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Underactuated nonlinear adaptive control approach using U-Model incorporated with RBFNN for multivariable underwater glider control parameters

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Underwater glider platform represents the maturing technology with a large cost saving over current underwater sampling process. It can survey and monitor the sea environment cost-effective manner combining survey capabilities, simultaneous water sampling and environmental data gathering capacities. It can perform a wide range of fully automated monitoring data measurement over an extended period of time. This paper will focus on the design of multivariable underactuated nonlinear adaptive control using U-model methodologies. Underwater glider control, modelling and identification approach was reviewed in order to formulate the design, development and control approach of underwater glider development using multivariable adaptive U-model nonlinear control approach. U-model methodology simplifies the control synthesis with the influence of the uncertainties and external disturbances by selecting appropriate control structures. Most of the autonomous underwater vehicle (AUV) neglected the coupling effect of the dynamics during process modelling while U-model enables to include the coupling effect using the inverse Jacobian matrix. U-model incorporated with RBFNN enhance the adaptive nonlinear control synthesis. Thus contributes towards the underactuated nonlinear adaptive control development and process modelling.

[**Keyword:** Multivariable, underactuated, coupled, MIMO, Nonlinear adaptive & Underwater glider]

Introduction

Most of the underwater vehicles control scheme are based on the underactuated system due to the restriction of shapes, cost, complexity, power consumption and etc[1-5]. The system is considered underactuated when a number of control actuators are less than the degree of freedom of the system. The underactuated control design for unmanned underwater vehicles application continues to pose challenges for scientists and designers. Major elements that make it difficult to control underwater vehicles such as coupled and highly nonlinear time varying dynamic behaviour of the underwater vehicles, uncertainties in hydrodynamic coefficients and disturbances by the ocean currents. Therefore, it is desirable to have a control system that includes coupled model and has adaptation capabilities when the control performance degrade during the mission due to changes in the vehicle's dynamics and its environment[6]. Underwater glider platform operates using less control actuator in order to perform its mission with less energy. With fewer control actuators, underwater glider platform needs to overcome the coupled and nonlinearity of the dynamics and disturbances from the underwater environment. In order to implement good control strategies for the underwater glider, the appropriate hydrodynamic model shall be estimated and calculated in the early stage of design and development. Underwater vehicle must overcome the unstructured environment that can change the dynamics over the operation time.

The effect of nonlinearities is not severe if the operating conditions are constant and limited or mild.

However, when the conditions are not clear due to the disturbances or unknown effect, linear approximation model fails to perform. Again, most of the underwater vehicles control system is the multivariable system. Then again, there is no such broad precise methodology for nonlinear frameworks. In significant cases, control framework outline strategies for nonlinear control system vary from one framework to the others. There are a few methodologies for nonlinear control framework plan in literature in which attempting to remunerate nonlinear framework practices.

An adaptive fuzzy sliding mode controller is proposed to estimates the nonlinearity of MIMO underwater vehicles in [7]. The fuzzy logic control approximates the couple dynamics of the AUV. However, this method needs to be integrated with sliding mode controller for stability analysis and systematic control design method. The controller design is more complex and higher computational demand. The fuzzy logic control can reduce the chattering effect caused by the discontinuity of the sliding mode control system excites by unmodeled dynamics. The performance of the control system is demonstrated via simulation by tracking the velocities in 3 degrees-of-freedom dynamics with the 3 degrees-of-freedom added disturbances. Another method using sliding mode control to overcome nonlinear external disturbances in underwater vehicles application demonstrate by[8]. The chattering effect can be minimised using a novel robust dynamic region-based control scheme. The region boundary technique is compared with the adaptive sliding mode control without the region technique and a fuzzy sliding mode control method and has a better performance in underwater thrusters power consumption. However, it is difficult to determine the appropriate rules to obtain a good result in the fuzzy sliding mode controller.

In [9], predictive control method using the neural network controller based on multi-layer perceptron has been designed and simulates for the hybrid-driven underwater glider to overcome the nonlinearity. The control system consists of MIMO (6 inputs, 14 states and 14 outputs) however the nonlinear plant of the hybrid-driven underwater glider need to be linearized first. Using a three-layer network with 6 input nodes, 6 hidden layer nodes and 14 output nodes as a forward model of the control system. The backpropagation training algorithm was used to train the neural network model and the simulation results converge with the desired output. However there some system outputs that cannot be accomplished by the controller that is a combination of desired roll angle and heave velocity. Later the work in [9] has been extent to overcome the weakness by designing a biologically inspired weight tuning algorithm in [10]. The homeostatic controller is inspired by a biological process known as homeostasis, which maintains stable which keeps up a steady state despite hugely dynamic conditions. It was shown in the simulations that the homeostatic controller algorithm was successfully optimised the glider's motion control system and produced better control performance although the optimisation percentage is considered low and higher modelling complexity.

