# Estimation of water momentum and propeller velocity in bow thruster model of autonomous surface vehicle using modified Kalman filter

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**ABSTRACT**

Autonomous surface vehicle (ASV) is a vehicle in the form of an unmanned on-water surface vessel that can move automatically. As such, an automatic control system is essentially required. The bow thruster system functions as a propulsion control device in its operations. In this research, the water momentum and propeller velocity were estimated based on the dynamic bow thruster model. The estimation methods used is the Kalman filter (KF) and ensemble Kalman filter (EnKF). There are two scenarios: tunnel thruster condition and open-bladed thruster condition. The estimation results in the tunnel thruster condition showed that the root mean square error (RMSE) by the EnKF method was relatively smaller, that is, 0.7920 and 0.1352, while the estimation results in the open-bladed thruster condition showed that the RMSE by the KF method was relatively smaller, that is, 1.9957 and 2.0609.



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## 1. INTRODUCTION

Indonesia is an archipelago country consisting of 17,508 islands, with sea area of about two-thirds of its territory and consisting of several main island groups [1]. This can provide income opportunities for the country, especially in the marine tourism sector. Along with the rapid development of modern technology in various fields, it also has an impact on the development of marine transportation, namely unmanned water surface vehicles that can move automatically, i.e., autonomous surface vehicle (ASV) or unmanned surface vehicle (USV). USV is controlled automatically by commands such as waypoints [2]. ASV can be used either as a research or survey vessel for river or lake area inspection, seismic survey, rescue operation, and others. The use of ASV as a research vessel has been carried out in several countries, most of which carry out research in either rivers or offshore automatically.

In the transportation sector, especially the marine transportation sector, a ship is required to work optimally. One way to support the smooth operation of a ship voyage requires a supporting device to support the ship when maneuvering, a bow thruster as a propeller installed on the ship bow. Ship maneuvering is the ship's ability to turn and turn around when the ship is about to dock or set off the port. This ability greatly determines the safety of the ship, especially when the ship operates in confined waters or operates around the port. The bow thruster installation can also increase the maneuverability of a ship. By utilizing the rotational energy of the propeller in the tunnel thruster of a ship, the direction of the ship can be turned faster than a ship without a bow thruster. By relying on the bow thruster's ability, it can be developed by adding an additional part to the tunnel thruster. It works by providing a cover on the bow thruster that can be opened and closed. The purpose of this tunnel cover is not only for opening and closing, but rather leads to an increase in the maneuverability of ships utilizing the bow thruster [3].

During the ship voyage, maneuvering process can be interrupted if a bow thruster does not operate properly. It is undeniable that (noise) interference may come from the bow thruster system itself. Disturbance can occur when the bow thruster functioning to smooth motion is damaged, so that the operating system of the bow thruster, which provides a transverse thrust on the bow of the ship is disturbed [4]. To overcome any disturbance to the ship voyage, its control system is equipped with an estimator. The estimator is used to provide predictions for the variables on the ship due to the disturbance that occurs. One of the algorithms for estimating a state system of a dynamic model was introduced by Kalman [5]. This algorithm is called the Kalman filter (KF), which is an algorithm that can be implemented in a stochastic linear dynamic model.

In the previous research, researches on estimation have been carried out. The study [6] conducted a research with the aim of designing a KF estimator on noise conditions by measuring instruments, noise by ship systems and inaccuracy in modeling. The ship dynamic variables estimated for steering purposes are sway-yaw dynamics with variables of angular velocity, angular position, and sway direction velocity. The results of the application of the KF algorithm are the estimated values of the three dynamic variables of the ship with the absolute integral percentage of error of the system-on-system noise and measurement noise. Ataei and Koma [7] investigated the navigation and guidance control system of autonomous underwater vehicle (AUV). Then Miller *et al.* [8] discussed estimation and control of AUV by using acoustic. In 2018, Wang *et al.* [9] described estimation of steam temperature in drum boiler. Then Schoniger *et al.* [10] estimated parameter of hydraulic tomography using ensemble Kalman filter (EnKF). In Nurhadi *et al.* [11] conducted a research related to the estimation of ASV position and motion due to the influence of wind speed and wave height by applying the EnKF. The results of the application of the EnKF algorithm showed the smallest position error and a high degree of accuracy [11]. Then [12], [13] used EnKF in blood transfusion management and crude oil price estimation, respectively. Recently, studies [14]–[20] discussed the application of KF in pneumatic artificial muscles, mobile robot, real-time RSSI based outdoor target tracking and autonomous underwater vehicle. Regarding researches on the bow thruster modeling, there are numerous references in the literature, such as [21]–[27]. In this research, we use the model proposed by Healey *et al.* [21] which produces a motion control system on the thruster, namely water momentum and propeller velocity which is a dynamic thruster model.

