Control of Autonomous Underwater Vehicles using Neural Network Based Robust Control System

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Abstract: - A neural network based robust control system design for the yaw angle of autonomous underwater vehicle (AUV) is presented in this paper. Two types of control structure were used to control prescribed trajectories of an AUV. The results of the simulation showed that the proposed neural network based robust control system has superior performance in adapting to large random disturbances such as water flow under sea. Finally, the proposed neural controller improved that this kind of neural predictors could be used in real time applications of an AUV.

Key-Words: - Neural network control, robust control, autonomous underwater vehicles, PID controller

1 Introduction

Nowadays, AUVs vehicle have been widely used for underwater investigations. A manoeuvring control of an underwater vehicle from the perspective of a combined discrete-event and discrete-time system simulation has been investigated by Son and Kim [1]. The proposed simulation model established on the basis of discrete-event system specification formalism, which was a representative modelling formalism of a discrete-event system simulation. The proposed approach made possible to build a simulation-based expert system which supports the decision making for the acquisition of the underwater vehicle.

Dynamic station keeping of an under actuated flat-fish type AUV has been analysed and a new method of station keeping has been proposed with an addition of dedicated thrusters [2]. Effect of introduction of additional thrusters on tracking performance analysed and a modular configuration suggested reducing its influence on tracking control. Also, a comparative analysis on power consumption during station keeping researched to prove the effectiveness of the proposed modular configuration.

An adaptive neuro-fuzzy sliding-mode-based genetic algorithm control system for a remotely operated vehicle with four degrees of freedom has been presented by Moghaddam and Bagheri [3]. A set-point controller for autonomous underwater vehicles was proposed by Herman [4]. The controller was expressed in transformed equations of motion with a diagonal inertia matrix. The stability of the proposed control law proved and the performance of the developed controller have been approved via simulation on the underwater vehicle.

Another investigation, a new control scheme for robust trajectory control has been presented for the underwater vehicles. The effectiveness of the controller was verified through simulations and execution issues were discussed [5]. Adaptive control of low speed bio-robotic autonomous underwater vehicles in the dive plane using dorsal fins was considered.

An indirect adaptive control system has been developed for depth control using dorsal fins. According to the simulation results, the adaptive control system accomplished precise depth control of the bio-robotic autonomous underwater vehicle using dorsal fins in spite of large uncertainties in the system parameters [6]. Autonomous underwater vehicle control architectures were reviewed and sensor data bus based control architecture was investigated by Kim and Yuh [7].

A wave drift force affecting severely the underwater vehicle in shallow water has presented by Luo et al. [8]. On the basis of wave force analysis, three dimension disturbances caused by wavy surge water measured and a control system using least squares multi-order data fitting polynomial prediction and fuzzy compensation combined with PID controller was put forward. The experimental results showed that the control system for disturbance of surge and wave was feasible and effective.

A chattering-free sliding-mode controller developed for the trajectory control of remotely operated vehicles. Also, a new approach for thrust allocation proposed that was based on minimizing the largest individual component of the thrust manifold [9]. Bessa et al., [10] developed an adaptive fuzzy sliding mode controller for remotely operated the underwater vehicles. Their study was adopted based on the sliding mode control strategy and enhanced by an adaptive fuzzy algorithm for uncertainty/disturbance compensation. The performance of the proposed control structure was also appraised using numerical simulations.

Naik and Singh, [11] investigated the problem of suboptimal dive plane control of autonomous underwater vehicles using the state-dependent Riccati equation technique. Simulation results presented which show that effective depth control was accomplished in spite of the uncertainties in the system parameters and control fin deflection constraints.

In other research, a neuro-fuzzy controller for autonomous underwater vehicles was been proposed by Kim and Yuh [12]. Simulation results showed effectiveness of the neuro-fuzzy controller for autonomous underwater vehicles. Akkizidis et al., [13] used a fuzzy-like PD controller for an underwater vehicle and experimental results were analyzed and presented. A switched control law for stabilizing an under actuated underwater vehicle was proposed by Sankaranarayanan et al. [14]. Simulation results were presented to validate the control law. Lapierre [15] designed and verified diving-control based on Lyapunov theory and back-stepping techniques. The results of the control system proved and simulations developed to demonstrate the performance of the solutions proposed.

