Sensors & Transducers, Vol. 164, Issue 2, February 2014, pp. 288-294

Sensors & Transducers

Hydrodynamic Coefficients Identification and Experimental Investigation for an Underwater Vehicle

[1] Shaorong XIE, [1] Qingmei LI, [1] Peng WU, [1] Jun LUO, [1] Feng LI, [2] Jason GU
[1] School of Mechatronics Engineering and Automation, Shanghai University,
149 Yanchang Road, Zhabei District, Shanghai, 200072, China
[2] Department of Electrical and Computer Engineering Dalhousie University,
Halifax, B3J 2X4, NS Canada
Tel.: 021-56331204
E-mail: li_qm@shu.edu.cn

Received: 16 December 2013 /Accepted: 28 January 2014 /Published: 28 February 2014

Abstract: Hydrodynamic coefficients are the foundation of unmanned underwater vehicles modeling and controller design. In order to reduce identification complexity and acquire necessary hydrodynamic coefficients for controllers design, the motion of the unmanned underwater vehicle was separated into vertical motion and horizontal motion models. Hydrodynamic coefficients were regarded as mapping parameters from input forces and moments to output velocities and acceleration of the unmanned underwater vehicle. The motion models of the unmanned underwater vehicle were nonlinear and Genetic Algorithm was adopted to identify those hydrodynamic coefficients. To verify the identification quality, velocities and acceleration of the unmanned underwater vehicle was measured using inertial sensor under the same conditions as Genetic Algorithm identification. Curves similarity between measured velocities and acceleration and those identified by Genetic Algorithm were used as optimizing standard. It is found that the curves similarity were high and identified hydrodynamic coefficients of the unmanned underwater vehicle satisfied the measured motion states well. *Copyright © 2014 IFSA Publishing, S. L.*

Keywords: Unmanned underwater vehicle, Hydrodynamic coefficients, System identification, Genetic algorithm.

1. Introduction

The accuracy of the mathematical model plays a fundamental role in guidance and control system design for the underwater vehicle. The most commonly used model for underwater vehicles is based on Newton's theorem and the Lagrange equation proposed by Fossen and Ola-Erik [1]. However, in this model, hydrodynamic forces and torques applied on the vehicle were presented through a set of unknown hydrodynamic coefficients, which were determined by the vehicle shape, motion conditions and flow field around. The increased uncertainties of the model as well as the difficulties in obtaining hydrodynamic coefficients that can accurately express underwater vehicle's motion has become a focus of interest for researchers in the last two decades. In order to precisely model and design controllers for a remotely operated underwater vehicle (ROV) in the laboratory, we used data from experiments with sensors and identifying methods to obtain its hydrodynamic coefficients.

Planar-motion-mechanism (PMM) tests carried out with towing in tank [2] are traditional methods used to identify parameters for marine vehicles. Although operation processes of PMM tests have been standardized already, scale effects [3] and errors involved [4] make measured coefficients using PMM are not completely reliable. With the development of computer science, computational fluid dynamics (CFD) software are adopted to analyze motion phenomenon in the fluid for underwater vehicles instead of PMM tests [5]. In spite of cutting down experimental expenses, numerical truncations and difficulties in setting boundary conditions [6] contribute for the uncertainties of the results getting by CFD method. System identification (SI) is a widely used method in recent years for obtaining hydrodynamic coefficients because of both time and cost savings. Furthermore, compared to PMM and CFD, SI can avoid model modification caused by ROV configuration change and becomes a more practical alternative.

The most basic SI method is LS for its simple principles and the fact that it is easy to be realized in hardware. M. Caccia *et al.* [7] used LS method to identify an open-frame underwater vehicle with propeller affects. But according to P. Ridao *et al.* [8], the volume of samples affects the quality and standard deviation of LS identification significantly. Moreover, when the model is not linear, LS will become invalid. Artificial intelligence algorithm has advantages in uncertain system identification. P. W. J. Van De Ven *et al.* [9] used neural network (NN) to identify underwater vehicles. The weakness of NN is that its network configuration affects effect of the algorithm and it relays on experience of designer.