To the best of our knowledge, the effect of noise on water momentum and propeller velocity using a dynamic thruster model was not yet studied in the literature. That motivates the current research of the authors. The main contribution of this paper is a numerical analysis on the comparison between the KF method and the EnKF method for estimating the water momentum and propeller velocity on a bow thruster autonomous surface vehicle (ASV). We compare the performance of KF and EnKF because EnKF is an extension of KF which can be used to estimate linear and nonlinear models by generating some ensembles. In this paper, first we linearize the bow thruster model. Then, we analyze the stability of the linearized model. After that, we discretize the model by using the zero-order hold method. Next, we implement the KF and the EnKF to the linearized model. Finally, we conduct some simulations and analyze the simulation results.

## 2. MODELS AND PRELIMINARIES

### 2.1. Bow thruster model of autonomous surface vehicle

The bow thruster model that was proposed in [9] is a continuous-time nonlinear model. The model has two state variables, i.e., motor rotational rate $\omega_m$ and section average flow velocity $U_a$. The model has two input variables, i.e., voltage source $V_s$ and vehicle velocity $U_0$. There is one output variable in the model, i.e., thrust force $T$. The state equations in the bow thruster model are:

$$\dot{\omega}_m = f_1(\omega_m, U_a, V_s, U_0) = -K_1\omega_m + K_2V_s - K_hQ$$
$$\dot{U}_a = f_2(\omega_m, U_a, V_s, U_0) = -K_4K_3^{-1}\bar{U}_a|\bar{U}_a| + K_3^{-1}T$$

and the output equation is given by

$$T = g(\omega_m, U_a, V_s, U_0) = Lift(\cos\theta) - Drag(\sin\theta)$$

where $Lift$ represents the lift force, $Drag$ represents the drag force and $\theta$ represents the angle of inlet to blades. In [28], we have linearized the bow thruster model by using the parameters for tunnel thruster test and open bladed thruster test.

When the parameters for tunnel thruster test are used, we obtain the following linear system [28]:

$$\begin{pmatrix} \dot{\omega}_m \\ \dot{U}_a \end{pmatrix} = \begin{pmatrix} -70.7 & 1.2 \\ -2.1 & -14.8 \end{pmatrix} \begin{pmatrix} \omega_m \\ U_a \end{pmatrix} + \begin{pmatrix} 1133.2 & 0 \\ 0 & 1.9 \end{pmatrix} \begin{pmatrix} V_s \\ U_0 \end{pmatrix}$$

$$T = \begin{pmatrix} -2.03 & -12.2 \end{pmatrix} \begin{pmatrix} \omega_m \\ U_a \end{pmatrix} + \begin{pmatrix} 0 & 0 \end{pmatrix} \begin{pmatrix} V_s \\ U_0 \end{pmatrix}$$

Next, we check the stability of the linear system by computing the eigenvalues. The eigenvalues of the state matrix are $\lambda_1 = -70.6549$ and $\lambda_2 = -14.8451$. Since the real parts of all eigenvalues are negative, the linear system is asymptotically stable. Furthermore, the linear system is observable because the rank of observability matrix is 2.

If we use the parameters for open-bladed thruster test, we obtain the following linear system [28]:

$$\begin{pmatrix} \dot{\omega}_m \\ \dot{U}_a \end{pmatrix} = \begin{pmatrix} -523.7 & -1519.8 \\ -1.15 & -0.13 \end{pmatrix} \begin{pmatrix} \omega_m \\ U_a \end{pmatrix} + \begin{pmatrix} 0.065 & 0 \\ 0 & 2.73 \end{pmatrix} \begin{pmatrix} V_s \\ U_0 \end{pmatrix}$$

$$T = \begin{pmatrix} -4.62 & -10.4 \end{pmatrix} \begin{pmatrix} \omega_m \\ U_a \end{pmatrix} + \begin{pmatrix} 0 & 0 \end{pmatrix} \begin{pmatrix} V_s \\ U_0 \end{pmatrix}$$

Then, as before, we determine the stability of the linear system. The eigenvalues of the system matrix are $\lambda_1 = -527.0172$ and $\lambda_2 = 31872$. The linear system is unstable because there exists an eigenvalue where the real part is positive. Moreover, this linear system is observable because the rank of observability matrix equals 2.

