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ADAPTIVE IDENTIFICATION OF UNDERWATER GLIDER USING U-MODEL FOR DEPTH & PITCH CONTROL UNDER HYDRODYNAMIC DISTURBANCES

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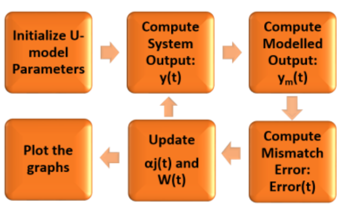
Graphical abstract

U-model Algorithm Summary



Abstract

This paper presents an adaptive identification method based on recently developed control oriented model called U-model for online identification of underwater glider. It is indicated from obtained results that the proposed technique can accurately and adaptively model nonlinearity and dynamics of underwater glider even in presence of hydrodynamic disturbances. Since the proposed identification U-model scheme is control oriented in nature, hence it can be further utilized to synthesize a simple law for depth and pitch control of glider.

Keywords: Adaptive algorithm, RBFNN, stability, underwater robotics

Abstrak

Kertas kerja ini membentangkan satu kaedah pengenalan penyesuaian berdasarkan model adaptif kawalan yang dibangunakn baru-baru ini dipanggil U-model untuk mengenal pasti talian gelungsur air. Ia menunjukkan keputusan yang diperolehi bahawa teknik yang dicadangkan boleh ketaklelurusan model dengan tepat dan adaptif dan gelungsur air dinamik walaupun dalam kehadiran gangguan hidrodinamik. Disebabkan cadangan pengenalan skim U - model adalah kawalan berorientasikan alam semula jadi, oleh itu ia boleh terus digunakan untuk mensintesis undang-undang yang mudah untuk kedalaman dan kawalan bunyi gelungsur .

Kata kunci: Adaptif algoritma, RBFNN, kestabilan, robotik dalam air

1.0 INTRODUCTION

Underwater glider has revolutionized the way that oceanographic data is collected. Gliders are winged autonomous mobile platform that use changes in buoyancy and changes in its center of mass as their source of propulsion [1]. This novel method of propulsion uses very little energy and allows the glider to perform long endurance missions at slow speed. These gliders are equipped with internal sensors that monitors the vehicle's heading, depth and attitude and external sensors that are constantly scanning the ocean to determine environmental properties. Gliders are more efficient mainly because they spend most of their time in stable steady motion, expending control energy only when changing their equilibrium state [1]. Motion control of glider thus reduces to varying the parameters (buoyancy and center of mass) that affect the state of steady motion.

Designing an effective control scheme for multivariable glider that can control its motion in highly dynamic nature of water is a key requirement for its smooth operation. Most controllers designed for UWG are model based, requiring to mathematically model dynamics and kinematics of glider. So performance of controller strongly depends on the accuracy of the derived mathematical model [2]. Each time, the dynamics change, the identified model has to be updated and as a result, controller has to be redesigned. Hence, this kind of offline identification method consumes lot of time and requires continuous effort from control engineer in redesigning the controller. Recently online techniques have been suggested to identify nonlinear systems that adapt itself to varying dynamics of system [3]. One of such attractive approach is based on state variable filter (SVF) and recursive least square (RLS) estimator that is used to rapidly identify autonomous underwater vehicle (AUV) online [4]. Similarly, intelligent modeling techniques like Fuzzy logic [5-7] and Neural network [8-9] offers an advantage as they don't explicitly need to derive mathematical model based on laws of physics and yet can approximate the system with high accuracy. However, intelligent techniques demands substantial computational power and with limited on-board computational power embedded on glider, use of controller based on artificial techniques becomes impractical and unfeasible. Further presence of hydrodynamic disturbances caused by ocean have to be taken into consideration for accurate identification and robust control design.

In this regards, a recently developed control-oriented identification method for multivariable systems called U-model can be beneficial [10]. U-model has the ability of adaptively identifying the dynamics of the system along with the external disturbances. Further U-model simplifies the control synthesis part by modelling the unknown system in a polynomial form. Based on this model, the plant inverse can be easily evaluated using standard root solving algorithms such as Newton Raphson Method. The focus of this paper is limited to system identification that is the building block on which controller can be designed. U-model has been successfully implemented in modelling and controlling in simulation [11-14] and real time [15-18] for nonlinear plants and robotic applications. The main advantages of the proposed approach are its generality and simplistic control law.