The hydrodynamics changes will affect the overall control system performance. To overcome this situation estimation of hydrodynamic parameters via system identification method can be utilised. System identification technique is based onboard sensor data rather than towing tank experiments that are more complex, expensive and time-consuming[11-13]. The modelling and identification method was implemented in the unmanned underwater vehicle platform such as in[14] for vehicle's hydrodynamic. The identification technique was used to estimates the drag and thruster installation coefficients without using towing tank facilities to obtain hydrodynamic coefficients, taking into account propeller-hull and propeller-propeller effects and inertia parameters using least squares method. This method, however, using decoupled technique. In[15] demonstrate the tracking or identification of AUV MIMO nonlinear adaptive control design techniques using neural networks. Neural networks represent as a nonlinear system with the ability to adapt itself according to a performance index based on the training algorithm used. It implements multilayer networks containing neurones and the complexity of the problems depending on the network size. The performance of the controller is validated thru convergence speed, tracking error and stability of the system by tuning the learning rates. The robustness of the controller is observed by disturbing the AUV parameters to see the tracking of command signal capabilities with different training rates. However, this method used 4 layers of the network for single-input and single-output (SISO) and demand high computational time. It is desirable to use less network layer for MIMO application in order to reduce the computational time. Most of the unmanned underwater vehicles used the decoupled control technique in practical application for simplicity in process modelling. However, simplification in process modelling will reduce the efficiencies of designing a good nonlinear controller. The dynamics of the underwater glider depends on the underwater conditions such as underwater currents and waves. The optimum design of the unmanned underwater vehicle platform can be achieved by conducting appropriate modelling of hydrodynamics and control system for better guidance and manoeuvrability. The control system of the underwater glider needs to overcome with the external disturbances and uncertainties due to the unstructured underwater environment. A MIMO nonlinear adaptive control approach can be implemented in process modelling for control system development. Depending on the control structure it could be complicated to be implemented in the onboard controller and computationally time-consuming because of its excessively complex structure. Thus, it is highly desirable to design a MIMO nonlinear adaptive controller that can simplify the control synthesis and to modelling the external disturbances and payload variation in order to design an adaptive control scheme which is robust to external perturbations. This paper is organized in three section of approach and methods. Method for nonlinear adaptive MIMO using recent U-model technique in subsection A. Underwater glider adaptive MIMO nonlinear U-model based Internal Model Control in subsection B and nonlinear U-model identification for adaptive control scheme. Finally results and discussion are presented after the approach and methods section.

Adaptive Nonlinear U-Model Approach

A. Underwater glider Adaptive MIMO Nonlinear U-Model Based System

Another method for nonlinear identification is using a recent U-model technique. It is a mathematically the solution of the controller output is converted into resolving a polynomial equation in the current control term U(t)[16]. U-model is an adaptive control oriented model and it is based on control input signal. It is more general compare to other estimation approaches and exhibits polynomial structure applicable with the control term. A nonlinear adaptive pole-placement control was used that further improves adaptive tracking of nonlinear dynamic plants[17]. This is because controller design methodologies derived from linear systems can be developed accordingly to design nonlinear discrete-time systems. A novel nonlinear dynamic plant tracking technique was introduce based on U-model approach. The U-model approach can also predict the unknown MIMO control parameter based adaptive tracking scheme[18]. The controller can be represented as the inverse of plant model based on the U-model algorithm using the numerical root solver method when the reference output error are minimised. The controller design methodology for the linear system can be implemented to design nonlinear discrete time system using U-model approach[19]. Underwater glider consists of multiple control actuators and multiple output condition such as velocity, angular velocities, internal mass location and momentum and etc.

These MIMO systems are exposed by the external disturbance and uncertainty that may cause the fluctuation of the system parameter during operation although the system dynamics may be well known in the beginning. The controller needs to identify or track the system online with a minimum error that enables the system working properly. Nonlinear adaptive control approach for the underwater glider enable the control system to track or learnt the dynamics and adjust themselves during external uncertainty or parameter disturbances and maintain an acceptable level of performance. Using the appropriate control scheme that can identify system online and follow the output based on certain trajectories. Such adaptive control scheme is Model Based Control (MBC) that widely used as a nonlinear adaptive system and provides usable tools for modelling, estimation and controller design methodologies[17,20-22]. Proper modelling and control structure selection contributes to the overall control system performance. This will lead to the ability to identify rapidly of the plant dynamics and the controller model.

Recently developed control oriented model for multivariable system call U-model can be implemented to acquire experiment data and to perform model identification of the underwater dynamics with the disturbances[20]. U-model is control oriented model and it is based on control input signal. MIMO system with m-inputs and p-outputs where *U(t)* is a vector consisting of control input signals and *Y(t)* is a vector containing the output as in (4). U-model expands the nonlinear NARMAX equation as a polynomial in the current control signal as in (1). U-model simplifies the control parameters term in a polynomial form[22,23]. The U-model can be obtained by expanding the NARMAX equation (1) as a polynomial with respect to *u(t-1)* as the following:

$$y(t) = \sum_{j=0}^{M} \alpha_j(t) u^j(t-1) + d(t) \qquad (1)$$

Where M is the degree of model input *u(t-1)*, $\alpha_j(t)$ is function of past inputs and outputs *u(t-2),…,u(t-n)*, *y(t-1),…,y(t-n)* and errors *d(t-1),…, d(t-n)*. $\alpha_j = [\alpha_0, \alpha_1, \dots, \alpha_M]$. Where M is the degree of model input *u(t-1)*, $\alpha_j(t)$ is function of past inputs and outputs *u(t-2),…,u(t-n)*, *y(t-1),…,y(t-n)* and errors *d(t-1),…, d(t-n)*. $\alpha_j = [\alpha_0, \alpha_1, \dots, \alpha_M]$, Consider the example in (2):

$$y(t) = 3y(t-1)y(t-2) - 0.3y(t-1)u^2(t-1) + 0.5(t-1)u(t-2), \qquad (2)$$

Which can be written as U-model format as,

$$y(t) = \alpha_0(t) + \alpha_1(t)u(t-1) + \alpha_2(t)u^2(t-1) \quad (3)$$

where $\alpha_0(t) = 3y(t-1)y(t-2)$, $\alpha_1 = 0.5u(t-2)$ and $\alpha_2 = -0.3y(t-1)$.