### 2.2. Kalman filter algorithm implementation

In this section, we discuss the KF algorithm. In the next section, the algorithm will be applied to the linearized bow thruster model. As mentioned before, the KF algorithm can be applied to discrete-time systems. As such, the model needs to be discretized first. The steps of the KF algorithm were as [29], [30]:

- Determine the system model and measurement model. The general form of system model was represented as:

  $$x_{k+1} = Ax_k + Bu_k + Gw_k$$

  where $x_k$ is the state at time $k$, $u_k$ is the input at time $k$ and $w_k$ is the system noise at time $k$. We assume that the system noise at time $k$ is normally distributed with mean 0 and variance $Q_k$, i.e., $w_k \sim N(0, Q_k)$. The general form of measurement model was represented as:

  $$z_k = Hx_k + v_k$$

  where $z_k$ is the measurement at time $k$ and $v_k$ is the measurement noise at time $k$. We assume that the measurement noise at time $k$ is normally distributed with mean 0 and variance $R_k$, i.e., $v_k \sim N(0, R_k)$.
- Initialization stage. Determine the initial state, the initial covariance for system noise and the initial covariance of measurement noise. The estimated initial state $\hat{x}_0$ was generated by a normally distributed random variable with mean $\bar{x}_0$ and covariance $P_0$.
- Time update. After the system model became a discrete-time linear system, then the estimation and covariance of the estimation could be calculated using the following equation:

  State estimation: $\bar{x}_{k+1}^- = A_k \bar{x}_k + B_k u_k$

  Covariance of estimation: $P_{k+1}^- = A_k P_k A_k^T + G_k Q_k G_k^T$

  Notation $\hat{x}_{k+1}^-$ represents the estimation of state at time $k+1$ before receiving the measurement data. The covariance of the estimation is denoted by $P_{k+1}^-$.
- Measurement update. After receiving the measurement data, we find out the Kalman gain, the updated estimation and updated covariance of estimation:

  Kalman gain: $K_k = P_{k+1}^- [H_{k+1} P_{k+1}^- H_{k+1}^T + R_{k+1}]^{-1}$

  Update covariance of estimation: $P_{k+1} = [(P_{k+1}^-)^{-1} + H_{k+1}^T R_{k+1}^{-1} H_{k+1}]^{-1}$

Update state of estimation: $\hat{x}_{k+1} = \hat{x}_{k+1}^{-} + P_{k+1}H_{k+1}^{T}R_{k+1}^{-1}(z_{k+1} - H_{k+1}\hat{x}_{k+1}^{-})$

Notation $\hat{x}_{k+1}$ denotes the estimation of state at time $k+1$ after receiving the measurement data. The covariance of the estimation is denoted by $P_{k+1}$.

– Once the measurement update was finished, the time update is executed again. The time update and measurement update are executed until all measurement data are processed.

### 2.3. Ensemble Kalman filter algorithm implementation

In this section, we describe the EnKF algorithm [2], [31], [32]. The algorithm was applied to the linearized bow thruster model. Before the EnKF algorithm was applied, the continuous-time model was discretized first. The steps in the EnKF method were as:

– Determine the system model and measurement model. The system and measurement model for EnKF is the same with the system and measurement model for KF.
– Initialization stage. Generate $N$ ensemble $[x_{0,1}\ x_{0,2} \ldots x_{0,N}]$ in accordance with the initial estimation, where $x_{0,i}$ for $i = 1, \ldots, N$ is generated from a normal distribution with mean $x_0$ and variance $P_0$. Determine the mean of the generated ensemble: $x_0 = \frac{1}{N}\sum_{i=1}^{N} x_{0,i}$
– Time update. In this stage, efforts were made to determine the estimation of ensemble, mean, and error covariance at the next time step.

Estimation of ensemble: $\hat{x}_{k,i}^{-} = A\hat{x}_{k,i} + Bu_{k-1} + w_{k,i}$ for $i = 1, \cdots, N$, where $x_{0,i}$ for $i = 1, \cdots, N$ is generated from a normal distribution with mean $x_0$ and variance $Q_k$.

Mean of ensemble estimation: $\hat{x}_{k}^{-} = \frac{1}{N}\sum_{i=1}^{N} \hat{x}_{k,i}^{-}$

Covariance of ensemble estimation: $P_{k}^{-} = \frac{1}{N-1}\sum_{i=1}^{N}\left(\hat{x}_{k,i}^{-} - \hat{x}_{k}^{-}\right)\left(\hat{x}_{k,i}^{-} - \hat{x}_{k}^{-}\right)^{T}$

– Measurement update. At this stage, the correction was done by generating N ensemble on measurement data to determine the estimation of ensemble, Kalman gain, mean, and error covariance. Estimation of ensemble measurement: $z_{k,i} = z_k + v_{k,i}$ for $x_{0,i} i = 1, \cdots, N$ where $v_{k,i}$ is generated from a normal distribution with mean 0 and variance $R_k$.