2.0 METHODOLOGY

2.1 The U-model Structure

The U-model structure is depicted in Figure 1, where the UWG is modeled adaptively by U-model in presence of hydrodynamic disturbances.

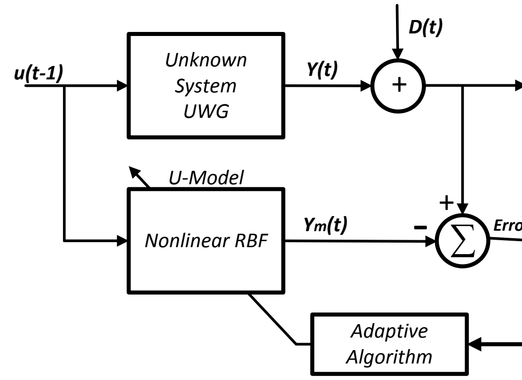


Figure 1 The U-model structure

To obtain U-model, consider a single input single output (SISO) nonlinear dynamic plant represented with a polynomial NARMAX model as given in Equation (1).

$$y(t) = f[y(t-1), \ldots., y(t-n), \ldots u(t-1), \ldots, u(t-n), e(t), \ldots, e(t-n)] \quad (1)$$

where *f(.)* is nonlinear function, *y(t)* and *u(t)* are output and input signals of the plant respectively at discrete time instant t while n represents the order of the plant. The error due to measurement noise, model mismatch, uncertain dynamics, plant variation is represented by *e(t)*. The U-model is obtained by expanding the nonlinear function *f(.)* of Equation (1) as a polynomial with respect to past input only that is *u(t-1)* as given in Equation (2). The expanded view of U-model is as given in Equation (3).

$$y_m(t) = \sum_{j=0}^{M} \alpha_j(t) u^j(t-1) \quad (2)$$

$$y_m(t) = \alpha_0(t) + \alpha_1(t)u(t-1) + \alpha_2 u^2(t-1) + \cdots + \alpha_M(t)u^M(t-1) \quad (3)$$

$$\alpha_j(t) = [\alpha_1, \alpha_2, \ldots, \alpha_M] \quad (4)$$

where M is the degree of model input *u(t-1)*, $\alpha_j(t)$ is a function of past inputs and outputs. Now the model can be treated as a pure power series of the input *u(t-1)* with associated time varying parameters $\alpha_j(t)$. As compared with other modelling techniques, U-model has following benefits.

- The discrete form of many nonlinear continuous time systems can be represented in the form given in Equation (2)
- Since the model exhibits a polynomial structure in the current control term *u(t-1)*, the control law can be synthesized simplistically using Inverse Model Control (IMC). This implies to design a controller that is inverse of polynomial expression based on *u(t-1)*. The inverse of polynomial expression can be computed using various nonlinear methods such as Newton Raphson, Bisection method etc. This is a clear advantage as many other methods leads to complex nonlinear equations.

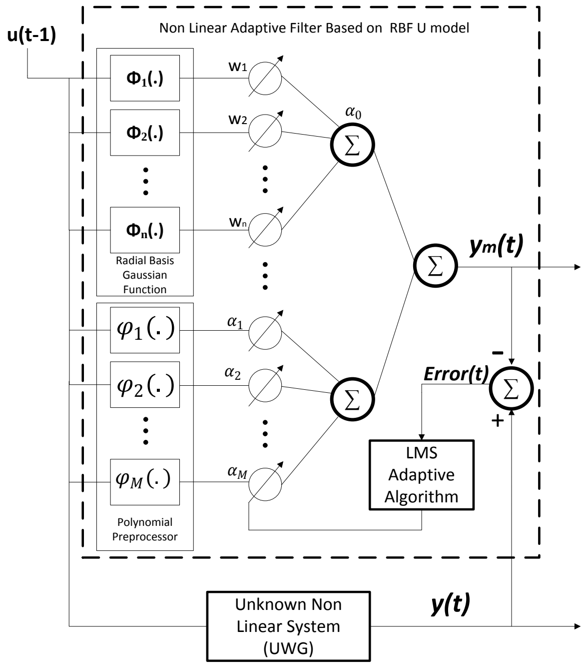


Figure 2 U-model filter with RBF

To assist system identification and achieve higher modelling accuracy in presence of additional disturbances and noises, Radial basis function neural network (RBFNN) is incorporated with U-model [19-20] to compute $a_0(t)$.

