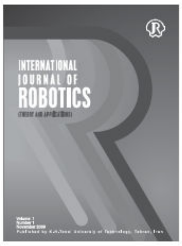

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Identification of an Autonomous Underwater Vehicle Dynamic Using Extended Kalman Filter with ARMA Noise Model

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ABSTRACT

In the procedure of designing an underwater vehicle or robot, its maneuverability and controllability must be simulated and tested, before the product is finalized for manufacturing. Since the hydrodynamic forces and moments highly affect the dynamic and maneuverability of the system, they must be estimated with a reasonable accuracy. In this study, hydrodynamic coefficients of an autonomous underwater vehicle (AUV) are identified using velocity and displacement measurements, and implementing an Extended Kalman Filter (EKF) estimator. The hydrodynamic coefficients are included in the augmented state vector of a six DOF nonlinear model. The accuracy and the speed of the convergence of the algorithm are improved by selecting a proper covariance matrix using the ARMA process model. This algorithm is used to estimate the hydrodynamic coefficients of two different sample AUVs: NPS AUV II and ISIMI. The comparison of the outputs of the identified models and the outputs of the real simulated models confirms the accuracy of the identification algorithm. This identification method can be used as an efficient tool for evaluating the hydrodynamic coefficients of underwater vehicles (robots), using the experimental data obtained from the test runs.

1. Introduction

In recent years, an extensive research has been conducted in the area of underwater robotics and underwater vehicles. Advanced estimation and control methods have been used in order to improve the capability of AUV positioning and path tracking. In [1], an experimental method is implemented for a mobile underwater vehicle to determine its hydrodynamic coefficients. In [2], EKF is used for localization and mapping of autonomous mobile robots. The hydrodynamic coefficients of an AUV were identified in [3] using an EKF. A six degree-of-freedom model of motion was developed in [4] for an underwater vehicle, where an autopilot system was designed for automatic sliding mode control of the vehicle.

To examine the maneuverability and performance of the control system of an AUV, a mathematical model of the vehicle must be identified. The mathematical model includes the hydrodynamic forces and moments, expressed in terms of hydrodynamic coefficients. Therefore, estimating the exact values of these coefficients is an important step in modeling of an AUV. It has been observed that the linear damping coefficients have crucial effects on the maneuverability of an AUV [5]. The hydrodynamic coefficients are determined through experiments, numerical analysis or using empirical formulas. The planar motion mechanism test is the most common experimental method for evaluating the hydrodynamic coefficients [6], however the results of this method are not accurate enough due to the practical limitations of the experimental methods. Moreover, the experimental methods are costly and time consuming. An identification method can be used as an alternative method for the evaluation of the hydrodynamic

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coefficients [7]. The identification of marine vehicle dynamic can be performed using the measurements of the vehicle motions [8]. In [9], different methods of time-domain system identification and noise modeling are discussed. It uses the autoregressive moving average (ARMA) spectrum estimator and artificial neural networks. Using an adaptive neuro-fuzzy algoritm, the model of an underwater vehicle has been identified in [10]. A limitation of this method is the requirement of a widespread range of and input/output data.

Kalman filtering is a method that is used widely in the past few decades for the estimation of parameters and state variables for various dynamic systems. Kalman observer estimates the state variables of a system, assuming a linear model for the system. In recent years, many studies have used Kalman Filter for the identification of AUV dynamic. For instance, [11] used the Kalman observer to identify a discrete time linear model for an autonomous vehicle, where some of the model parameters were estimated. Kalman filter can identify hydrodynamic parameters using a linear model of the system, by ignoring the couplings between different modes of motion. Many investigations have been carried out to apply system identification methods to underwater robots. Majority of these studies have considered decoupled motions in certain directions.

In this study, using the EKF algorithm, a method is presented for identifying the six degree of freedom nonlinear model of an AUV. The problem of parameter bias in the identification process, which results from the complexity of the mathematical model of system and the existence of the non-linear parameters, has been overcome. Considering a suitable time-variant form for the covariance of the process and measurement noise for an AUV model, using ARMA process enables us to identify the dynamic model of AUV with an acceptable accuracy and to eliminate biases in the parameters. The method has been applied to two sample AUVs and the results of the estimation are compared to the real values of the parameters.