Covariance between state and measurement: $P_{xz} = \frac{1}{N-1}\sum_{i=1}^{N}\left(\hat{x}_{k,i}^{-} - \hat{x}_{k}^{-}\right)\left(z_{k,i}^{-} - z_{k}^{-}\right)^{T}$

Covariance of measurements: $P_z = \frac{1}{N-1}\sum_{k=1}^{N}\left(z_{k,i}^{-} - z_{k}^{-}\right)\left(z_{k,i}^{-} - z_{k}^{-}\right)^{T}$

Kalman gain: $K_k = P_{xz}(P_z)^{-1}$

Update state estimation: $\hat{x}_{k+1} = \hat{x}_{k+1}^{-} + K_k\left(z_{k,i}^{-} - H\hat{x}_{k+1}^{-}\right)$

– Once the measurement update was finished, the process continues to the time update for the next time step. This process is repeated until all measurement data has been processed.

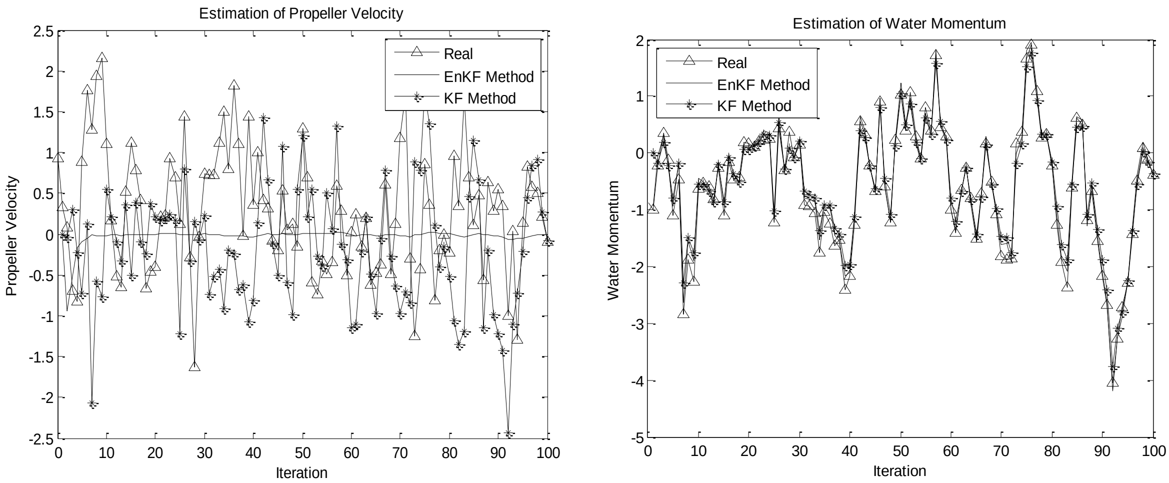
## 3. SIMULATION AND ANALYSIS RESULTS

In this section, we apply the KF and EnKF to the linearized bow thruster model. In each simulation, we define the initial state, i.e., the initial propeller velocity $\omega_m(0)$ and the initial water momentum $U_a(0)$. The covariance of system noise for all time is 0.5, i.e., $Q_k = 0.5$, for all $k$. The covariance of measurement noise for all time is also 0.5, i.e., $R_k = 0.5$ for all $k$.

### 3.1. Simulation I

In the first simulation, the parameters for tunnel thruster test are used. In this case, the duration of the simulation is $k = 100$ steps. In this simulation, we compare the real values and the estimation results obtained by using KF and EnKF. The comparison is based on the root mean square error (RMSE). Such comparison was shown to find out the better method to estimate the water momentum and propeller velocity in the linearized bow thruster model of ASV. Based on Figure 1 (a) the RMSE for estimating the propeller velocity using the KF method is 0.8678, whereas the RMSE for estimation result using the EnKF method is

0.8051. Figure 1 (b) shows that the RMSE for the water momentum estimation by the KF method is 0.8717, whereas the RMSE for estimation result using the EnKF method is 0.1344. Based on the simulation I result, the conclusion is that the EnKF method is more accurate than the KF, when we use the parameters for tunnel thruster test.