$$\alpha_0(t) = \hat{w}_0(t)\Phi\big(u(t-1)\big) + \hat{w}_1(t)\Phi\big(u(t-1)\big) + \cdots + \hat{w}_n(t)\Phi\big(u(t-1)\big) \tag{5}$$

$$W(t) = [\hat{w}_0, \hat{w}_1, \dots, \hat{w}_n\,] \tag{6}$$

Figure 2 shows structure of proposed U-model based RBF identification filter. Polynomial preprocessor generates the power series of the input signal $u(t-1)$ as given by Equation (7), whereas RBFNN transforms input space into higher space by using Equation (8).

$$\varphi i(u(t-1)) \;=\; u^i(t-1) \qquad \text{for i = 1, 2, 3,…, M} \tag{7}$$

$$\Phi_i\big(u(t-1)\big) = \exp\left(-\frac{\|u(t-1)-C_i\|^2}{\beta^2}\right) \qquad \text{for i = 1, 2, 3,…, n} \tag{8}$$

U-model time varying parameters $a_j(t)$ and weights of RBFNN $W(t)$ are updated online using Normalized Least Mean Square (nLMS) as given by Equation (9) and Equation (10).

$$\alpha_j(t+1) = \alpha_j(t) + \mu(t)Error(t)U(t) \tag{9}$$

$$W(t+1) = W(t) + \mu(t)Error(t)\Phi(t) \tag{10}$$

Here $\mu(t)$ represents learning rate ranging from 0 to 1. *Error*(t) is the mismatch error between actual and modeled output.

$$Error(t) = y(t) - y_m(t) \tag{11}$$

2.2 Adaptive Identification of Underwater Glider

U-model is a simplistic modelling technique that not only identifies unknown systems effectively but also lends itself to simplistic controller design. The purpose of adaptively identifying UWG using U-model is to simplistically synthesize control law based on Internal Model Control (IMC) Scheme. This study aims to adaptively identify USM underwater glider for depth and pitch control in simulation environment. The transfer function relating input ballast rate to depth and pitch angle of UWG as obtained from literature [21-22] is given in Equation (12) and (13) respectively.

$$G_{Depth}(z) = \frac{-0.662z^3+1.327z^2-0.665z}{z^4-2.02z^3+0.063z^2+1.934z-0.977} \tag{12}$$

$$G_{Pitch}(z) = \frac{10.1z^6+21.94z^5+16.84z^3-21.7z^2+9.56z}{z^7-1.95z^6+1.083z^5-1.17z^4+1.69z^3-0.37z^2-0.33z+0.05} \tag{13}$$