2 Dynamics equations of autonomous underwater vehicle

The motion for an underwater vehicle's generalized six-degree of freedom equations of is derived under the following assumptions:

- The vehicle behaves as a rigid body
- The earth's rotation is negligible as far as acceleration of the mass centre are concerned
- The vehicle moves at low speed
- The hydrodynamics parameters are constant

The equations of motion for an underwater vehicle can be represented as [16, 17]

$$\mathbf{M\dot{\nu} + C(\nu)\nu + D(\nu)\nu + g(\eta) = \tau} \tag{1}$$

where M is the matrix of inertia and added inertia, C is the matrix of Coriolis and centrifugal terms, D is the matrix of the hydrodynamic damping terms, $g(\eta)$ is the vector of gravity and buoyant forces, τ is the resultant vector of thrusters forces and moments.

$$\mathbf{\dot{\eta} = J(\eta)\nu} \tag{2}$$

where $J(\eta)$ is the kinematics transformation matrix and $\mathbf{\eta = (x, y, z, \phi, \theta, \psi)^T}$. The linear steering equations of motion as:

$$\begin{bmatrix} \dot{\nu} \\ \dot{r} \\ \dot{\varphi} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} \nu \\ r \\ \varphi \end{bmatrix} + \begin{bmatrix} b_{11} \\ b_{21} \\ b_{31} \end{bmatrix} \delta_r \tag{3}$$

where the components of the matrix are as follow;

$$a_{11} = \frac{u_0\left[Y_v(m - Y_{\dot{v}})^2(I_{zz} - N_{\dot{r}}) - (mx_G - Y_{\dot{r}})N_v\right]}{(m - Y_{\dot{v}})(I_{zz} - N_{\dot{r}})}$$

$$a_{12} = \frac{u_0[(m - Y_{\dot{v}})^2(Y_r - m)(I_{zz} - N_{\dot{r}}) - (mx_G - Y_{\dot{r}})(N_r - mx_G)]}{(m - Y_{\dot{v}})(I_{zz} - N_{\dot{r}})}$$

$$a_{13} = 0$$

$$a_{21} = \frac{u_0\left[N_v(m - Y_{\dot{v}})(I_{zz} - N_{\dot{r}})^2 - (mx_G - N_{\dot{v}})Y_v\right]}{(m - Y_{\dot{v}})(I_{zz} - N_{\dot{r}})}$$

$$a_{22} = \frac{(I_{zz} - N_{\dot{r}})^2(N_r - mx_G)(m - Y_{\dot{v}}) - (mx_G - N_{\dot{v}})(Y_r - m)u_0}{(m - Y_{\dot{v}})(I_{zz} - N_{\dot{r}})}$$

$$a_{23} = 0$$

$$a_{31} = 0$$

$$a_{32} = 1 - \frac{(mx_G - N_{\dot{v}})(mx_G - Y_{\dot{r}})}{(m - Y_{\dot{v}})(I_{zz} - N_{\dot{r}})}$$

$$a_{33} = 0$$

$$b_{11} = \frac{(I_{zz} - N_{\dot{r}})(m - Y_{\dot{v}})^2 Y_\delta - (mx_G - Y_{\dot{r}})N_\delta}{(m - Y_{\dot{v}})(I_{zz} - N_{\dot{r}})}$$

$$b_{12} = \frac{(I_{zz} - N_{\dot{r}})^2(m - Y_{\dot{v}})N_\delta - (mx_G - N_{\dot{v}})Y_\delta}{(m - Y_{\dot{v}})(I_{zz} - N_{\dot{r}})}$$

$$b_{13} = 0$$

The linearized forms for equations of the AUV motion containing heave and pitch are as follows:

$$\begin{bmatrix}\dot{q}\\ \dot{\theta}\\ \dot{z}\end{bmatrix}=\begin{bmatrix}a_{11} & a_{12} & 0\\ 1 & 0 & 0\\ 0 & a_{32} & 0\end{bmatrix}\begin{bmatrix}q\\ \theta\\ z\end{bmatrix}+\begin{bmatrix}b_{11}\\ 0\\ 0\end{bmatrix}\delta_s \tag{4}$$

where the components of the matrix as follows;

$$a_{11}=\frac{M_q-mx_G u_0}{I_{yy}-M_{\dot{q}}}$$

$$a_{12}=\frac{-W(z_G-z_B)}{I_{yy}-M_{\dot{q}}}$$

$$a_{32}=-u_0$$

$$b_{11}=\frac{M_\delta}{I_{yy}-M_{\dot{q}}}$$

Schematic representation of the AUV system with coordinates is shown in Fig.1. The hydrodynamics parameters and the AUV parameters are given in Table 1.

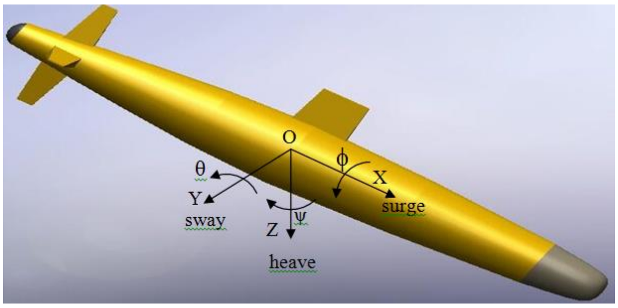

Fig.1. Schematic representation of the AUV system with coordinates

Table 1. The hydrodynamics parameters and the AUV parameters

m	250 kg	**Mq**	300 N.m
g	9.81 m/s^2	$M_{\dot{q}}$	-30 kgm^2
u_0	2 m/s	**Nv**	300 N.m
x_G	-0.15 m	$N_{\dot{v}}$	10 kg.m
z_G	0.03 m	**Y_δ**	8047 N
z_B	0	**N_δ**	-76 N.m
Izz	140 kg.m^2	**Yr**	100
Iyy	150 kg.m^2	$Y_{\dot{r}}$	10 kg.m
Nr	300 N.m	**Yv**	100 N
$N_{\dot{r}}$	-30 kg.m^2	$Y_{\dot{v}}$	-250 kg

3 Descriptions of Controllers

3.1. Robust Neural Feedback Control System (RNFCS)

A designed control system is employed to control the yaw angle of the AUV. The purpose of this proposed control system is to provide the appropriate control action. The mathematical expression of the force of the RNF control system is given by;

$$\mathbf{u(t)=u_R(t)+u_{NN}(t)} \tag{5}$$

where $u_R(t)$ is the force of the robust controller and $u_{NN}(t)$ is the force of the neural controller. The sum of these two forces, control force signal $u(t)$ is given. The first part of control input for the robust controller can be described as follows:

$$\mathbf{u_R(t)=\left(K_P e(t)+K_D\frac{de(t)}{dt}\right)*e^{(-Rt)}} \tag{6}$$

where K_P, K_D and R are the proposed control system parameters and are empirically set to $K_P = 10$, $K_D=7$ and R=0.0001. In the following equation, $e(t)$ is the control error;

$$\mathbf{e(t)=y_r(t)-y(t)}$$

where $y_r(t)$ is the reference input signal and $y(t)$ is the system output signal. Neural Network structure is shown in Fig.2. The second part of control input for the proposed control system is explained in the following sub section.