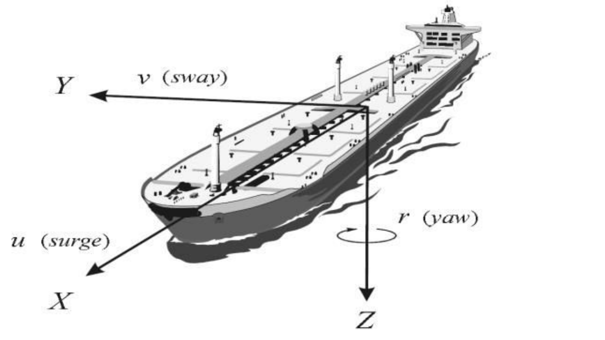


Fig.1: Coordinate system definition for marine vehicles [12].

2. AUV Equations of Motion

Modeling of an AUV, because of the nature of the hydrodynamic forces, involves nonlinearities and coupling between different modes. Consider the nonlinear state space equation:

$$\dot{\mathbf{x}} = f(\mathbf{x}, \mathbf{u}), \quad (1)$$

Where, x and u represent respectively the state and the input vectors. Using the body coordinate system shown in Fig. 1 and Newton-Euler equations, the equations of motion of an AUV are obtained as

$$\begin{aligned}
& m[\dot{u} + qw - r\upsilon + z_G(pr + \dot{q})] = X \\
& m[\dot{\upsilon} + ru - pw + z_G(qr - \dot{p})] = Y \\
& m[\dot{w} + pv - qu - z_G(p^2 + q^2)] = Z \\
& I_x\dot{p} + (I_z - I_y)qr + I_{xy}(pr - \dot{q}) - I_{yz}(q^2 - r^2) \\
& - I_{xz}(pq + \dot{r}) - mz_G(\dot{\upsilon} + ur - wp) = K \\
& I_y\dot{q} + (I_x - I_z)pr - I_{xy}(qr + \dot{p}) + I_{yz}(pq - \dot{r}) \\
& + I_{xz}(p^2 - r^2) + mz_G(\dot{u} - \upsilon r + wq) = M \\
& I_z\dot{r} + (I_y - I_x)pq - I_{xy}(p^2 - q^2) - I_{yz}(pr + \dot{q}) \\
& + I_{xz}(qr - \dot{p}) = N
\end{aligned} \quad (2)$$

where, u, v and w are linear velocities, in the x, y and z directions, respectively and p, q and r are the angular velocities around x, y and z axes respectively. The variables X, Y and Z are the external force components, and K, M and N are the external moments in the x- y -z coordinate.

3. System Identification

A detailed physics-based description of a rotating tool in this study the hydrodynamic coefficients of an AUV are identified. Since the external force and moment components are the function of hydrodynamic coefficients, these coefficients determine the AUV dynamics. The identification method is based on a limited number of discrete-time measurements of the system output vector $\{\mathbf{y}(t_k)\}_{k=1}^{N}$, given the input vector $\{\mathbf{u}(t_k)\}_{k=1}^{N}$. Due to the lack of correspondence between the dimension space of the unknown coefficients and the dimension space of inputs and outputs, the hydrodynamic coefficients cannot be determined directly [13]. Estimation problems usually are represented in the prediction error form. In [7], it is tried to maximize the likelihood function of the vector of unknown parameters, which is equivalent to the minimization of a cost function defined as [7]:

$$J(\boldsymbol{\theta}) = \det \frac{1}{N} \sum_{k=1}^{N} \boldsymbol{\varepsilon}(t_k) . \boldsymbol{\varepsilon}(t_k)^T \quad (3)$$

Where, $\boldsymbol{\varepsilon}(t_k)$ is the prediction error vector in t_k, which is equal to the difference between the measurement vector

$\mathbf{y}(t_k)$ and prediction of the measurement vector $\hat{\mathbf{y}}(t_k)$ in each step:

$$\boldsymbol{\varepsilon}(t_k)=\mathbf{y}(t_k)-\hat{\mathbf{y}}(t_k). \tag{4}$$

For nonlinear filtering problems, the EKF is one of the most appropriate tools [14]. This filter is based on linearization of model and measurements, using Taylor's series expansion. Using EKF the unknown parameters can be estimated by adding them as the state variables to be estimated [15]. Consider a nonlinear system containing unknown parameters as:

$$\mathbf{x}_{k+1}=f(\mathbf{x}_k,\boldsymbol{\beta}_k,k)+\mathbf{w}_k \tag{5}$$

$$\mathbf{y}_k=h(\mathbf{x}_k,\boldsymbol{\beta}_k,k)+\mathbf{v}_k \tag{6}$$

where, $\mathbf{x}\in R^n$ is state vector, $\mathbf{y}\in R^m$ is measurement vector, $\boldsymbol{\beta}\in R^p$ is the unknown parameters vector, $\mathbf{w}$ is process noise, and $\mathbf{v}$ is sensor noise. In order to estimate the unknown parameters, they are added in the state vector $\mathbf{x}$ and the augmented state vector $\mathbf{x}_k^*$ is defined. Therefore, system equations (5) and (6) take a new form as:

$$\mathbf{x}_{k+1}^*=\begin{bmatrix}\mathbf{x}_{k+1}\\ \boldsymbol{\beta}_{k+1}\end{bmatrix}=\begin{bmatrix}f(\mathbf{x}_k,\boldsymbol{\beta}_k,k)\\ 0\end{bmatrix}+\begin{bmatrix}\mathbf{w}_k\\ \boldsymbol{\eta}_k\end{bmatrix} \tag{7}$$

$$\mathbf{y}_k=h(\mathbf{x}_k^*,k)+\mathbf{v}_k \tag{8}$$

where, $\mathbf{w}\in R^n$, $\boldsymbol{\eta}\in R^p$ and $\mathbf{v}\in R^m$ are Gaussian white noise sequences, and $\mathbf{x}^*\in R^{n+p}$ is the augmented state vector. The discrete-time extended Kalman filter step for the above system, using uniform sampling time $T=t_k-t_{k-1}$, can be represented as [3]:

Time Update:

$$\hat{\mathbf{x}}_{k+1}^*(-)=f\left(\hat{\mathbf{x}}_k^*(+),k\right) \tag{9}$$

$$\mathbf{P}_{k+1}(-)=\mathbf{A}_k^*\mathbf{P}_k(+)\mathbf{A}_k^{*T}+\mathbf{Q}_k \tag{10}$$

Measurement Update:

$$\mathbf{K}_k=\mathbf{P}_k(-)\mathbf{H}_k^{*T}[\mathbf{H}_k^*\mathbf{P}_k(-)\mathbf{H}_k^{*T}+\mathbf{R}_k]^{-1} \tag{11}$$

$$\hat{\mathbf{x}}_k^*(+)=\hat{\mathbf{x}}_k^*(-)+\mathbf{K}_k[\mathbf{y}_k-h(\hat{\mathbf{x}}_k^*(-),k)] \tag{12}$$

$$\mathbf{P}_k(+)=[\mathbf{I}-\mathbf{K}_k\mathbf{H}_k^*]\mathbf{P}_k(-) \tag{13}$$

where,

$$\mathbf{A}_k^*=\left.\frac{\partial f(\mathbf{x}^*,k)}{\partial\mathbf{x}^*}\right|_{\mathbf{x}^*=\hat{\mathbf{x}}_k^*(+)} \tag{14}$$

$$\mathbf{H}_k^*=\left.\frac{\partial h(\mathbf{x}^*,k)}{\partial\mathbf{x}^*}\right|_{\mathbf{x}^*=\hat{\mathbf{x}}_k^*(-)} \tag{15}$$

and $E(\mathbf{w}(t)\mathbf{w}(t)^T)=\mathbf{Q}$, $E(\mathbf{w}(t))=\mathbf{0}$, $E(\mathbf{v}(t)\mathbf{v}(t)^T)=\mathbf{R}$, $E(\mathbf{v}(t))=\mathbf{0}$, $\mathbf{P}$ is the estimation error covariance and $\mathbf{Q}$ is the process noise covariance. The gain matrix $\mathbf{K}$ will be determined from Ricatti equation and measurement error covariance $\mathbf{R}$, can be determined from Lyapanov equation. Measurement update ((Eqs. (11)-(13)) reflects measurement process through the gain matrix $\mathbf{K}$ [16]. When we add the hydrodynamic coefficients to the state vector, the augmented state vector dimension increases, so that we face computational complexities like singularity in calculations of the Jacobian matrix in EKF [17]. In this study, for ISIMI model [18], we use the ARMA process model and consider $\mathbf{Q}_k$ and $\mathbf{R}_k$ as time variable covariance matrices. The ARMA model is appropriate when a system is a function of a series of unobserved shocks. Given a time series of data, the ARMA model is a tool for understanding and predicting the future values in this series. In this method, the covariance matrix is calculated as [19]:

$$\mathbf{Q}_{k+1}=(1-\gamma)\mathbf{Q}_k+\gamma\lambda^2\boldsymbol{\omega}_k\boldsymbol{\omega}_k^T \tag{16}$$

$$\mathbf{R}_{k+1}=(1-\gamma)\mathbf{R}_k+\gamma\lambda^2\mathbf{v}_k\mathbf{v}_k^T \tag{17}$$

$$\hat{\boldsymbol{\omega}}_k=\frac{1}{T}(\hat{\boldsymbol{\theta}}_{k+1}-\hat{\boldsymbol{\theta}}_k) \tag{18}$$

$$\mathbf{v}_k=\mathbf{y}_{k+1}-h(\mathbf{y}_k,\mathbf{u}_k,\hat{\boldsymbol{\theta}}_k) \tag{19}$$

where, γ is forgetting factor that determines the effect of error vectors $\boldsymbol{\omega}_k$ and $\mathbf{v}_k$ on the covariance of errors. Therefore, $\mathbf{Q}_k$ and $\mathbf{R}_k$ enter the error information into the model. The forgetting factor can be defined as an exponential function:

$$\gamma=1-e^{-T/\tau}, \tag{20}$$

where, T the sampling time and τ is the system time constant.

The variable λ another system noise modeling parameters [20]. In [21], a value of $0<\lambda<1$ is recommended. The parameter λ removes the mathematical expectation of error during the identification process [19]. Here, $\lambda=2\times10^{-3}$ is selected.

4. Implementation and Results

The ultimate goal of haptic rendering is to provide smooth In order to examine the identification method presented in this work, two nonlinear sample models of AUV's ISIMI [18] and NPS-AUV II [12] are used. The motions of the AUVs are simulated and the hydrodynamic coefficients of the system are identified using the input/output data of these simulation. The input vector that is used for AUV attitude control is defined as:

$$\mathbf{u}=[\delta_r,\delta_s,\delta_b,\delta_{bp},\delta_{bs},n] \tag{21}$$

which respectively are rudder, stern plane, top and bottom bow plane, starboard bow plane, port bow plane, and propeller shaft speed. The first five elements are the angle values that enable the AUV maneuverability, and n is the propeller shaft speed. The values of δ_b, δ_{bp} and δ_{bs} for ISIMI model are assumed to be zero. Different functions can be considered as the actuator input for the control surfaces. We considered the input angles as zigzag and step functions with variable amplitudes to produce three-dimensional motions for the AUVs.

Because of the physical limitations, the rudder angle is limited to $\delta \in [-20,20]$. In this study, the input data from [10] is used for δ_r and δ_s. The propeller speed n is considered at constant speed of 500 rpm. The time step for the simulation is $T = 0.05$ seconds.

The augmented state vector is defined as:

$$\mathbf{x}^* = [u, v, w, p, q, r, x, y, z, \varphi, \theta, \psi, \boldsymbol{\beta}] \tag{22}$$

Where, $\boldsymbol{\beta}$ contains $Z_{\delta S}$, Z_q, Z_w, $M_{\delta S}$ and K_v for NPS-AUV II. For ISIMI model, $\boldsymbol{\beta}$ contains M_w, $Y_{\delta r}$, Y_v, Z_w.

The output vector, which consists of speed and position data, is considered as:

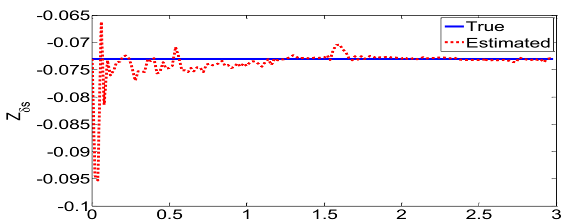
$$\mathbf{y} = [u, v, w, p, q, r, x, y, z, \varphi, \theta, \psi] \tag{23}$$

The hydrodynamic coefficients that identified using the algorithm of section III for NPS-AUV II are shown in Fig. 2. The results are compared with the real coefficients that are available from [12].

As it can be seen from Fig. 2 and Table 1, the estimation algorithm has converged to true data with appropriate accuracy. The only exception is K_v. The main reason for this discrepancy can be related to lack of excitation of the roll motion by the inputs. K_v is defined as $\partial K/\partial v$. Because of inadequate excitation of the roll motion by the sway movement, a relatively less accurate estimation has been obtained.

