin(\phi),$$

$$j_{13} = \sin(\psi)\sin(\phi) + \cos(\psi)\cos(\phi)\sin(\theta),$$

5 Simulation Results

Consider the control of the AUV “r2D4” decomposed multirate model for the case of hybrid control system with one neurocontroller.

Initial conditions and desired constant depth level for multirate control subsystems are chosen to be:

$$x(0) = 0m, y(0) = 0m, z(0) = 0m, z^0 = -16m.$$

Simulation results for the offered block scheme (see Fig. 1) are shown in Figs. 3-4.

The Model Reference Adaptive Control (MRAC) configuration [9] uses two neural networks: a controller network and a model network (see Fig. 2).

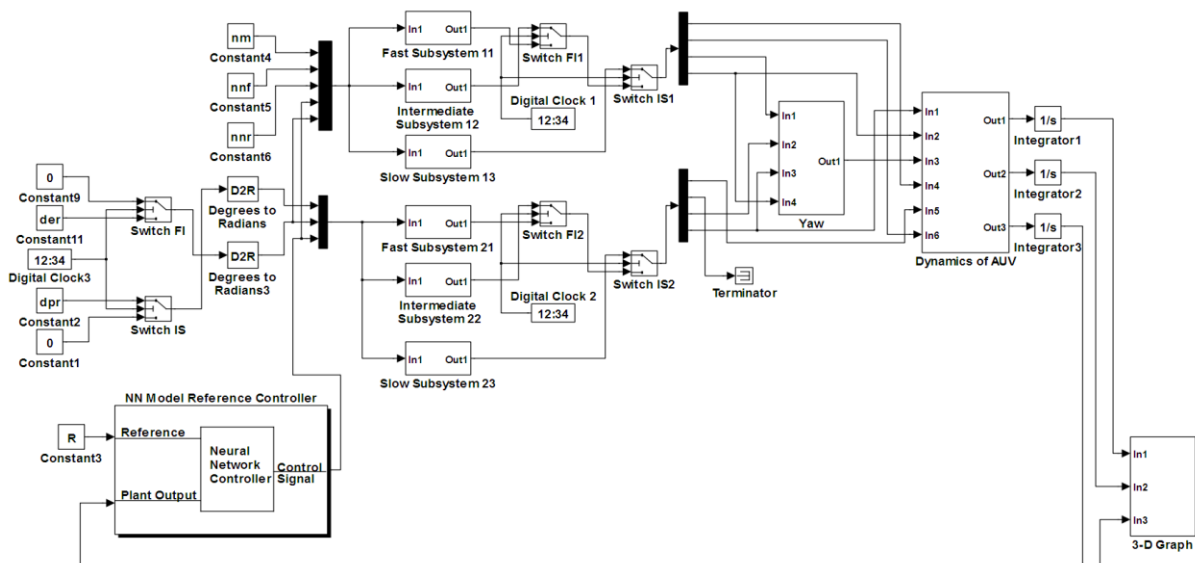


Fig. 1. Block diagram of hybrid control system.

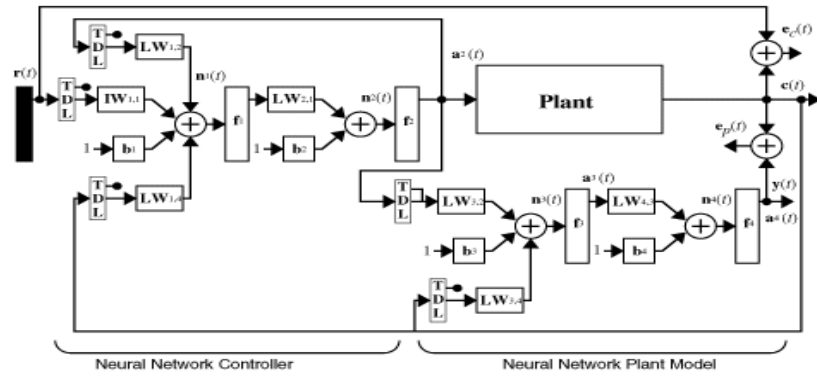


Fig. 2. Structure of NN representation.