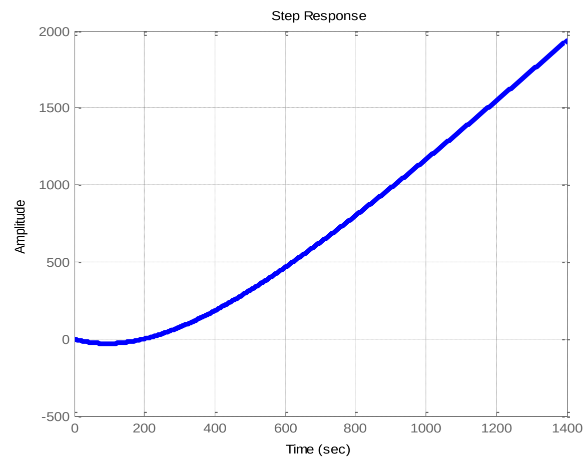


Figure 3 Open loop response for depth

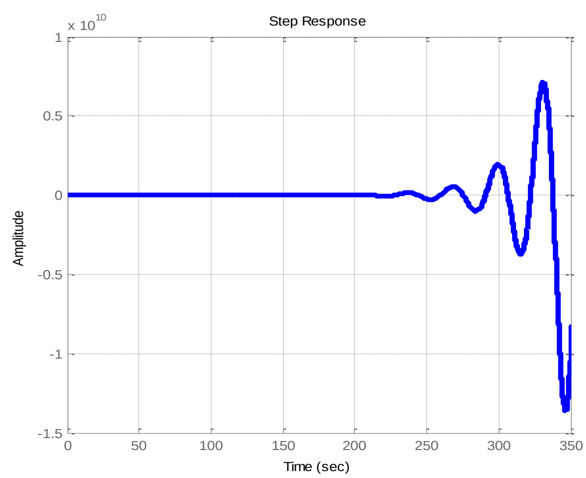


Figure 4 Open loop response for pitching angle

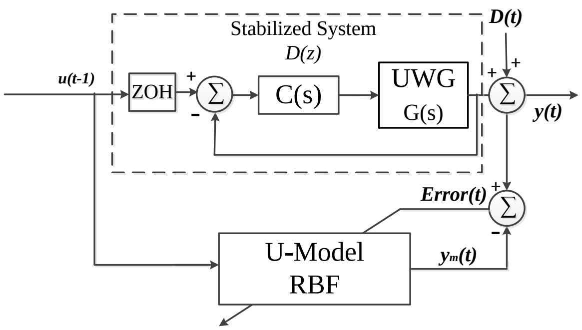


Figure 5 Proposed U-model Identification Filter

From open loop response as shown in Figure 3 and 4, it can be inferred that glider dynamics for controlling both depth and pitch angle are unstable. In order for U-model to be stable, the glider dynamics to be identified has to be stabilized priori. An unstable system will lead the whole structure of U-model and IMC to be unstable. Hence if the system is inherently unstable, it must be stabilized using robust techniques prior to applying proposed identification scheme.

2.2.1 Stabilization of UWG

In this section, the technique used to stabilize UWG before identifying is discussed. The structure of U-model is modified to add an inner stability loop consisting of a PID compensator *C(s)* as shown in Figure 5. By trial and error method, the gain values for PID compensator that stabilizes depth and pitching angle are selected.

For depth control of UWG, compensator selected to stabilize is as given in Equation 14. The open loop response after stabilization (as shown in Figure 6) gives a bounded response and settles to desired value.

$$C_{depth}(s) = \frac{-25s-40}{s} \tag{14}$$

$$G_{depth}(s) = \frac{-0.6764s^4-6.605s^3-26.44s^2+0.2396s-5.031e^{-13}}{s^5+0.9004s^4+39.48s^3+0.1198s^2+2.336e^{-13}s+1.692e^{-14}} \tag{15}$$

$$D_{depth}(z) = \frac{0.9419z^5-2.383z^4+1.976z^3-0.517z^2+0.03571z+0.0008807}{z^6-2.62z^5+2.344z^4-0.8347z^3+0.1166z^2-0.005582z+0.0001357} \tag{16}$$

For pitch control of UWG, compensator is obtained from [22] as given in Equation 17. The open loop response after stabilization (as shown in Figure 7) gives a bounded response and settles to desired value with oscillation at the beginning.

$$C_{pitch}(s) = \frac{82s^2+0.00003s+1.5}{s} \tag{17}$$

$$G_{pitch}(s) = \frac{-2.265s^7-103.5s^6-230.2s^5+1379s^4-9344s^3+3.147e^4s^2+1.23e^5s+2.428e^5}{s^8+7.978s^7+75.23s^6+299s^5+942.5s^4+2714s^3+276.8s^2+78.92s+19.82} \tag{18}$$

$$D_{pitch}(z) = \frac{1.005z^9-9.246z^8+5.288z^7-16.12z^6+75.9z^5-95.67z^4+49.88z^3-11.48z^2+0.3063z-0.001263}{z^9-9.201z^8+5.234z^7-16.04z^6+75.5z^5-94.91z^4+49.24z^3-11.21z^2+0.2536z+1.087e^{-10}} \tag{19}$$

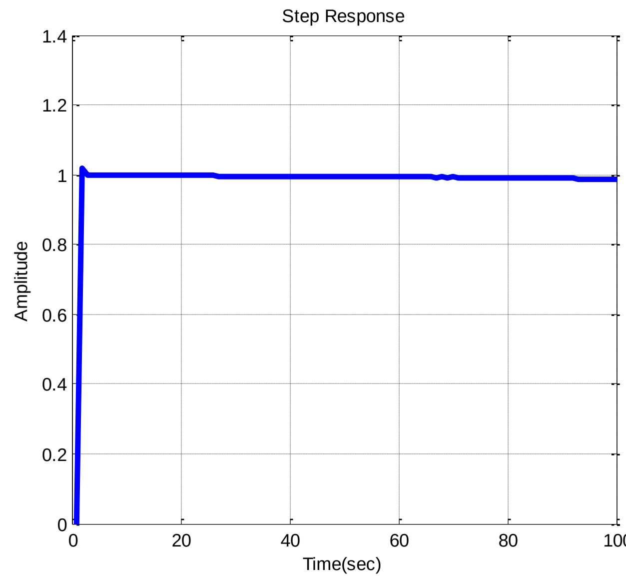


Figure 6 Open loop Response for depth (stabilized)