Table 1. Hydrodynamic coefficients for NPS AUV II

Hydrodynamic coefficients	Real values [12]	Estimated values	Error (%)
$Z_{\delta s}$	0.073	-0.07275	<1
Z_w	-0.3	-0.2990	1
K_v	0.0031	0.0035	13
Z_q	-0.14	-0.139	<1
$M_{\delta s}$	-0.041	-0.04132	<1



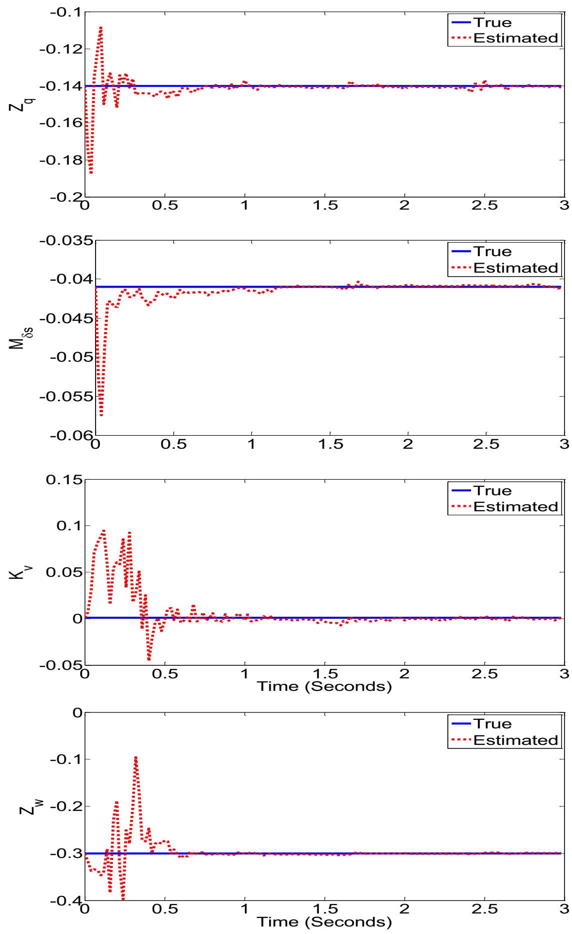


Fig.2: The identified coefficients for NPS-AUV II in comparison with the real coefficients from [12].