3.1.1. Neural Controller

A neural controller with Resilient Backpropagation Algorithm is one of the popular neural network structures for control and prediction. Fundamentally, two steps are involved when using this control: system identification and control design. The identification stage of this control is to train a neural network to present the forward dynamics of the plant. The neural network model of the plant that needs to be controlled is developed using two sub networks for the model approximation. The neural model is as follows:

$$y(t+d)=N[y(t),...,y(t-m+1),u(t-1),...,u(t-n+1)] \tag{8}$$

where $y(t)$ is the system output, $u(t)$ is the system input and d is the relative degree (d≥2). Multilayer neural networks can be used to identify the function F. The identification model has the form;

$$\begin{aligned}\hat{y}(t+d)=&f[y(t),...,y(t-m+1),u(t-1),...,u(t-n+1)]+\\ &g[y(t),...,y(t-m+1),u(t-1),...,u(t-n+1)].u_{NN}(t)\end{aligned} \tag{9}$$

where $\hat{y}(t+d)$ is the estimate of $y(t+d)$. Identification is carried out at every instant t by adjusting the parameters of the neural network using the error $e(t) = \hat{y}(t) - y(t)$. In order for a system output, y(t+d), to follow a reference trajectory $y_r(t+d)$.

$$y(t+d) = f[y(t),..., y(t-m+1), u(t-1),..., u(t-n+1)] + g[y(t),..., y(t-m+1), u(t-1),..., u(t-n+1)].u_{NN}(t) \quad (10)$$

f and *g* are activation functions of the hidden layer in the first and second sub networks, respectively, as follows:

$$f(t) = g(t) = \frac{1}{e^{-t} + 1} \quad (11)$$

For each sub network, the linear activation function used the output layer. The controller output would have the form of;

$$u(t) = \frac{y_r(t+d) - f[y(t),..., y(t-m+1), u(t-1),..., u(t-n+1)]}{g[y(t),..., y(t-m+1), u(t-1),..., u(t-n+1)]} \quad (12)$$

Using the equation directly, causes a realization problem, based on the output at the same time, y(t). So, instead, the model;

$$y(t+d) = f[y(t),..., y(t-m+1), u(t-1),..., u(t-n+1)] + g[y(t),..., y(t-m+1), u(t-1),..., u(t-n+1)].u_{NN}(t+1) \quad (13)$$

Using Eq.(13) , the controller;

$$u(t+1) = \frac{y_r(t+d) - f[y(t),..., y(t-m+1), u(t-1),..., u(t-n+1)]}{g[y(t),..., y(t-m+1), u(t-1),..., u(t-n+1)]} \quad (14)$$

The proposed RNF control system architecture is shown in Fig.2.

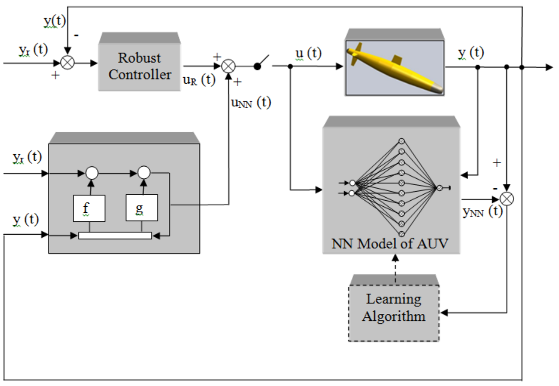

Fig.2. Proposed RNF control system architecture

Moreover, for comparison purposes, the classical PID controller was used for yaw angle control of the AUV. The PID controller was initially tuned using the Ziegler-Nichols method, and the PID parameters are found as K_p=1.2, K_i= 0.5 and K_d= 0.75.

4 Simulation Results

This section presents simulation results of the AUV system with neural network based controller for yaw angle. Figs.3.(a)-(c) show the response of these parameters without any controller, in the presence of a PID controller and the proposed RNF control system, respectively. Fig.3.(a) shows the yaw angle of the AUV for sinusoidal input signal. The response of the AUV unstable behaviour (shown with dashed lines) is also seen in Fig.3.(a). Fig.3.(b) depicts the response of yaw angle of the AUV for sinusoidal input signal using the standard PID controller. As seen in the figure, the system response does not show unstable behaviour, but the desired sinusoidal input signal does not follow. The results show that the proposed RNF control system has better performance in terms of adapting a sinusoidal input signal.