Inspired by biological genetic and evolvement process, GA is able to globally search optimal solution once initial population is set randomly. Then the influence of samples for results is lessened. In addition, GA has several appealing properties, like parallel optimization and robustness to disturbance, making it suitable for identification of nonlinear perturbed system as underwater vehicles. W. Yuan *et al.* [10] applied GA and simulated motion to get hydrodynamic coefficients of horizontal plane motion for AUV CRanger-01. The validity of GA in parameters identification for underwater vehicles was proved and the errors between real and identified hydrodynamic coefficients ranged from 0.17 % to -3.13%. However, when operated in the shallow water or near the sea surface, wave disturbances in the motion of underwater vehicles cannot be ignored as in [10]. What is more important, using measured motion data from sensors to identify parameters for underwater vehicles can better reveal their movement characteristics.

In this paper, we used GA to obtain both horizontal and vertical planes motion for an underwater vehicle while took wave disturbances into consideration at the same time. In order to improve identification accuracy, data used for identifying processes was measured with sensor module in the underwater vehicle. The hydrodynamic coefficients identified with method in this paper were compared with those identified with classical LS under the same conditions and the results of GA turned out to be better.

2. ROV Identification Mathematic Model

2.1. ROV Dynamics

The ROV used for experiments is shown in Fig. 1. It is equipped with three thrusters: one vertical thruster and two stern thrusters. As other marine vehicles, two coordinate systems are used to describe the motion of this ROV: the earth-fixed ($o-\xi\zeta\eta$) and body-fixed ($o'-xyz$) reference frames. Its motion contains translational motion in three directions: surge, sway, and heave; and rotational motions: roll, pitch and yaw [1]. The position of ROV in the earth-fixed system is given by linear displacement $\chi_1=[x,y,z]^T$ and Euler angle $\chi_2=[\phi,\theta,\varphi]^T$. The corresponding velocity and angular velocity are $V_1=[u,v,w]^T$ and $V_2=[p,q,r]^T$. The gravity center of the vehicle is represented by $r_g=[x_g,y_g,z_g]^T$.

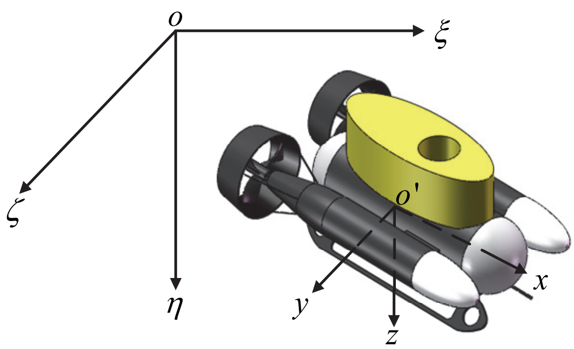


Fig. 1. Coordinate systems for ROV.

According to Newton's Theory, the motion of a rigid body with respect to its body-fixed reference frame is:

$$M\dot{v}+C(v)+D(v)v+g(\chi)=\tau, \quad (1)$$

$$\dot{\chi}=J(\chi)v, \quad (2)$$

$$\tau=\tau_A+\tau_w, \quad (3)$$

where M is the sum of rigid body inertial mass and added fluid inertial mass, $C(v)$ represents Coriolis and centripetal forces and moments, and $g(\chi)$ is the restoring $J(\chi)$ forces and moments from the ROV and the water are the Euler transformation matrix between the body and earth-fixed coordinate systems. τ_A and τ_w are the forces and moments generated by thrusters and water wave respectively and τ is total external forces and moments acting on the ROV. τ_A is controlled by the voltages of the thrusters while τ_w is related to the interaction between water and the ROV:

$$\tau_w = -\mu_s \dot{\chi} - k_s \chi + h_w \cos(\Omega t) , \tag{4}$$

where μ_s and k_s are the constants; h_w and Ω are the amplitude and encounter frequency of the wave.