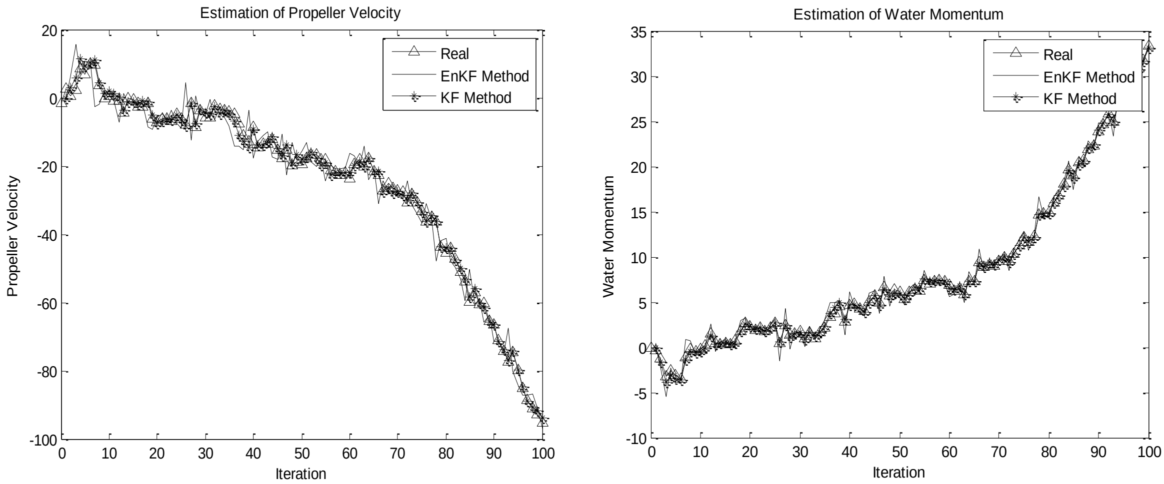



(a) (b)

Figure 1. Estimation results of (a) propeller velocity ($\omega_m$) and (b) water momentum ($U_a$) by tunnel thruster test

### 3.2. Simulation II

In simulation II, the simulation was carried out based on the open-bladed thruster test with a value of $k = 100$ steps. Simulation II is carried out by comparing the RMSE between the real value and both the KF and EnKF estimation results. Such results were shown to determine the better method for estimating the water momentum and propeller velocity in the linearized ASV bow thruster model. The results of simulation II is displayed in Figure 2(a) and (b).




(a) (b)

Figure 2. Estimation results of propeller velocity ($\omega_m$) and water momentum ($U_a$) by open-bladed thruster test

Based on Figure 2 (a) the RMSE value for the propeller velocity estimation result using the KF method is 1.6749, whereas the RMSE value for that using the EnKF method is 4.0858. Figure 2 (b) shows that the RMSE value for the water momentum estimation using the KF method is 1.6820, whereas the RMSE value for that using the EnKF method is 0.6795. Based on the estimation results of Simulation II, it could be concluded that the KF method has higher accuracy than the EnKF method, when the parameters for open-bladed thruster test are used.

### 3.3. Simulation III

In simulation III, we observe the effect of noise covariance to the accuracy of estimation results by using KF and EnKF, both for parameters of tunnel thruster test and open-bladed thruster test. In all simulations, the number of iterations is $k = 100$ steps. In the first case, we try the following covariance of noises 0.6, 0.8 and 1. Then for each covariance of noises, we implemented the KF and EnKF to the linearized bow thruster model where the parameters are tunnel thruster test. The different noise covariance values were expected to affect the estimation results in each method.

#### 3.3.1. Variety of noise covariance values by tunnel thruster test

According to results in simulation III in Figures 3 to 5, it is shown that the higher noise covariance value would affect the results of estimation. The values of RMSE are represented in Table 1. According to Table 1, EnKF has a better performance than KF in almost all cases. There is only one case where KF has a better performance than EnKF, i.e., the estimation of propeller velocity $(\omega_m)$ when the noise covariance equals 1.