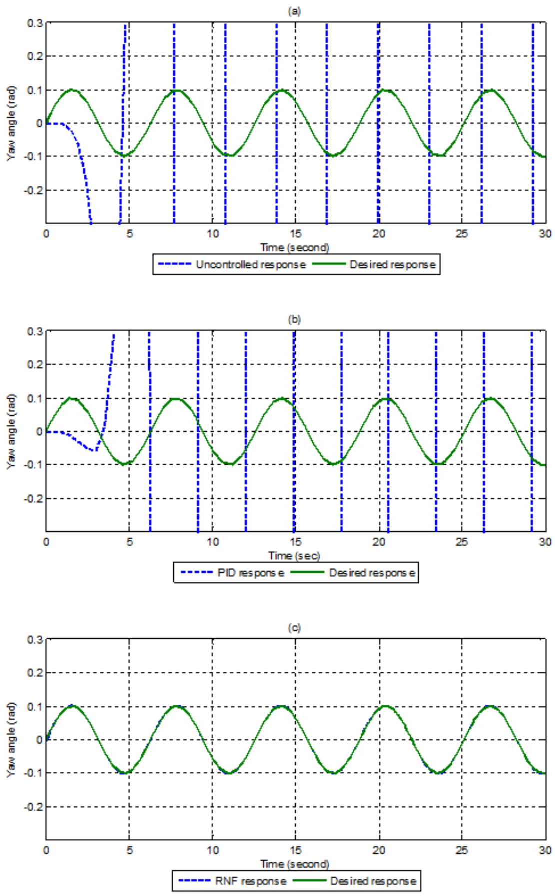

Fig.3. Yaw angle of AUV for sinusoidal input signal (a) Uncontrolled response b) PID controller response and c) RNF control system response

Fig.4.(a) represents yaw angle of the AUV for a random input signal, and in Fig.4.(a) response of the AUV is unstable behaviour. The result of the PID controller for yaw angle of the AUV is shown in Fig.4.(b). As seen in Fig.4.(b), the yaw angle response of the AUV with the PID controller does not track the desired random input signal. Fig.4.(c) indicates the result of the RNF control system. This

graph shows a small overshoot error between the desired random input signal and the proposed control system. According to simulation results, the proposed control system has excellent performance for controlling the AUV parameters.

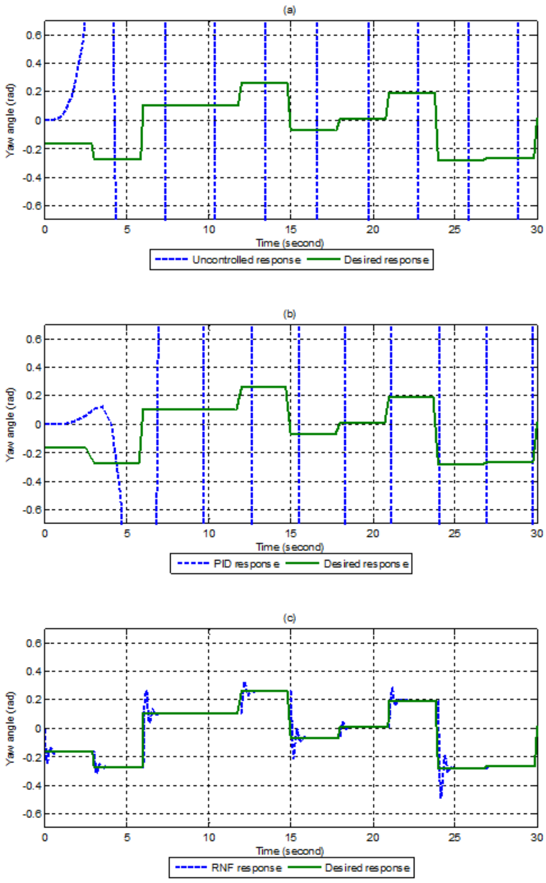

Fig.4. Yaw angle of AUV for random input signal (a) Uncontrolled response b) PID controller response and c) RNF control system response