2.2. ROV Hydrodynamic Analysis

In the fluid medium, ROV gravity W and buoyancy B act collinearly through the center of gravity O'. They provide restoring force and moment $g(\chi)$ if vehicle inclines.

$$g(\chi) = \begin{bmatrix} (W-B)\sin(\theta) \\ -(W-B)\cos(\theta)\sin(\phi) \\ -(W-B)\cos(\theta)\cos(\phi) \\ y_B B\cos(\theta)\cos(\phi) - z_B B\cos(\theta)\sin(\phi) \\ -z_B B\sin\theta - x_B B\cos(\theta)\cos(\phi) \\ x_B B\cos(\theta)\sin(\phi) + y_B B\sin\theta \end{bmatrix}, \tag{5}$$

where $r_B = (x_B, y_B, z_B)$ is the center of buoyancy. When ROV is moving, surrounding water moves together with vehicle so its effect is considered as added mass and inertia. Forces and moments caused by them are proportional to vehicle acceleration. For the vehicle is tested in low speed, the added mass inertial matrix M_a is simplified as (Fossen, 2002):

$$M_a = -diag\{X_{\dot{u}}, Y_{\dot{v}}, Z_{\dot{w}}, K_{\dot{p}}, M_{\dot{q}}, N_{\dot{r}}\} , \tag{6}$$

where $X_{\dot{u}}$, $Y_{\dot{v}}$, $Z_{\dot{w}}$, $K_{\dot{p}}$, $M_{\dot{q}}$ and $N_{\dot{r}}$ are the hydrostatic coefficients. And the added mass Coriolis and centripetal matrix is:

$$C(v) = \begin{bmatrix} 0 & 0 & 0 & 0 & -Z_{\dot{w}}w & Y_{\dot{v}}v \\ 0 & 0 & 0 & Z_{\dot{w}}w & 0 & -X_{\dot{u}}u \\ 0 & 0 & 0 & -Y_{\dot{v}}v & X_{\dot{u}}u & 0 \\ 0 & Z_{\dot{w}}w & Y_{\dot{v}}v & 0 & -N_{\dot{r}}r & M_{\dot{q}}q \\ Z_{\dot{w}}w & 0 & -X_{\dot{u}}u & N_{\dot{r}}r & 0 & -K_{\dot{p}}q \\ -Y_{\dot{v}}v & X_{\dot{u}}u & 0 & -M_{\dot{q}}q & K_{\dot{p}}p & 0 \end{bmatrix}, \tag{7}$$

Besides, due to skin friction and vortex shedding, fluid brings damping force and moments which are proportional to vehicle speed. Damping force and moments matrix is simplified as:

$$\begin{aligned} D(v) = -diag\{&X_u + X_{u|u|}|u|, Y_v + Y_{v|v|}|v|, \\ &Z_w + Z_{w|w|}|w|, K_p + K_{p|p|}|p|, \\ &M_q + M_{q|q|}|q|, N_r + N_{r|r|}|r|\} \end{aligned} , \tag{8}$$

where X_u, Y_v, Z_w, K_p, M_q and N_r are the linear viscous hydrodynamic coefficients. $X_{u|u|}|u|$, $Y_{v|v|}|v|$, $Z_{w|w|}|w|$, $K_{p|p|}|p|$, $M_{q|q|}|q|$ and $N_{r|r|}|r|$ are the quadratic viscous hydrodynamic coefficients.