The U-model representation is mathematically simple and can be used to represent a wide class of nonlinear plant. The control structure of U-model is more general than another nonlinear model such as NARMAX, Hammerstein, Bilinear, Lur'e, Nonlinear Autoregressive model with Exogenous Input (NARX), Nonlinear Finite Impulse Response (NFIR) and Output Affine Model[24]. Equation (31) can be expanded to the MIMO U-model structure as the following,

$$Y_m(t) = \sum_{j=0}^{M} A_j\, U^j(t-1) = F(U(t-1)) \quad (4)$$

Y_m(t) is a vector *p* x 1 and *U(t-1)* is the current control signal with *m x* 1 control input vector. M is the degree of multivariable polynomial while U^j is the vector with j^{th} power of control inputs $u_i(t-1)$ as,

$$U^j(t-1) = [u_1^j(t-1)u_2^j(t-1) \ldots u_m^j(t-1)]^T, \quad (5)$$

Since the U-model is a polynomial equation structured in control signal u(t-1), the control law can be synthesised using inverse model control. The controller output u(t-1) is obtained using the Newton-Raphson algorithm for root solving method. Selecting the previous control signal as the initial value for the next time instant using Newton-Raphson is given by,

$$u_{i+1}(t-1) = u_i(t-1) - \frac{y_m - x(t)}{y_m'(t)} \quad (6)$$

$$u_{i+1}(t-1) = u_i - \frac{\sum_{j=0}^{M} \alpha_j(t)u^j(t-1) - \mathrm{x(t)}}{d\sum_{j=0}^{M} \alpha_j(t)u^j(t-1)/\mathrm{d}u_i(t-1)} \quad (7)$$

Where *i* is the iteration index. *x(t)* is the input of the controller, *u(t-1)* is the output of the controller and y_m is the model output The parameters of the U-model are identified online and used in the control signal as,

$$u_{i+1}(t-1) = u_i(t-1) - \frac{\sum_{j=0}^{M} \widehat{\propto_j}(t)u^j(t-1) - \mathrm{x(t)}}{d\sum_{j=0}^{M} \widehat{\propto_j}(t)u^j(t-1)/\mathrm{d}u_i(t-1)} \quad (8)$$

Where $\widehat{\propto_j}$ are the estimates of α. The plant parameters can be estimates and updated online using any parameter estimation algorithm such as Normalized Least Mean Squares (nLMS).

Newton-Raphson based controller solution for MIMO U-model can be express as,

$$U_{k+1}(t-1) = U_k(t-1) + F'(U_k(t-1))^{-1}(X(t) - F(U_k(t-1))) \quad (9)$$

The term $F'(U_i(t-1))$ is the *Jacobian* matrix with elements $df_i/du_{kj}\,(t-1)$, corresponding to the j^{th} input and i^{th} ouput.

$$F'(U_i(t-1)) = \begin{pmatrix} df_1/du_{k1}(t-1) & df_1/du_{k2}(t-1) & df_i/du_{kp}(t-1) \\ df_2/du_{k1}(t-1) & df_2/du_{k2}(t-1) & \vdots \\ df_p/du_{k1}(t-1) & \cdots & df_p/du_{kp}(t-1) \end{pmatrix} \quad (10)$$

The *Jacobian* matrix takes care of the process interactions and coupling between system variables. Thus the MIMO U-model based schemes are taking care of nonlinear coupling effect between dynamics. In the case of the non-square matrix and singular *Jacobian* matrix during updating process one of the following techniques can be implemented[21]:

a) Employing pseudoinverse,
b) Using the inverse of *Jacobian* matrix from the previous instant,
c) Adding a small number to the *Jacobian* matrix to avoid the singularity.

B. Underwater glider Adaptive MIMO Nonlinear U-Model Based Internal Model Control

The proposed nonlinear identification using U-model for an adaptive control scheme for underwater glider platform. An adaptive Internal Model Control (IMC) structure implemented for the nonlinear identification for the process modelling. Figure 1 shows the online adaptive Internal Model Control (IMC) using U-model approach. IMC control structure is composed of the plant model and a stable feed-forward controller. The IMC control structure guaranty the internal stability of the closed loop and the parameters can be tuned online without disturbing the stability of the system[19,22-23]. IMC can be used for both linear and nonlinear systems. The control structure includes the plant model in parallel with the U-model, *Pm.* The nonlinear controller provides the input for the U-model and the plant *U(t-1)*. The error signal *e(t)* is used a feedback to the nonlinear controller. The unknown parameters of the plant are estimates by the

U-model using the nLMS algorithm such that *e(t)* is minimised. These updated U-model parameters are then fed to the nonlinear controller. The controller then calculates the *U(t-1)* online by root solver algorithm. The evaluated inputs then are used to drive the plant and U-model. Thus when *e(t)* has been minimised, the inverse of the plant is obtained and *U(t-1)* ultimately cause the plant to follow the command input *r(t)*. IMC structure will remain stable if both of the plant and controllers are stable[22]. Therefore the stability of the proposed U-model based IMC depends on the stability of the U-model and U-model based controller.