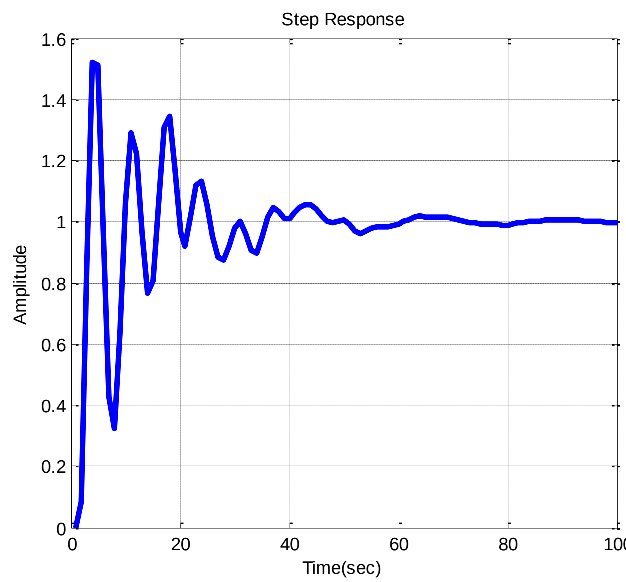


Figure 7 Open loop response for pitch (stabilized)

3.0 RESULTS & DISCUSSION

In this section, proposed U-model identification filter is implemented in simulation environment to identify UWG under hydrodynamic disturbances for depth and pitch control. The hydrodynamic disturbances considered in this work are simulated using signal builder block function in MATLAB as shown in Figure 8. Hence, it's an approximation of actual water current wave.

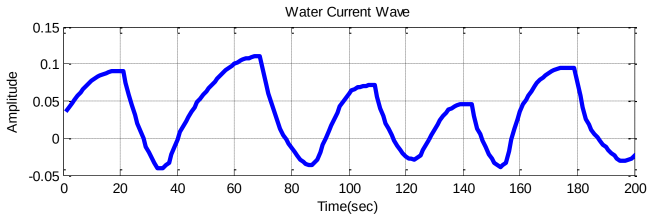


Figure 8 Water current wave

Figure 9 to 12 shows recorded identification results for depth and pitch control with and without consideration of hydrodynamic disturbances. The recorded results are obtained from third order U-model with learning rate of 0.5. The centers of RBFNN are chosen between -2 and 2 with a constant width of 0.25 to cover large input space for both control variables. Initial values of U-model parameters $a_j(t)$ and RBFNN weights $W(t)$ are chosen randomly and adjusted through NLMS algorithm until modeled output tracks the actual output with minimal error. In order to verify the proposed U-model scheme, the modelled output $Y_m(t)$ as obtained from U-model is compared with actual output $Y(t)$ that is obtained from given transfer function. It is evident from the result that within first few time samples, modelled output adapts to the actual output with nearly zero error. Further, it is also apparent that performance of proposed identification filter remains unchanged even under hydrodynamic disturbances caused by approximated water wave current.