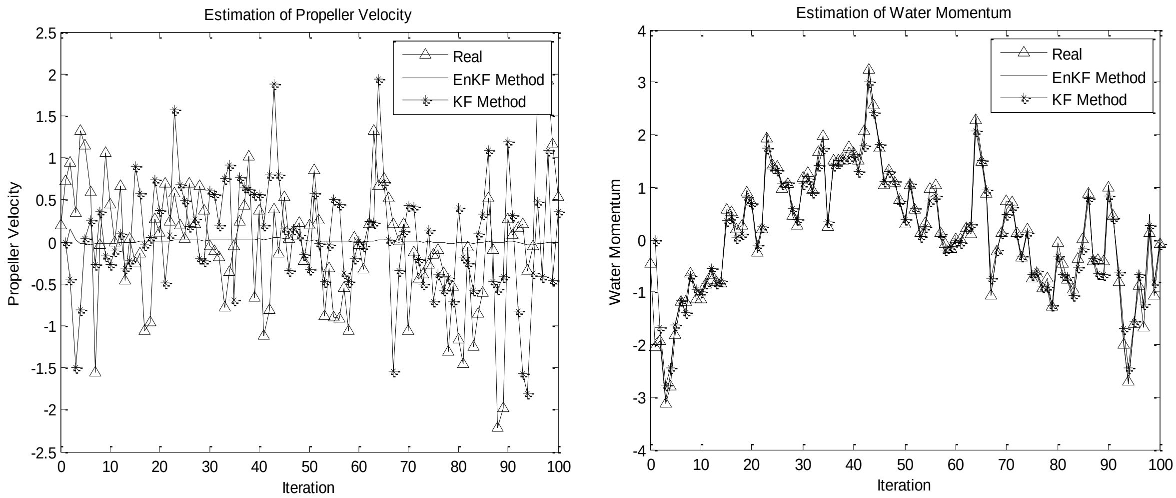



Figure 3. Estimation of propeller velocity $(\omega_m)$ and water momentum $(U_a)$ by tunnel thruster test with covariance of noise equals 0.6

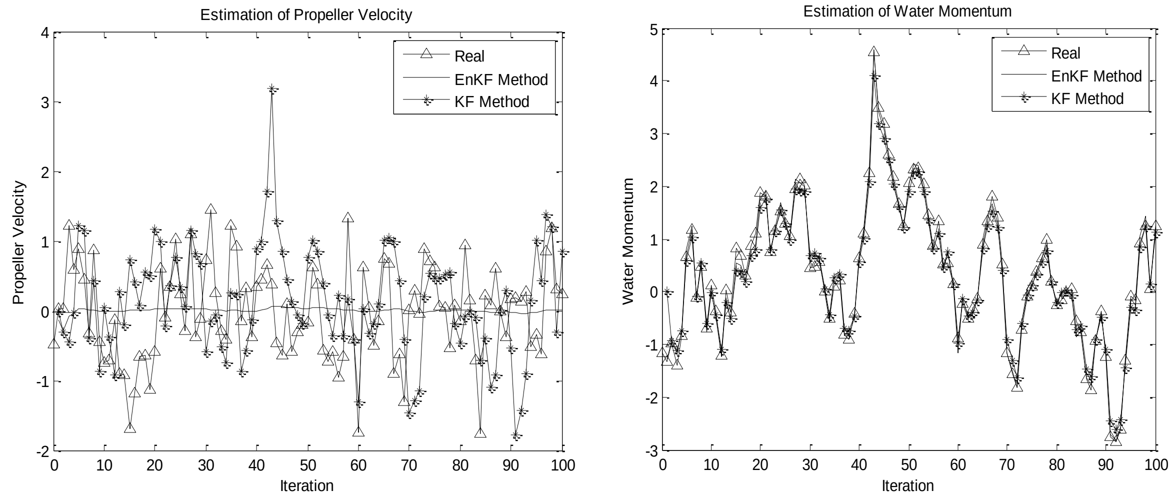



Figure 4. Estimation of propeller velocity $(\omega_m)$ and water momentum $(U_a)$ by tunnel thruster test with covariance of noise equals 0.8

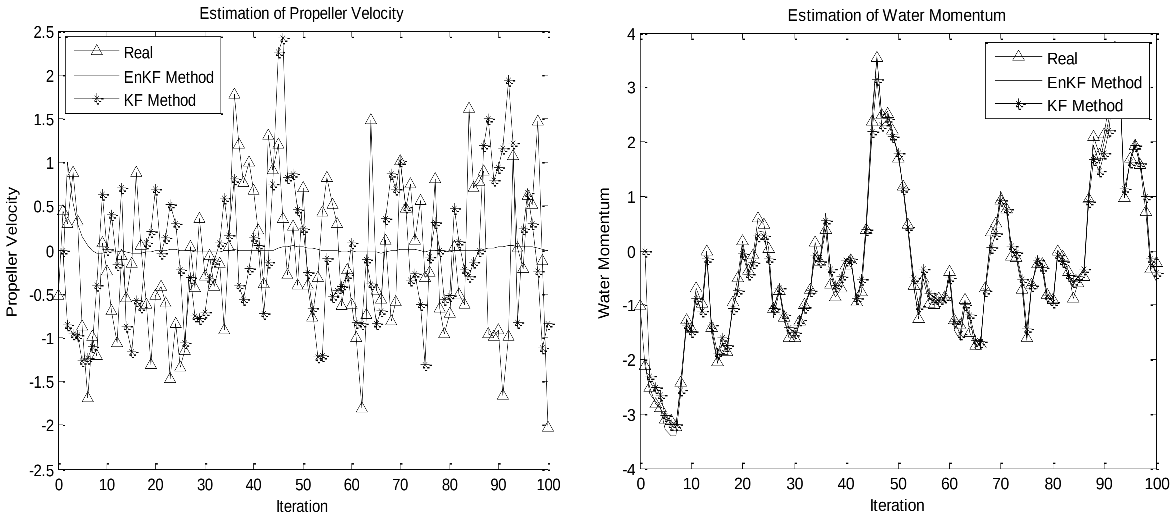



Figure 5. Estimation of propeller velocity $(\omega_m)$ and water momentum $(U_a)$ by tunnel thruster test with covariance of noise equals 1