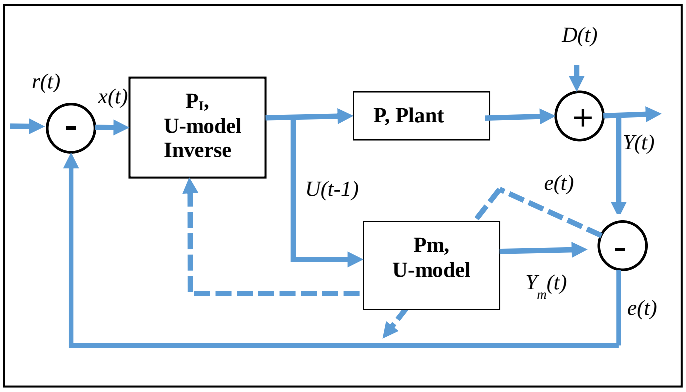

Fig. 1 - Online adaptive Internal Model Control using U-model

C. Adaptive Radial Basis Function Neural Networks

In order to acquire higher modelling accuracy with less error correlation, neural networks are integrated with the U-model methodology. Radial basis function neural networks (RBFNN) consist of single layered feedforward networks and offer faster learning time compared with multilayered feedforward neural networks (MFNN). RBFNN capable to approximate the linear and nonlinearity in the systems. This algorithm has been used in multi-application such as control system, signal processing, medical, renewable energy, machine learning such as in[25-30]. The RBFNN is incorporated with U-model by computing $A_0(t)$ while $A_1(t), A_2(t), \ldots A_M(t)$ by nLMS algorithm.

$$A_0(t) = Y(t) = \widehat{w_1}\varphi\big(u(t-1)\big) + \widehat{w_2}\varphi\big(u(t-1)\big) + \cdots \widehat{w_n}\varphi\big(u(t-1)\big) \quad (11)$$

Where $\widehat{w_n}$ and φ are the weights with n number of neurons and basis function. The input of the ith hidden neuron as in equation (12).

$$\varphi_i(\|u(t) - c_i\|) \quad (12)$$

Where c_i is the center of the ith hidden layer node while the weight vector for each neuron as in (13) below.

$$W(t) = [\widehat{w_0}\ \widehat{w_1}\ \widehat{w_2} \ldots \widehat{w_n}] \quad (13)$$

Equation (11) can be simplified as in (14) below.

$$A_0(t) = W\varphi(t) \quad (14)$$

The Gaussian function is chosen as the basis function as in (15).

$$\varphi_i(u(t-1)) = \exp\left(-\frac{\|u(t)-c_i\|^2}{\beta^2}\right) \quad (15)$$

Where c_i is the center of the neuron and $\|u(t) - c_i\|$ is the Euclidean distance (distance from the center and the input value) β is the width which the range of input passing through the basic function. U-model time varying parameters $A_0(t)$ and $W(t)$ are updated using online nLMS as given by equation (16) and (17).

$$W(t+1) = W(t) + \mu(t)e(t)\varphi(t) \quad (16)$$

$$A_i(t+1) = A_i(t) + \mu(t)e(t)U(t) \quad (17)$$

Where μ(t) is the nLMS learning rate which ranges from 0 to 1. The error of the mismatch between the U-model and actual output is *e(t)*.

D. Nonlinear U-Model Identification for Adaptive Control Scheme

The kinematics of the vehicle can be explained based on the Fig. 2[31]. Consider an inertial frame *x*, *y* and *z*. Let *x* and *y* inertial axes lie in the horizontal perpendicular to gravity. The *z* axis lies in the direction of the gravity vector and is positive downwards. The inertial value for *z*=0 coincides with the water surface, in which case *z* is depth. Based on Fig. 2, the centre of the origin of the vehicle is the centre of buoyancy (CB) and the angle of attack, α is the angle between the components V_1 and projection of V (speed in the vertical plane) to (V_1-V_3) plane while V_2 is the lateral speed component. The sideslip angle β is defined as the angle from the projection of V to (V_1-V_3) plane and V. In the standard of aircraft literature, the orientation of the wind frame relative to the body frame will be described by two dynamic angles; the angle of attack, α and side slip angle, β. The wind reference frame is defined such as that one axis aligned with the velocity of the body relative to the V.

$$\alpha = \tan^{-1}(V_3/V_1) \text{ and } \beta = \tan^{-1}(V_2/|V|) \quad (18)$$

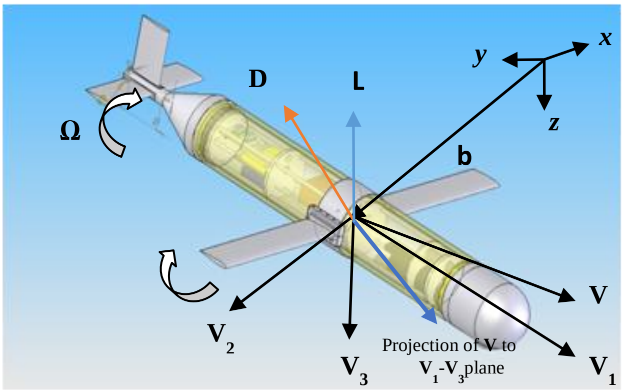

Fig. 2 - Underwater glider dynamics[31]

The orientation of the vehicle is given by the rotation matrix R which maps vectors expressed with respect to the body frame into internal body coordinates. Yaw ψ, pitch θ, and roll φ are the three rotation angles from the inertial body frame. Yaw ψ is defined as positive right (clockwise) when viewed above, pitch θ is positive nose-up and roll φ is positive right wing down. The position of the vehicle, b = $(x,y,z)^T$, is the vector from the origin of the vehicle's body. The vehicle moves with translational velocity V = $(V_1, V_2, V_3)^T$ relative with angular velocity **Ω** = $(\Omega_1, \Omega_2, \Omega_3)^T$ as shown in Fig. 2. Based on the modelling of underwater vehicle the equations $v_1 = (u\ v\ w)^T$ and $v_2 = (p\ \ q\ \ r)^T$ have been replacing by the translational velocity V = $(V_1, V_2, V_3)^T$ and angular velocity **Ω** = $(\Omega_1, \Omega_2, \Omega_3)^T$ for more convenient in the derivation and analysis.