ROV's motion is highly nonlinear and different controllers are used to control its different degrees of freedom. In order to simplify the mathematical model, it is assumed that when the ROV is working, it approaches the location first without changing depth; then it changes depth to reach the working point without changing course. Thus, the motion can be analyzed in a vertical plane and a horizontal plane respectively. For vertical motion, only heave is considered while for horizontal motion, only surge, sway and yaw are considered. Also, it is assumed that the vehicle is well balanced and can return to zero pitch and zero roll state by itself, so p, q, θ and ϕ are approximately equal to zero. Thus, combined with the equations mentioned above, the ROV motion identification model can be simplified as:

$$(m + Z_{\dot{w}})\dot{w} = Z_w w + Z_{w|w|} w|w| + \tau_z , \tag{9}$$

$$(m + X_{\dot{u}})\dot{u} = -(m + Y_{\dot{v}})vr + X_u u + X_{u|u|} u|u| + \tau_x , \tag{10}$$

$$(m + Y_{\dot{v}})\dot{v} = -(m + X_{\dot{u}})ur + Y_v v + Y_{v|v|} v|v| , \tag{11}$$

$$(I_{ZZ} + N_{\dot{r}})\dot{r} = N_r r + N_{r|r|} r|r| + \tau_z , \tag{12}$$

where $Z_{\dot{w}}$, Z_w, $Z_{w|w|}$, $X_{\dot{u}}$, X_u, $X_{u|u|}$, $Y_{\dot{v}}$, Y_v, $Y_{v|v|}v$, $N_{\dot{r}}$, N_r and $N_{r|r|}$ are the hydrodynamic coefficients need to be identified. Geometric dimension of vehicle is: length $30\,cm$, width $23\,cm$ and height $23\,cm$. The vehicle is arranged to be a symmetrical structure, so I_{xy}, I_{xz} and I_{yz} are approximate zero while $I_{zz} = 0.0253\,kg \cdot m^2$. The quality m is $4.5\,kg$.

3. Hydrodynamic Coefficients Identification Using GA

We can derive from equations (9)~(12) that the motion of the ROV is decided by forces and moments of thrusters and water wave as well as hydrodynamic coefficients. When applied a set of forces and moments on the ROV, generated velocities correspond to the hydrodynamic coefficients of the ROV.

3.1. Objective function for Identification

Associative relation between measured velocities and hydrodynamic coefficients is nonlinear and noises produced by sensors also bring errors. GA can overcome these problems with good nonlinear mapping characteristics. In order to decide which group of hydrodynamic coefficients satisfies the measured velocities best, the best matching standard between them should be established first, and then GA can automatically search in a range for the optimal global solutions of hydrodynamic coefficients complying with given velocities.

With the same external forces and moments, if the curves of simulated velocities using hydrodynamic coefficients identified by GA get close to the curves of velocities measured by sensors in tank, hydrodynamic coefficients identified by GA are effective and can be used for the controllers design for the ROV.

The velocities similarity function is defined as:

$$\rho_k = \frac{\sum_{i=1}^{M}(V_i(t)-\overline{V}_i(t))(\hat{V}_i(t)-\overline{\hat{V}}(t))}{\sqrt{\sum_{i=1}^{M}(V_i(t)-\overline{V}_i(t))^2(\hat{V}_i(t)-\overline{\hat{V}}(t))^2}}, \quad (13)$$

where $V=[u_0, v_0, w_0, r_0]$ is the measured velocity and acceleration matrix. $\overline{V}$ is the mean measured value. $\hat{V}=[u_1, v_1, w_1, r_1]$ is the simulated value and $\overline{\hat{V}}$ is the mean simulated value. The closer $\rho_k=[\rho_u, \rho_v, \rho_w, \rho_r]$ gets to [1, 1, 1, 1] the better the identification quality.

GA can only optimize single objective function. So, ρ_u, ρ_v, ρ_w and ρ_r are combined together to be a weighted fitness function for GA:

$$\rho_{best} = \mu_1 * \rho_u + \mu_2 * \rho_v + \mu_3 * \rho_w + \mu_4 * \rho_r, \quad (14)$$

where weights μ_1, μ_2, μ_3 and μ_4 are 0.2, 0.2, 0.25 and 0.35. Since parameters u, v are coupled with r, proportion of ρ_r is set to be bigger than ρ_u and ρ_v.

