# Particle Filter Based Ship States and Parameters Estimation for Vessel Maneuvers

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## ABSTRACT

Vessel states and parameters estimation is essential for maneuvering and collision avoidance. This study presents an application of particle filter (PF) algorithm to estimate vessel states and parameters. Particularly, to reduce the impact of the vessel's underactuated property and complex environmental disturbance, the estimation process contains a kinematic curvilinear motion model that describes vessel's motion. The estimated result can help navigators or ship onboard computers well comprehend the current vessel maneuvering condition. Besides, it can also serve as the necessary data source for vessel's future trajectory prediction. Therefore, it can be integrated into vessel's situation awareness (SA) module that supports safety navigation for both conventional and autonomous vessels.

KEY WORDS: State and parameter estimation; Particle Filter; Kinematic motion model; Situation awareness; Autonomous shipping.

## INTRODUCTION

Researches about replacing onboard human activities with autonomous systems that are controlled by artificial intelligence (AI) become prevalent currently. With the advancement of various reliable sensors and further development of AI, high-level autonomous vessels would finally become a reality in the coming era. Based on the review of "maritime transport 2020" from the United Nations Conference on Trade and Development (UNCTAD, 2020), promotion of greater technology updating especially in digitalization and unmanned transportation is suggested for the post-pandemic world. As a potential solution, autonomous vessels that can transport either containers or bulk cargo are already attracted by several shipbuilders. An eye-catching example is that the prototype of the autonomous vessel built from the Yara-Birkeland project in Norway has started to test. This ambitious project is aimed at finding commercialized solutions for both autonomous and climate-friendly navigation.
To ensure a safe and efficient navigation behavior, an adequate level of SA is required. A well-known definition of SA is explained as SA is the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and a projection of their status in the near future (Endsley, 1995). Based on this definition, a SA module can be divided into three levels, i.e., perception of the current situation (level 1); comprehension of the current situation (level 2); projection of future situation (level 3). The 3 levels work in a sequential process. Decisions and corresponding maneuvering actions such as change of course, speed, or heading are implemented after SA is achieved. Endsley's model also contains a feedback mechanism. The performance of actions will feed back to SA module so that SA can be updated recurrently and support actions in the next step. Because SA is essential in decision-making process, insufficient SA or loss of SA may result in a wrong decision or action that could cause near-miss or collision accidents. Many marine casualties are reported to involve with human errors. A survey from European Maritime Safety Agency (EMSA) shows that human errors are the most substantial contributing factor with 58% in 1645 marine accidents (Hoem et al., 2019). Therefore, it is necessary to develop navigation tools that can enhance and support SA in all three levels. Enhancing SA is not just the safety guarantee in conventional navigation but will serve as the fundamental part of autonomous operation. To outperform manual operation, SA in autonomous ships should be more sophisticated.

In general, actions against collision or near-miss situations are regulated by International Regulations for Preventing Collisions at Sea 1972 (COLREGs). In inland or other specific areas, additional local navigation rules or regulations may also come into force. Though COLREGs is amended for manned vessels, yet it is expected that remote-controlled and autonomous vessels should also follow the same law. It is worth mention that COLREGs regulations are focus on the vessel encounter situations that have collision risk. Such encounter situations will become further complicated in a mixed environment where manned, remote-controlled, and autonomous vessels coexist. When considering the actions taken by vessels for the collision avoidance, because most vessels are typical rudder-propeller-thrust type, the controllability is considered as underactuated. This factor together with external disturbance from weather and sea will also affect the vessel maneuvers. Therefore, a continuous and reliable vessel maneuvering prediction must be implemented which can support SA.

There are two steps in vessel maneuvering prediction: states and parameters estimation and future trajectory prediction. They are consistent with the three levels in SA module. States and parameters estimation take priority over the future trajectory prediction since the latter requires the estimation result. Nowadays, linear predictions of vessel's future trajectory based on the current speed and course are popular in marine navigation (Perera, 2017). Such linear prediction is a limitation to support SA when making decisions in complex encounter situations. When vessels have a steady turning motion, or their motion have impact from underactuated property or environmental disturbance, linear prediction cannot be trustful. Consequently, appropriate tools and techniques for vessel maneuvering prediction that can support SA and serves future's autonomous shipping should be developed.

This study focuses on states and parameters estimation through simulation method. A curvilinear kinematic model is used to describe the vessel motion. PF algorithm is chosen for estimation. It is expected that such an approach can overcome the challenges of vessel maneuvering prediction under complex navigation conditions, whereas the high quality of measurement is not always guaranteed. The paper is structured as follows. Background about research is presented at first. The previous researches listed here cover both theoretical and applied point of views in marine engineering. The search problem in this paper is formulated by introducing the curvilinear kinematic model and PF algorithm. Coming next, simulation preparation, initial conditions, and simulation result are demonstrated. The simulation result is validated by the comparison among the actual, measurement, and estimated values. An evaluation of the result and future improvement suggestions are in the last part.