Based on Fig. 3, the vehicle has buoyancy control and controlled internal moving mass and will manipulate the CB to change the glide angle and speed. The total mass of the vehicle or body mass can be defined by $m_v = m_h + m_w + m_b + \hat{m}$. The fix mass is represented by m_h, uniformly distributed mass. The point mass, m_w and the variable ballast mass, m_b are given by the vector r_w and r_b from the CB to the respective masses. The vector r_p describes the position of the moving mass $\hat{m}$ in the body fixed frame at time, *t*. The static mass parameters m_w and r_w can be rearranged to set the balance of the pitching and rolling moment on the vehicle from the other point masses. The mass of the fluid displaced by the vehicle is denoted by *m*. We define the net buoyancy $m_o = m_v - m$ so that the vehicle is negatively buoyant if m_o is positive (downward motion/sink) and it is positively buoyant if m_o is negative (upward motion/float).

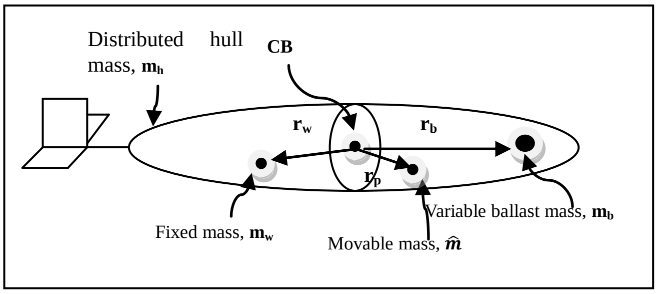

Fig. 3 - Underwater glider mass definitions

Simulation equation of motions in the vertical plane for underwater glider platform suggested by[31,32] are[33] conducted using the MATLAB software. Based on the[13,33] the forces and moment constant are modelled as:

$$\dot{x} = v_1 \cos\theta + v_3 \sin\theta \quad (19)$$

$$\dot{z} = -v_1 \sin\theta + v_3 \cos\theta \quad (20)$$

$$\dot{\theta} = \Omega_2 \quad (21)$$

$$\dot{\Omega}_2 = \frac{1}{J_2}\Big((m_3 - m_1)v_1 v_3 - (rp_1 Pp_1 + rp_3 Pp_3)\Omega_2 - \bar{m}g(rp_1 \cos\theta + rp_3 \sin\theta) + M_{DL} - rp_3 u_1 + rp_1 u_3\Big) \quad (22)$$

$$\dot{v}_1 = \frac{1}{m_1}(-m_3 v_3 \Omega_2 - Pp_3 \Omega_2 - m_0 g \sin\theta + L\sin\alpha - D\cos\alpha - u_1) \quad (23)$$

$$\dot{v}_3 = \frac{1}{m_3}(m_1 v_1 \Omega_2 + Pp_1 \Omega_2 + m_0 g\cos\theta - L\cos\alpha - D\sin\alpha - u_3) \quad (24)$$

$$\dot{rp}_1 = \frac{1}{\bar{m}}(Pp_1 - v_1 - rp_3 \Omega_2) \quad (25)$$

$$\dot{rp}_3 = \frac{1}{\bar{m}}(Pp_3 - v_3 - rp_1 \Omega_2) \quad (26)$$

$$\dot{Pp}_1 = u_1 \quad (27)$$

$$\dot{Pp}_3 = u_3 \quad (28)$$

$$\dot{m}_b = u_4 \quad (29)$$

$$D = (K_{Do} + K_D \alpha^2)(v_1^2 + v_3^2) \quad (30)$$

$$L = (K_{L0} + K_L \alpha)(v_1^2 + v_3^2) \quad (31)$$

$$M_{DL} = (K_{M0} + K_M \alpha)(v_1^2 + v_3^2) \quad (32)$$

$$V = \sqrt{(v_1^2 + v_3^2)} \quad (33)$$

K_{Do} = 18 N$(s/m)^2$; K_D = 109 N$(s/m)^2$; K_{Lo} = 0 N$(s/m)^2$; K_L = 306 N$(s/m)^2$; K_{Mo} = 0 N$(s/m)^2$; K_{Mo} = -36.5 N$(s/m)^2$

Coefficients are define as the followings:
J_2 = 0.1 kgm^2 ; m_o = 0.36 kg; m_h = 8.22 kg; m = 11.2 kg;
$\hat{m}$ = 2 kg; m_1 = 2 kg; m_3 = 14 kg.

The simulation of motion is conducted for downward and upward gliding conditions with the above value of added-mass coefficients. The motion conditions are depending on these coefficients. The initial condition are as the followings: v_1 = 0.3 m/s; pitching angle, θ = -0.5 radian; $m_b = \Omega = r_p = 0$. The ballast rate and position of movable mass are the control inputs for the simulation while net buoyancy, pitching angle and depth as the outputs. The equation of motion results are being implemented in the nonlinear underactuated MIMO identification using U-model IMC scheme. The U-model identification is obtain using third order U-model based in equation (1) with learning rate of 0.09 for nLMS algorithm. The identification and control synthesis of U-model were conducted by into two approach first by assuming input vector $u(t\text{-}1) = [1\ u(t\text{-}1)\ u(t\text{-}1)^2\ u(t\text{-}1)^3]$ and second approach by incorporated RBFNN with U-model. The input vector for RBFNN with U-model is $u(t\text{-}1) = [A_0(t)\ u(t\text{-}1)\ u(t\text{-}1)^2\ u(t\text{-}1)^3]$. $A_0(t)$ is modelled using RBFNN to assist nonlinear modelling. This can be achieved by implementing equation (14) with 3 neurons to compute $A_0(t)$. The centers of RBFNN are chosen between -0.02 and 0.02 with a constant width of 0.018. This is because the range of reference output is between -0.02 to 0.02. The learning rate value can be choose between 0 to 1 in order to guarantee the convergence process. The initial value for both approach of U-model parameters α_j, equation (5) are chosen randomly and updated every iteration via nLMS algorithm until the U-model tracks the reference output with minimal error. The controller effort for each input reference are calculated using Newton-Raphson root-solving method. In the case of underactuated control or non-square matrix, pseuodoinverse Jacobian matrix is implemented for taking care of the coupling effects without considering any restricting assumptions.