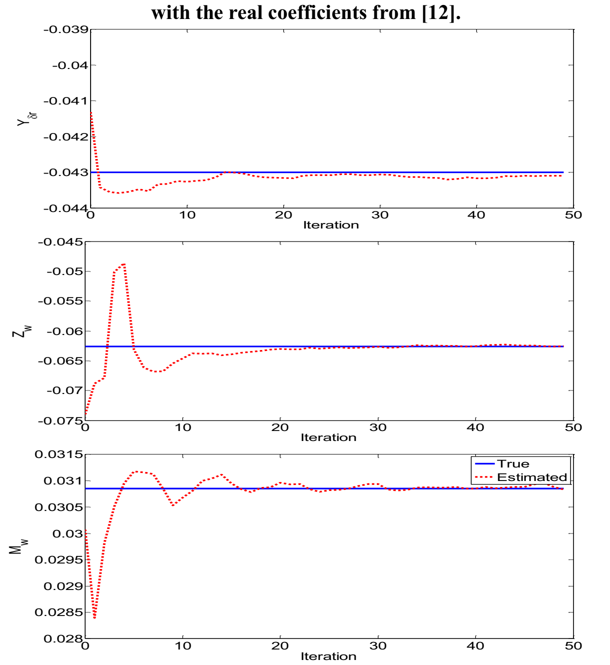


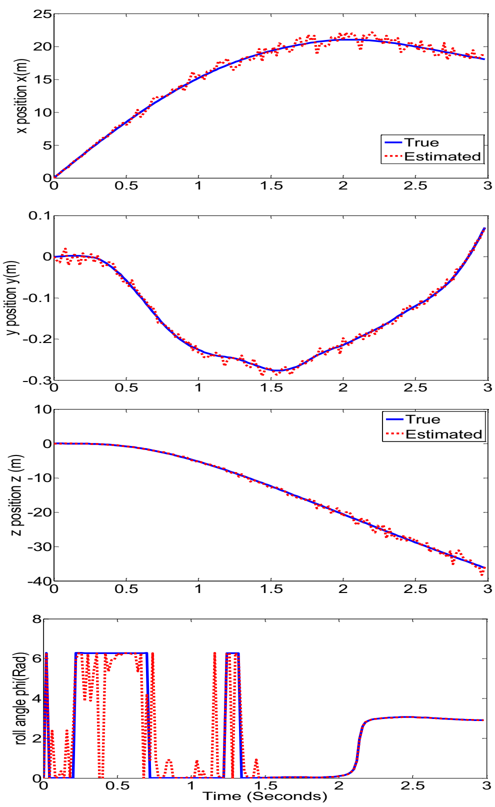
Fig.3: Identified coefficients for ISIMI using ARMA noise model in comparison with the real coefficients from [18].

The results of iterative identification of the hydrodynamic coefficients of ISIMI AUV [18] are shown in Fig. 3. The identified values shown in Table 2 are derived using an ARMA model for the process noise. It can be seen that using the ARMA noise model, provides precise results in the estimation of coefficients.

Table 2. Hydrodynamic coefficients for ISIMI AUV

Hydrodynamic coefficients	Real Values [18]	Estimated values	Error (%)
M_w	0.030853	0.032	4
Y_v	-0.062586	-0.065	4
$Y_{\delta r}$	-0.043008	-0.045	5
Z_w	-0.062586	-0.063	1

Having the real values for hydrodynamic coefficients, the identified values can easily be compared with the real values. But, the validity of the identified model should be examined by simulating the AUV motion and comparing it with the real trajectory. The identified coefficients for NPS AUV II are used for simulation, where step inputs are considered for the rudders angles and process noise is added to the model. Figure 4 shows the performance of the identified model in producing the simulated path. The figure contains the position and the orientation of the AUV during simulation time.



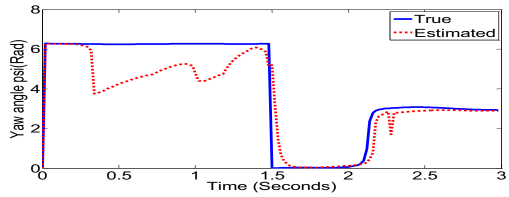


Fig.4: Simulation of the movements of ISIMI with the true and identified coefficients.

Fig. 5 shows estimated speed using the identified coefficients in comparison with the true speed. The true speed is obtained using the true coefficients for the simulation. Figs. 4 and 5 show a good compatibility for the speeds and positions of the models which simulated with the true and identified values of the hydrodynamic coefficients.

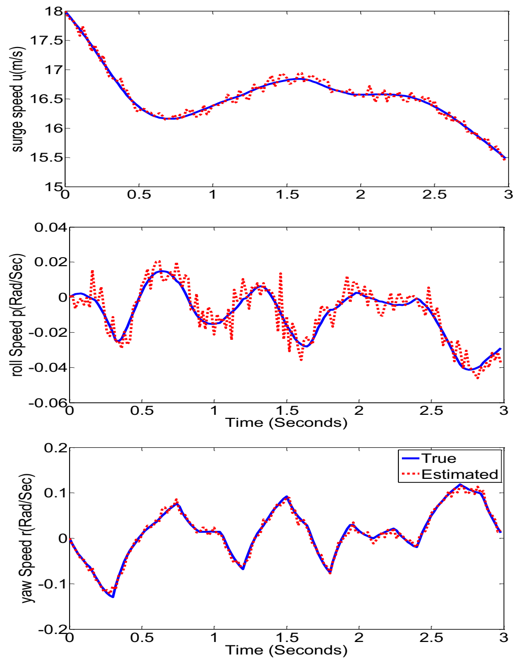


Fig.5: Estimated surge, roll and yaw speed versus real speed using real coefficients

5. Conclusion

In this study, a recursive method is proposed for the identification of dynamic models of AUVs. The comparison of the simulation results of the identified and true models shows the accuracy of the identification algorithm. It is shown that using an ARMA process noise model leads to accurate values of the identified coefficients and prevents the bias of the coefficients from their true values. Results showed that the method is able to identify dynamic model of AUVs with an acceptable accuracy. Thence, the resulting identified models can suitably be used for the simulation and control purposes. Some preliminary results of this work were presented in [23].

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