3.2. GA Algorithm

Before identification, a set of hydrodynamic coefficients tested from PMM are given as the searching region. $\pm 10\ \%$ of the ranges of the original values are chosen as the searching scope for GA. Generate n parent individuals in searching region randomly and assign maximum number of iteration $t_{\max}$. Calculate the initial fitness function $\rho_{\max 0}$. Convert individuals to gene strings using binary coding method.

Then stochastic tournament method is used to select a pair of individuals each time and the one with better fitness is inherited to the new generation. This operation is repeated until the number of new generation reaches n'. In order to maintain good characteristics of parent and expand group diversity, individuals pair randomly and change part of their chromosomes at a single point. The crossover probability is 0.5. When inherit from parent, deviation may happen in certain probability and new individuals will generate. The mutation probability is 0.005.

Through the processes before, population is renewed and fitness function $\rho_{\max 1}$ is calculated. If $\rho_{\max 1} > \rho_{\max 0}$, then $\rho_{\max 0} = \rho_{\max 1}$.

When iterative times reach $t_{\max}$ or $\rho_{\max 0}$ does not change for five generations, iteration stops; otherwise, selection, crossover and mutation processes should be repeated until iteration reaches stopping criteria.

4. Experiments and Results

The ROV motion control and data acquisition system is shown in Fig. 2. The management platform is designed for adjusting the control instructions and ROV motion states observation.

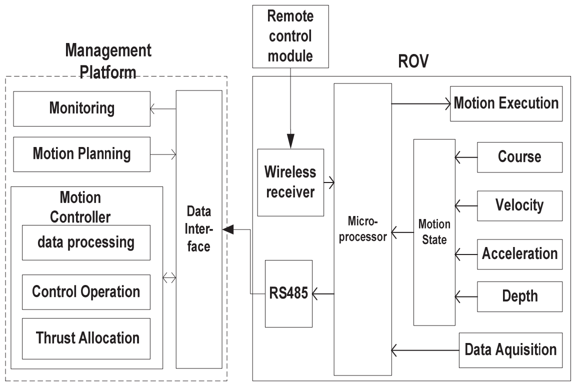


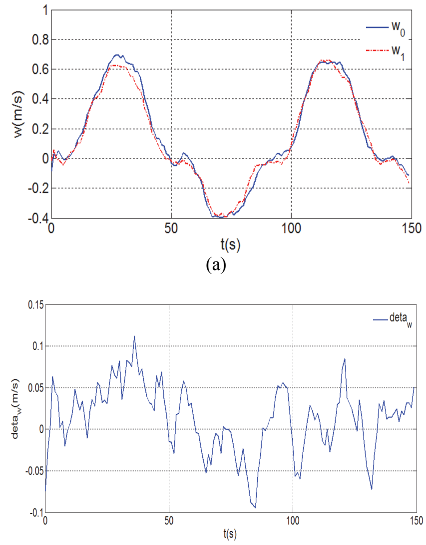
Fig. 2. ROV system.

The position, velocities and attitude information of ROV are obtained by inertial sensor 3DM-GX3-45 which contains Kalman filter itself so the accuracy of data is improved. All of the motion state of the ROV is transmitted by wireless module to the on-earth management platform.

GA identification need fixed searching region to find the best solutions for problems, so hydrodynamic coefficients obtained by PMM are chosen as optimizing references. Then combined with tests in water, GA is independent of the deterministic or stochastic nature of the system and the systems can be identified without linearly separating parameters. The coefficients identified by GA and comparisons between them and those obtained by PMM are shown in the Table 1. It is clear that errors of yaw motion are much smaller than surge and sway motion. This is mainly because yaw motion is independent while surge and sway is coupled with acceleration, so the errors are superposed for velocity. The hydrodynamic coefficients identified by GA are used to simulate velocities and acceleration of the ROV. Fig. 3-6 shows the comparison between measured w_0, u_0, v_0 and r_0 and the simulated ones w_1, u_1, v_1 and r_1 using hydrodynamic coefficients from GA, respectively.