Results and Discussion

A. Nonlinear U-Model Identification without RBFNN

The MIMO underactuated IMC system considered is a 2-inputs and 2-outputs system as in Figure 4. Based on the Fig. 4 the control synthesis is compute using only 1 controller input for both plant and U-model. The modelling and identification process was done without neglecting the coupling effect between the subsystem using Jacobian matrix approach. The results of the U-model identification and control synthesis process are presented from Fig. 4 to Fig. 17. Only several results are discussed in the next paragraph.

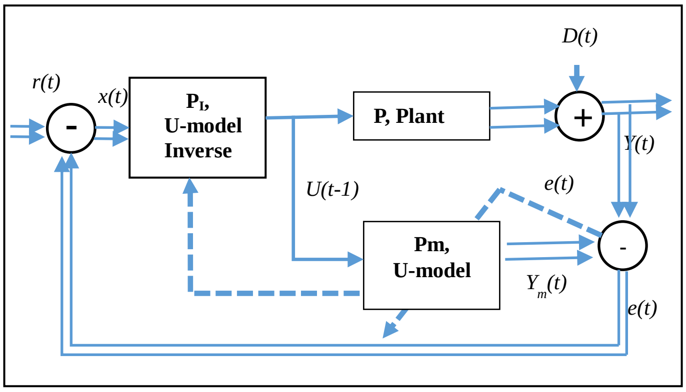

Fig. 4 – MIMO 2-inputs and 2-outputs underactuated IMC control structure

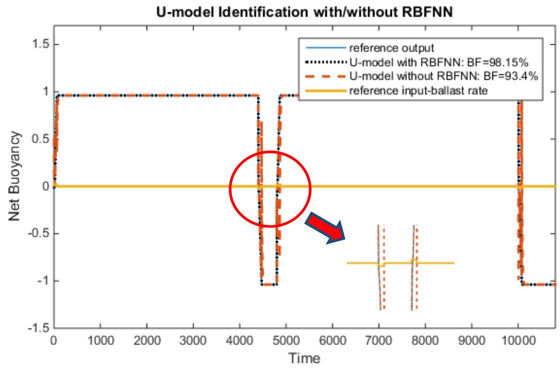

Fig. 5 – 2-inputs and 2-outputs coupled U-model Identification output 2 (net buoyancy) to input ballast rate

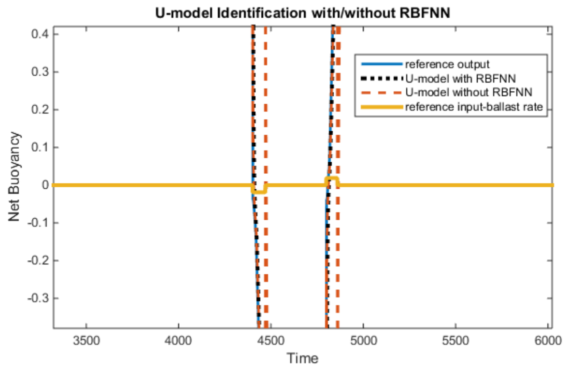

Fig. 6 – Zoom in 2-inputs and 2-outputs coupled U-model Identification output 2 (net buoyancy) to input ballast rate

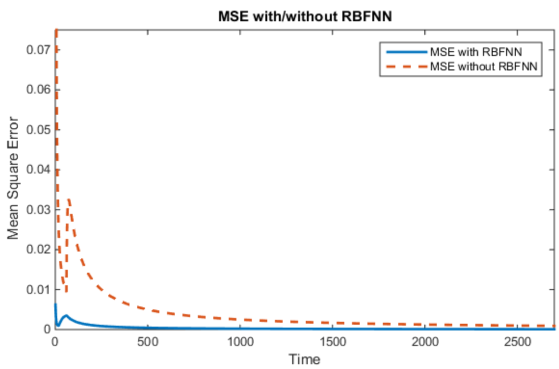

Fig. 7 – Mean square error 2-inputs and 2-outputs U-model Identification output 2 (net buoyancy) to input ballast rate

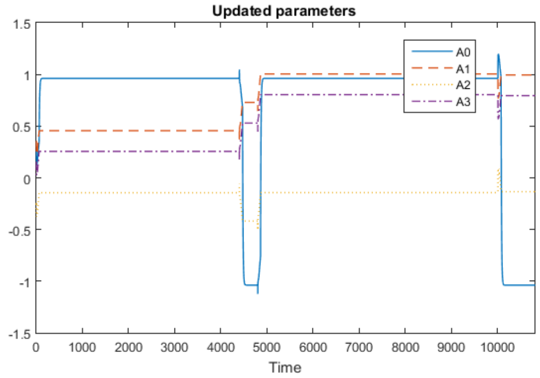

Fig. 8 - Updated Parameters A_0, A_1, A_2 & A_3 2-inputs and 2-outputs U-model Identification output 2 (net buoyancy) to input ballast rate without RBFNN