5 Conclusions

A robust control system with neural network was designed for yaw angle controlling of the AUV system. Moreover, for comparison, the standard PID controller, tuned using Ziegler-Nichols methods, was also employed to control the AUV. The results of both control systems showed that the use of the proposed robust neural feedback control system proved to be effective in controlling the AUV and more robust for the PID controller. The strong performance of the proposed RNF control system was caused by the inclusion of both linear and non-linear neurons in the network. As depicted from simulation results, the proposed control system can effectively track the given trajectory for experimental applications.

6 References

[1] Son M.J., Kim T., Maneuvering control simulation of underwater vehicle based on combined discrete-event and discrete-time modeling, *Expert Systems with Applications*, 39, 2012, 12992–13008.

[2] Santhakumar M., Asokan T., Power efficient dynamic station keeping control of a flat-fish type autonomous underwater vehicle through design modifications of thruster configuration, *Ocean Engineering*, 58, 2012, 11–21.

[3] Moghaddam J., Bagheri A., An adaptive neuro-fuzzy sliding mode based genetic algorithm control system for under water remotely operated vehicle, *Expert Systems with Applications*, 37, 2010, 647-660.

[4] Herman P., Decoupled PD set-point controller for underwater vehicles, *Ocean Engineering*, 36, 2009, 529–534.

[5] Kumar R.P., Dasgupta A., Kumar C.S., Robust trajectory control of underwater vehicles using time delay control law, *Ocean Engineering*, 34, 2007, 842–849.

[6] Narasimhan M., Singh S.N., Adaptive optimal control of an autonomous underwater vehicle in the dive plane using dorsal fins, *Ocean Engineering*, 33, 2006, 404–416.

[7] Kim T.W., Yuh J., Development of real-time control architecture for a semiautonomous underwater vehicle for intervention missions, *Control Engineering Practice*, 12, 2004, 1521–1530.

[8] Luo J., Tang Z., Peng Y., Xie. S., Cheng T., Li Hengyu, Anti-disturbance control for an underwater vehicle in shallow wavy water, *Advanced in Control Engineering and Information Science, Procedia Engineering*, 15, 2011, 915 – 921.

[9] Soylu S., Buckham B.J., Podhorodeski R.P., A chattering-free sliding-mode controller for underwater vehicles with fault tolerant infinity-norm thrust allocation, *Ocean Engineering*, 35, 2008, 1647–1659.

[10] Bessa W.M., Dutra M.S., Kreuzer E., An adaptive fuzzy sliding mode controller for remotely operated underwater vehicles, *Robotics and Autonomous Systems*, 58, 2010, 16-26.

[11] Naik M.S., Singh S. N., State-dependent Riccati equation-based robust dive plane control of AUV with control constraints, *Ocean Engineering*, 334, 2007, 1711–1723.
[12] Kim T.W., Yuh J., 2 Application of on-line neuro-fuzzy controller to AUVs, *Information Sciences*, 145, 2002, 169–182.
[13] Akkizidis I.S., Roberts G.N., Ridao P., Batlle J., Designing a fuzzy-like PD controller for an underwater robot, *Control Engineering Practice*, 11, 2003, 471–480.
[14] Sankaranarayanan V., Mahindrakar A.D., Banavar R. N., A switched controller for an under actuated underwater vehicle, *Communication in Nonlinear Science and Numerical Simulation*, 13, 2008, 2266–2278.
[15] Lapierre L., Robust diving control of an AUV, *Ocean Engineering*, 36, 2009, 92–104.
[16] Fossen T.I., *Guidance and control of ocean vehicles*, 1994, John Wiley, Chichester.
[17] Aranda J., Armada M.A., Cruz J.M., *Automation for the maritime industries*, 2004 PGM, Spain.