Table 1. RMSE values $\omega_m$ and $U_a$ for some covariance of noise by tunnel thruster test

| | 0.6 | | 0.8 | | 1 | |
|---|---|---|---|---|---|---|
| | $\omega_m$ | $U_a$ | $\omega_m$ | $U_a$ | $\omega_m$ | $U_a$ |
| KF | 1.0751 | 1.0804 | 1,1638 | 1,1598 | **1.1969** | 1.8830 |
| ENKF | **0.8051** | **0.1344** | **0.9951** | **0.1659** | 1.2049 | **0.2017** |

### 3.3.2. Variation of noise covariance value by open-bladed thruster test

In this case, we vary the noise covariance values in 0.6, 0.8 and 1. For each noise covariance, we implement the KF and EnKF to the linearized bow thruster model where the parameters are the open-bladed thruster test. It was the condition under which the different noise covariance values was expected to affect the estimation results of each method. Based on the results in simulation III in Figure 6-8, it was shown that the higher noise covariance value affected the estimation results. The RMSE values are presented in Table 2. From Table 2, we can conclude that KF has a better performance in the estimation of propeller velocity $(\omega_m)$, whereas EnKF has a better performance in the estimation of water momentum $(U_a)$.

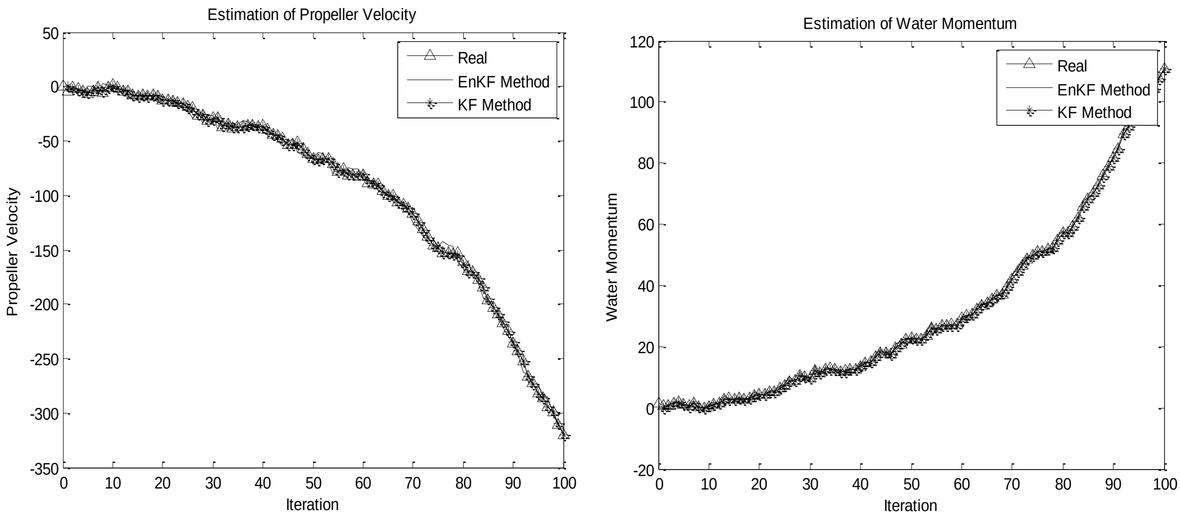



Figure 6. Estimation of propeller velocity $(\omega_m)$ and water momentum $(U_a)$ by open-bladed thruster test where the covariance of noise is 0.6