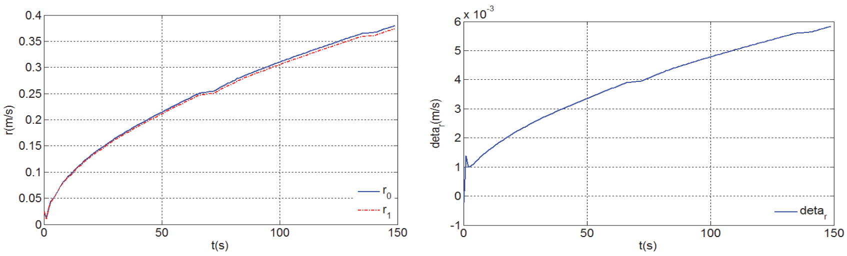
Table 1. Identified Results.

Hydrodynamic coefficients	PMM	GA	Error (%)
Z_w	5.81	5.8047	0.53
$Z_{\dot{w}}$	3.95	3.9684	-1.84
$Z_{w\|w\|}$	20.52	20.5114	0.86
X_u	2.3	2.2701	-2.99
$X_{\dot{u}}$	1.94	1.8906	-4.94
$X_{u\|u\|}$	8.28	8.2621	-1.79
Y_v	8.01	7.989	-2.1
$Y_{\dot{v}}$	6.05	6.03	-2
$Y_{v\|v\|}$	23.69	23.628	-6.2
N_r	0.0048	0.0044	-0.04
$N_{\dot{r}}$	0.0321	0.0289	-0.32
$N_{r\|r\|}$	0.0089	0.008	-0.09



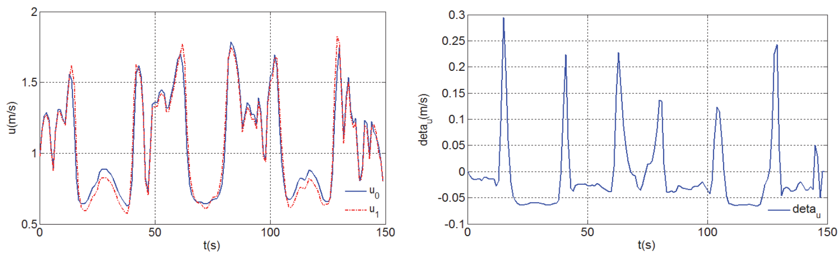
(a) (b)

Fig. 3. Comparison between measured and simulated w (a) and error (b).



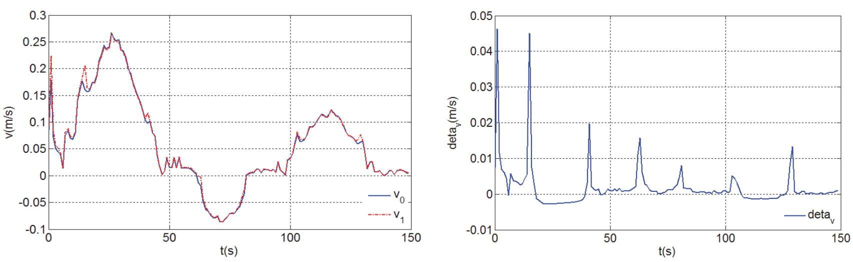
(a) (b)

Fig. 4. Comparison between measured and simulated r (a) and error (b).



(a) (b)

Fig. 5. Comparison between measured and simulated u (a) and error (b).



(a) (b)

Fig. 6. Comparison between measured and simulated v (a) and error (b).

In Fig. 3, the correlation coefficient of the w_0 and w_1 curves is 0.9116; the error ranges between $\pm 0.1\, m/s$. Correlation coefficients for the r_0 and r_1 curves is 0.9780. In the Fig. 4-6, correlation coefficients for u, v and r are 0.9485, 0.9551 and 0.9780, respectively. The trends of simulated curves agree with measured curves. The error range for r is $0 \sim 0.058 m/s$, for u it is $-0.054 \sim 0.27 m/s$ while for v it is $-0.004 \sim 0.046 m/s$. Velocities and acceleration identified by GA for the ROV model approximate with the real measured motion. So, the hydrodynamic coefficients obtained in this paper are effective and they appropriately reflect the hydrodynamic forces and moments in ROV's motion.