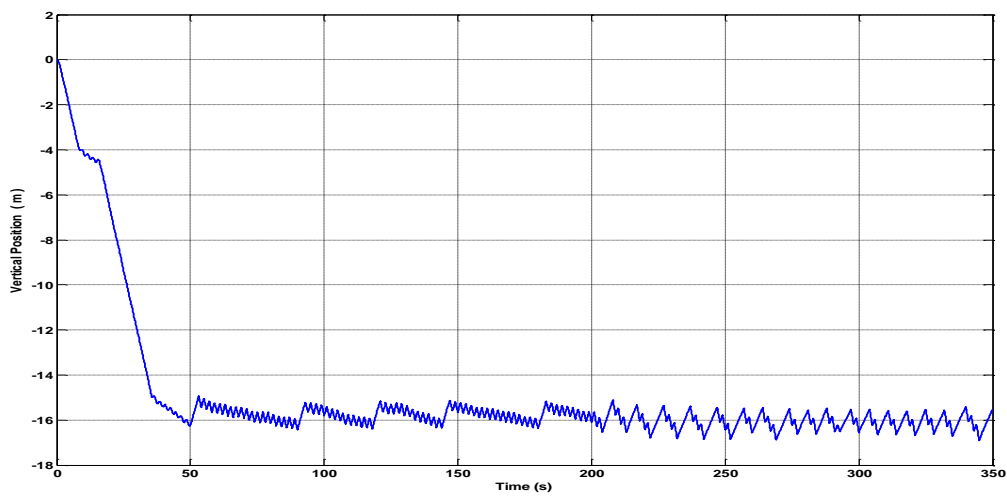


Fig. 3. AUV depth trajectory.

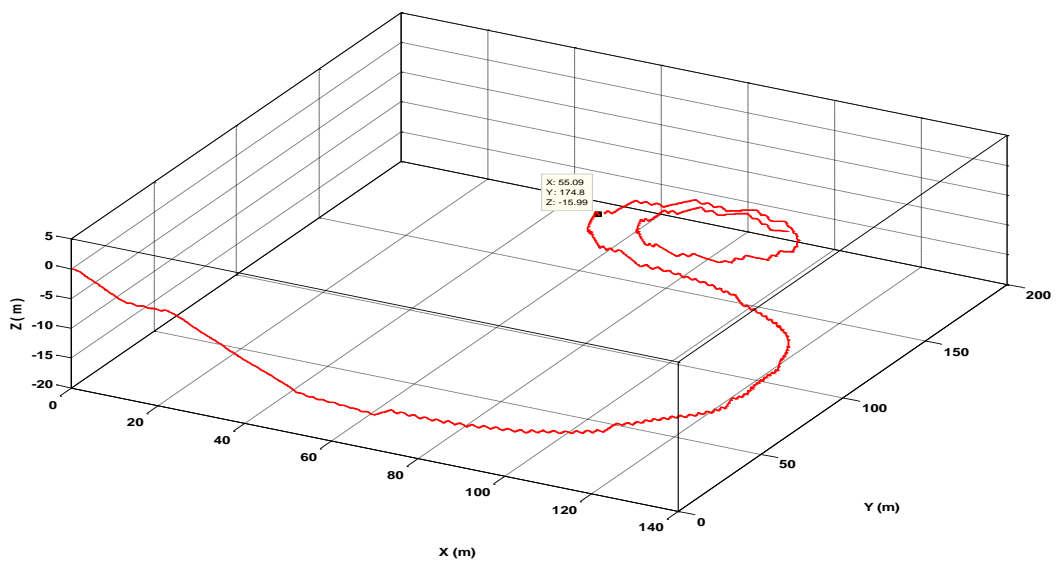


Fig. 4. 3-D motion of the AUV.

The goal of these simulations is twofold. First, we verify that this neurocontroller is able to control the diving trajectory. Second, we observed the effect of enhanced SA because the variety of such trajectory parameter as constant depth flight easily can be changed the possible diving trajectory of an AUV.

The model network can be trained off-line using historical plant measurements. The controller is adaptively trained to force the plant output to track a reference model output. The model network is used to predict the effect of controller changes on plant output, which allows the updating of controller parameters.

These results support the theoretical predictions well and demonstrate that this research technique would work in real-time diving conditions.

6 Conclusions

The need for accurate and directionally stable diving for AUV class autonomous vehicles has increased morbidly for critical situations in real-time search-and-rescue operations with existence of system disturbances, cross-flow and the coupling effects for fast SA.

A new research technique is presented in this paper for enhanced SA in possible AUV mission. The effectiveness of this technique has been verified in field of diving simulation tests for chosen model of the AUV "r2D4" using software package Simulink.

From the applications viewpoint, we believe that this depth multirate neural control using NN model reference controllers furnish a powerful approach for enhancing SA in applications to AUV class autonomous vehicles in real-time search-and-rescue operations.

Although many of the details inevitably relate with this particular AUV model, there is sufficient generality for this research technique to be applied to similar AUV models for simulation of diving maneuvers.

Future work will involve further validation of the performance of the proposed research technique and exploring other relevant and interesting AUV missions.

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