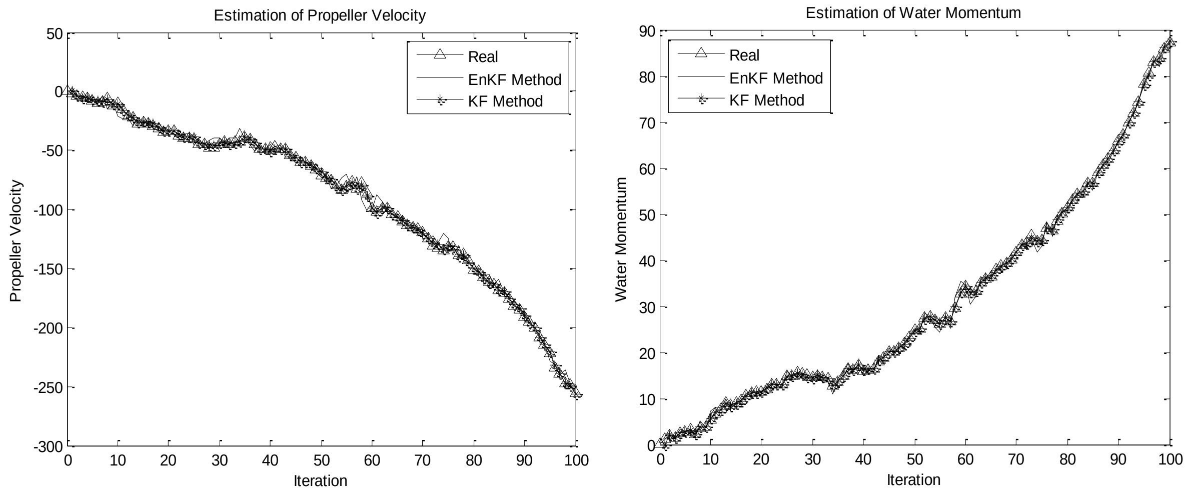



Figure 7. Estimation of propeller velocity ($\omega_m$) and water momentum ($U_a$) by open-bladed thruster test where the covariance of noise is 0.8

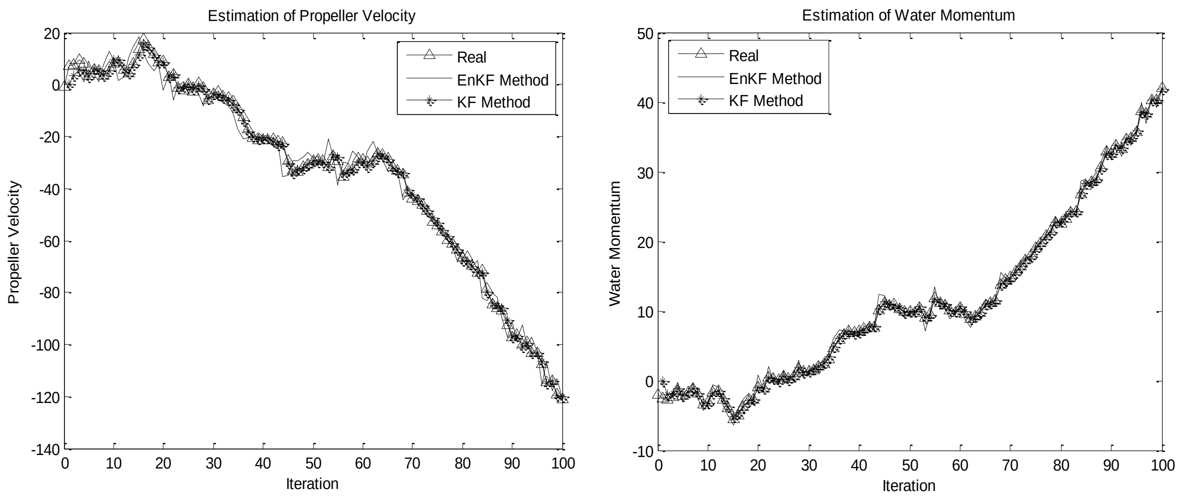



Figure 8. Estimation of propeller velocity ($\omega_m$) and water momentum ($U_a$) by open-bladed thruster test where the covariance of noise equals 1

Table 2. RMSE values $\omega_m$ and $U_a$ for some covariance of noise by open-bladed thruster test

| | 0.6 | | 0.8 | | 1 | |
|---|---|---|---|---|---|---|
| | $\omega_m$ | $U_a$ | $\omega_m$ | $U_a$ | $\omega_m$ | $U_a$ |
| KF | **1.7762** | 1.7748 | **1,8369** | 1,8449 | **2.2645** | 2.2752 |
| ENKF | 4.1879 | **0.6980** | 5.0252 | **0.8365** | 5.8559 | **0.9749** |

## 4. CONCLUSION

Based on the research results, the estimation results by the tunnel thruster test for the propeller velocity ($\omega_m$) and the water momentum ($U_a$) was more accurate when we use the EnKF method due to the relatively lower RMSE value, whereas in open-bladed thruster test for the estimation of propeller velocity ($\omega_m$) and water momentum ($U_a$), KF was more accurate than EnKF.

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