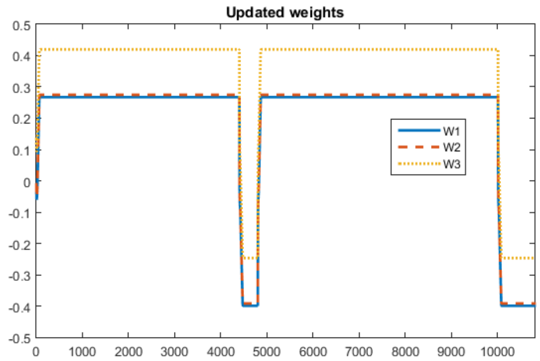

Fig. 9 – Updated weights $A_0 = \varphi_i(\|u(t) - c_i\|) * (W_1+W_2+W_3)$ 2-inputs and 2-outputs U-model with RBFNN Identification output 2 (net buoyancy) to input ballast rate with RBFNN

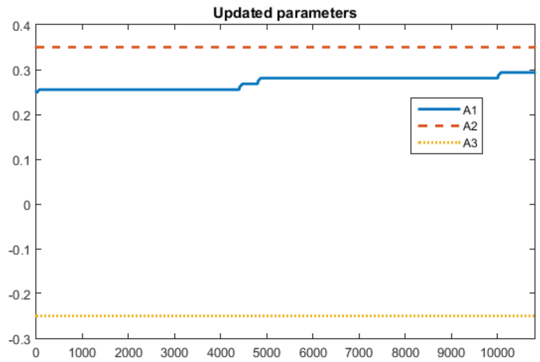

Fig. 10 – Updated Parameters A_1, A_2 & A_3 2-inputs and 2-outputs U-model with RBFNN Identification output 2 (net buoyancy) to input ballast rate

Fig. 5 and 6 shows the comparison between the nonlinear identification with and without RBFNN incorporated with U-model algorithm based on IMC control structure in Fig. 4. The reference input is the ballast rate with range of amplitude from -0.02 to 0.02. The different between this two approach are the input vector related to parameter A_0 . This parameter is modelled using RBFNN. The complexity of the model is depending on a number of neurones. All the parameters related to $A_{0\text{-}3}$ and $W_{1\text{-}3}$ are estimated online using adaptive nLMS algorithm for both approaches in equation (16) and (17). Both approaches in the nonlinear identification U-model process can perform 90% and above for best-fit criteria with a minimum mean square error. Best fit (BF) criteria can be defined as:

$$\mathrm{BF} = \left(1 - \frac{|y-\hat{y}|}{|y-\bar{y}|}\right) x\ 100\% \qquad (34)$$

where y is the simulated output, $\hat{y}$ is the estimated output and $\bar{y}$ is a mean of y. The best-fit criteria show improvement when U-Model incorporated with RBFNN. The best fit criteria of IMC increase from 93.4% to 98.15%. It can be varify by the zoom-in view in Fig. 6 that U-model with RBFNN tracks the reference output closely compare the U-model without RBFNN. Another comparison using mean square error (MSE) analysis in Fig. 7 that show the U-model with RBFNN out perform the U-model without RBFNN. Fig.8 shows the updated parameters A_0, A_1, A_2 and A_3 using adaptive nLMS algorithm without RBFNN while in Fig. 9 and Fig. 10 updated parameters and weights A_1, A_2 and A_3 and W_1, W_2 *and* W_3 with RBFNN. In this approach $A_0 = \varphi_i(\|u(t) - c_i\|) * (W_1+W_2+W_3)$ represent three neurons with activation function multiply by the updated weights.

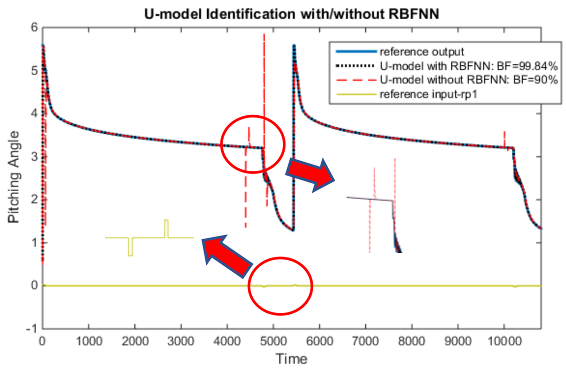

Fig. 11 - 2-inputs and 2-outputs coupled U-model Identification output 2 (pitching angle) to input rp1

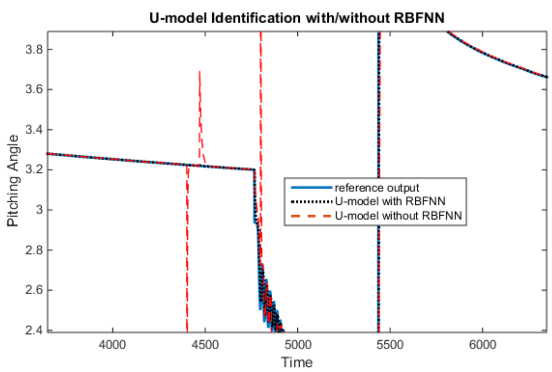

Fig. 12 - Zoom in 2-inputs and 2-outputs coupled U-model Identification output 2 (pitching angle) to input rp1

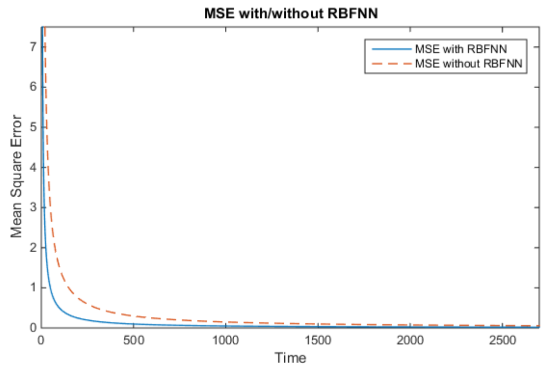

Fig. 13 - Mean square error *2-inputs and 2-outputs coupled U-model Identification output 2 (pitching angle) to input rp1*