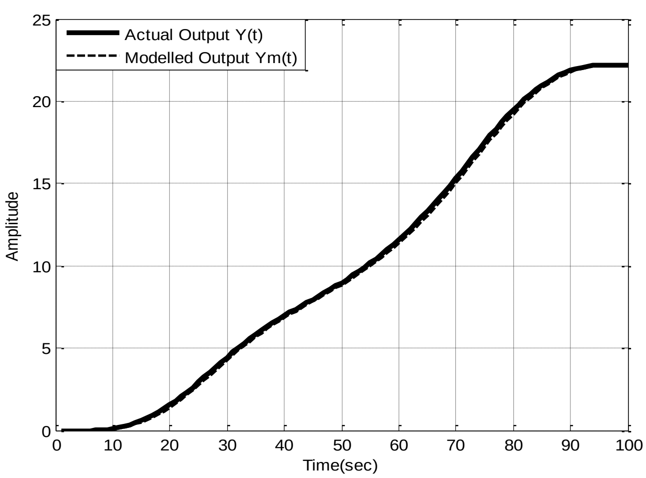


Figure 9 U-model Identification for depth control

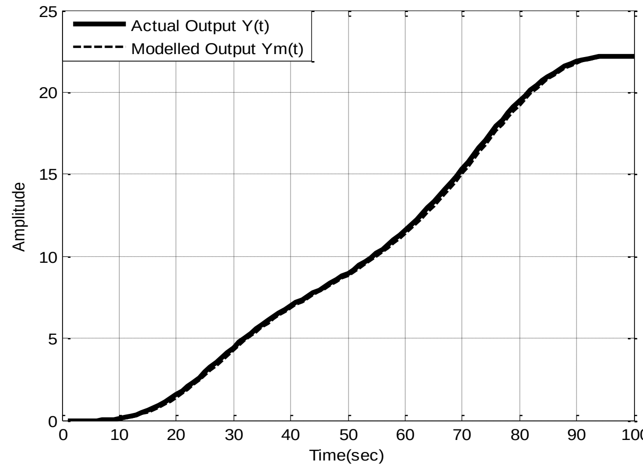


Figure 10 U-model identification for depth control under hydrodynamic disturbances

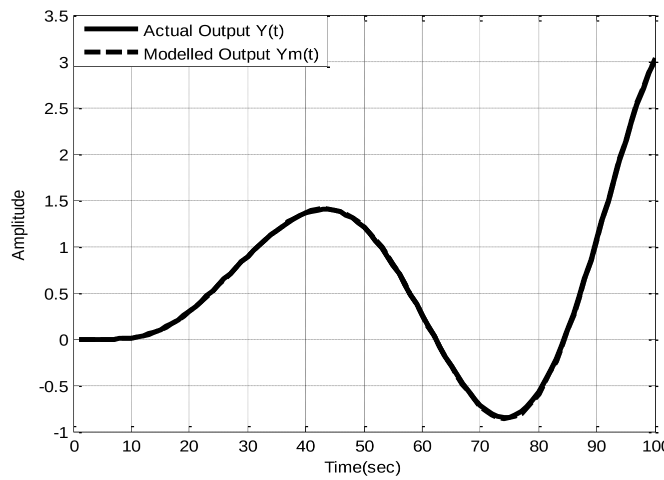


Figure 11 U-model identification for pitch control

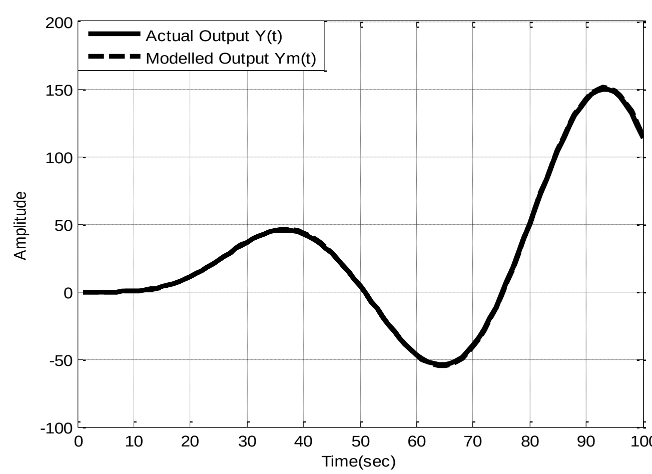


Figure 12 U-model identification for pitch control under hydrodynamic disturbances

4.0 CONCLUSION

In conclusion, an adaptive identification scheme based on U-model is proposed. RBFNN is combined with U-model to achieve higher accuracy in modelling underwater glider. The performance of proposed identification filter has been evaluated in presence of hydrodynamic disturbances caused by approximated water wave current. It is shown that the U-model is able to identify underwater glider adaptively and accurately even under presence of hydrodynamic disturbances. Since the proposed identification filter is control oriented in nature, hence it can be further used to synthesize a simple law for control inputs to control depth and pitch of UWG.

Acknowledgement

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