5. Conclusions

In this paper, a dynamic model for an ROV was built. In order to reduce the number of hydrodynamic coefficients to be identified and for convenience in designing controllers, the 6 DOFs model is decoupled to a vertical plane model and a horizontal model. Hydrodynamic characteristics of the ROV are analyzed. Then GA is used to identify ROV motion. In order to verify identification validity, hydrodynamic coefficients obtained by GA are used for motion simulation of the ROV. Simulated curves of velocities and acceleration are compared with those measured by sensors when the ROV is operated in tank. Results show that simulated curves can well follow the variation trends of measured curves and correlation coefficient is higher than 0.9 and the errors are small. This indicates that the hydrodynamic coefficients identified in this paper agree with the actual motion of the ROV and they are accuracy enough for further controllers design.

Acknowledgments

This work was supported by Shanghai Rising-Star Tracking Program (12QH1400900) and Shanghai Committee of Science and Technology Foundation (12111101200 and 12140500400).

References

[1]. T. I. Fossen, Guidance and control of ocean vehicles, Second Edition, *John Wiley and Sons Ltd.*, New York, 1994.

[2]. S. B. Fan, L. Lian, P. Ren and G. L. Huang, Oblique towing test and maneuver simulation at low speed and large drift angle for deep sea open-framed remotely operated vehicle, *Journal of Hydrodynamics*, Vol. 24, Issue 2, 2012, pp. 280-286.

[3]. J. Julca Avila, K. Nishimoto, J. C. Adamowski, C. Mueller Sampaio, Experimental investigation of the hydrodynamic coefficients of a remotely operated vehicle using a planar motion mechanism, *Journal of Offshore Mechanics and Arctic Engineering*, Vol. 134, Issue 2, 2012, pp. 021601.1-021601.6.

[4]. J. Kim, K. Kim, H. S. Choi, W. Seong, K. Y. Lee, Estimation of hydrodynamic coefficients for an AUV using nonlinear observers, *IEEE Journal of Oceanic Engineering*, Vol. 27, Issue 4, 2002, pp. 830-840.

[5]. H. Zhang, Y. Xu, and H. Cai, Using CFD software to calculate hydrodynamic coefficients, *Journal of Marine Science and Application*, Vol. 9, Issue 2, 2010, pp. 149-155.

[6]. Q. Meng, Y. Guan, A. Xie, A review of CFD-based system identification, in *Proceedings of the IEEE Control and Decision Conference*, Mianyang, China, May 2011, pp. 3268-3273.

[7]. M. Caccia, G. Indiveri G. Veruggio, Modeling and identification of open-frame variable configuration unmanned underwater vehicles, *IEEE Journal of Oceanic Engineering*, Vol. 25, Issue 2, 2000, pp. 227-240.

[8]. P. Ridao, J. Batlle and M. J. Carreras, Model identification of a low-speed UUV, in *Proceedings of the 1st IFAC Workshop on Guidance and Control of Underwater Vehicles*, Glasgow, Scotland, UK, April 2003, pp. 47-52.

[9]. P. W. J. Van De Ven, T. A. Johansen, A. J. Sørensen, C. Flanagan, D. Toal, Neural network augmented identification of underwater vehicle models, *Control Engineering Practice*, Vol. 15, Issue 6, 2007, pp. 715-725.

[10]. W. J. Yuan, G. J. Liu, S. F. Zhu, Identification method of hydrodynamic parameters of autonomous underwater vehicle based on genetic algorithm, *Journal of Mechanical Engineering*, Vol. 46, Issue 11, 2010, pp. 96-100.