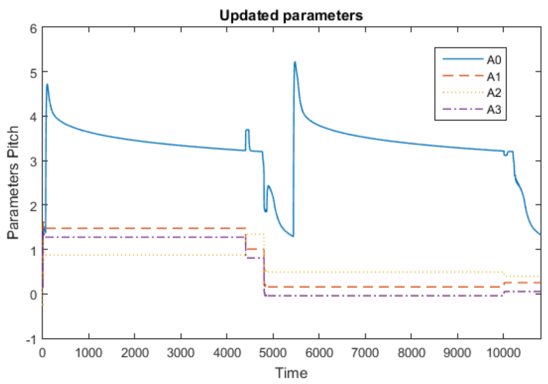

Fig. 14 - Updated Parameters A_0, A_1, A_2 & A_3 2-inputs and 2-outputs coupled U-model Identification output 2 (pitching angle) to input rp1

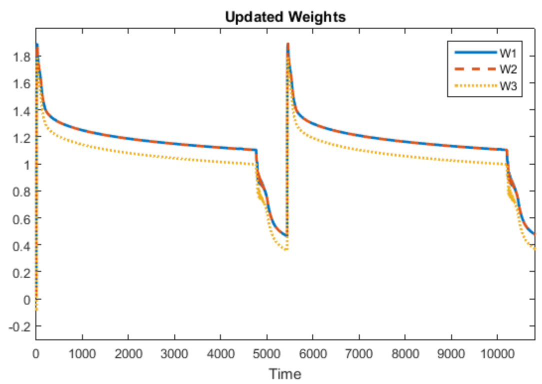

Fig. 15 – Updated weights $A_0 = \varphi_i(\|u(t) - c_i\|) * (W_1+W_2+W_3)$ 2-inputs and 2-outputsU-model with RBFNN Identification output 2 (pitching angle) to input rp1

Next the comparison between the nonlinear identification with and without RBFNN incorporated with a U-model algorithm based on IMC control structure for pitching angle as the output and *rp1* as the reference input. The amplitude of the reference input is between -0.019 to 0.019 with the same range of reference input ballast rate hence the same U-model for RBFNN algorithm. The best fit criteria of IMC increase from 90% to 99.84%. Fig. 11 and 12 shows a close tracking by U-model with RBFNN algorithm compare without RBFNN. MSE analysis in Fig. 13 the U-model with RBFNN has a better convergence than the U-model without RBFNN.

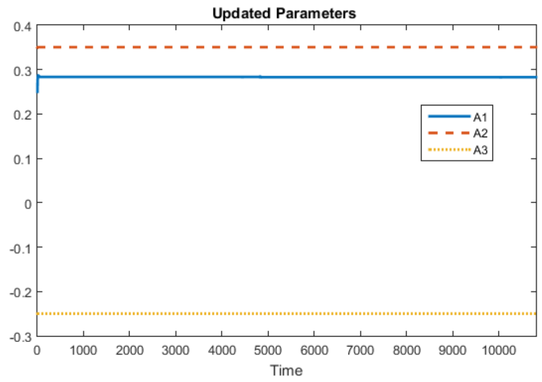

Fig. 16 – Updated Parameters A_1, A_2 & A_3 2-inputs and 2-outputs U-model with RBFNN Identification output 2 (pitching angle) to input rp1

Fig. 17 present the estimated control effort or control law for the underactuated or couple dynamic system without neglecting some of the nonlinear parameters interaction effects as in equation (9). Thus an appropriate controller can be designed according to estimated control effort for nonlinear underactuated and coupled system. When the adaptive tracking performances improve in accuracy, the control synthesis using U-Model methodology will represent better control performances.

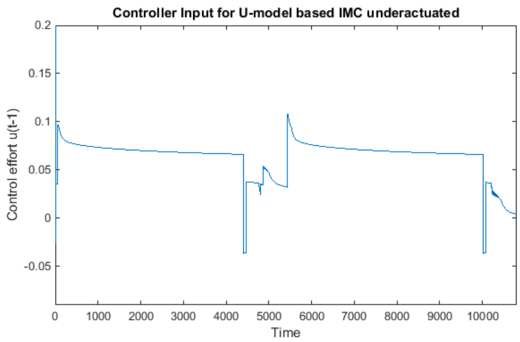

Fig. 17– Estimated control effort 2-inputs and 2-outputs couple IMC scheme

U-model incorporated with RBFNN capable of estimates the linearity and nonlinearity in system dynamics. It can be shown in Fig. 5 and Fig. 11 that the RBFNN have a better recursive capability compare to without RBFNN.

Conclusion

The high nonlinearity of underwater vehicle dynamics and underwater disturbances are the main reasons that make it difficult to control. Adaptive nonlinear control strategies can be implemented for the unmanned underwater vehicle application due to parameters uncertainties and unstructured environment which include learning capabilities. U-model adaptive control scheme combines the identification, learning and control within the same control structure for SISO and MIMO nonlinear model. U-model adaptive control scheme capable of identifying nonlinear coupled or underactuated control system using Jacobian matrix and make it possible to find the controller effort via matrix inverse. U-Model can be incorporated with the RBFNN to enhance the adaptive nonlinear control synthesis. This will contribute towards coupled modelling without neglecting some parameters in unmanned underwater vehicle process modelling.

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