## BACKGROUND

### Vessel Encounter Situation

For various maritime applications, ship motions can be understood from different degree of freedom (DoF) (Fossen, 2010). Considering a ship encounter situation presented in Fig. 1, it is convenient to express the ship motion with 3-DoF in the horizontal space, i.e. surge, sway, and yaw. The two vessels shown in Fig.1 have different course-speed vectors ($V_a$ and $V_b$) and they can be decomposed into surge ($u_a$ and $u_b$) and sway velocity vector ($v_a$ and $v_b$) based on the vessel's body-fixed frame. It is well-known that most modern vessels that equip with the typical rudder-propeller-thrust control system are underactuated. This indicates that such vessels may not have the controllability in the sway direction. Even though some modern vessels own maneuvering thruster or azimuth thruster, yet the controllability in sway direction cannot be so effective when the vessel is in a normal cruising state. Besides, external forces and moments from wave, wind, and ocean current also have an unneglected influence on the sway direction (Johansen et al., 2016). These outer disturbances may also alter vessel's seakeeping and maneuvering behavior. Consequently, action towards the encounter situations can be complex when considering these factors. It is required to use more sophisticated controlling techniques and strategies (Pettersen and Nijmeijer, 2001).

It can be observed that if the predicted trajectories are only based on linear motion models with course-speed information, then the possible collision position cannot be detected in advance. A decision of keeping current states may cause the collision accident. Therefore, it is necessary to acquire sufficient and accurate vessel states and parameters. This is also the starting point for a more trustworthy trajectory prediction and collision risk assessment.

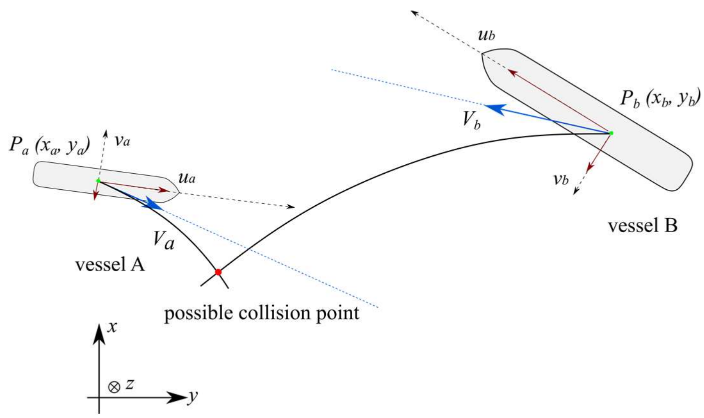

Fig. 1. Possible ship encounter situation

### Vessel Motion Model

The common solution for states and parameters estimation is based on the models which usually depend on the mathematical expression. Motion models can be classified into kinematic, dynamic, and hybrid ones. Among these models, dynamic type can be a challenge in real-world applications. An advance dynamic model usually contains nonlinear factors, such as hydrodynamic forces, moments, and other related coefficients. These nonlinear forces and moments are difficult to measure or observe by onboard sensors (Perera and Murray, 2019). Without enough measurement, estimation algorithms may not guarantee converged results. Kinematic models can be used as an alternative approach. Regarding the object's motion models, an all-inclusive survey was made (Li and Jilkov, 2003). It reports that the curvilinear kinematic model (Best and Norton, 1997) combined with a suitable yaw rate model can be one of the most reliable target maneuver models for 2D horizontal motions. It is well-known that vessels with large drafts have relatively slow responses. This slow reaction can occur even when the surrounding environment changes quickly (Perera, 2017). Therefore, kinematic models can be well suited for vessel's motion prediction during a short time range.

Considering the particularity of vessel's turning motion, the pivot point can play an important role. Pivot point is treated as the vessel's center of rotation when vessel turns. Veteran navigators usually estimate the position of pivot point by their experience in turning operation. A more academic study of pivot point concluded that this imaged position comes from the combined influence of yaw, surge, and sway velocity (Seo. S.G, 2016). By acknowledging this concept, a scientific method of calculating the position of pivot point is introduced (Perera, 2015). This method is also based on a curvilinear kinematic model where the surge and sway are included as the system states. It proposes to use various sensors to obtain sufficient measurement data. It is also expected that future vessel bridge systems can integrate such methods to improve motion prediction. The discretized model of this curvilinear kinematic model is used in this study.

## Estimation Algorithm

Kalman Filter (KF) and its correlates are used to solve the estimation problems with the uncertainties of system and measurement errors. KF is designed for linear models and the estimated result is statistically optimal. An application of KF to estimate the velocity by using the measurement from microelectromechanical accelerator is introduced in (Jeon, 2010). For nonlinear models, Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) can generate suboptimal estimates. An application of EKF that estimates the vessel's position, heading, and speed from the vessel's AIS data is presented in (Juraszek et al., 2020). UFK is considered with higher accuracy and low computational cost compared with EKF (St-Pierre and Gingras, 2004). The quality of measured data is another factor that influences the estimated result. Certain improvements of KF, EKF, and UKF can be implemented when dealing with non-Gaussian noises (Charles and Chen, 2016). A more robust method is to use PF which is available for all kinds of noise distribution. Several studies report that PF can increase accuracy and it is a promising solution for navigation and tracking (Gustafsson et al., 2002; Wu and Pi, 2006; Xiao et al., 2020). PF can be also applied to the data or multi-sensor fusion (Khaleghi et al., 2013) and the simultaneous localization and mapping (SLAM) problem (Durrant-Whyte and Bailey, 2006) which are all important approaches in autonomous navigation. It is concluded that more applications and searches about PF are yet to be discovered (Godsill, 2019).

PF used in this study is the standard bootstrap filter, in which the kinematic model is directly used as the importance distribution. The simplicity to draw the particle samples and the implementation are the advantages of bootstrap filter (Sarkka, 2013). However, because the drawing of the particle samples does not consider the latest information from measurement, it may require a large number of particles to ensure the estimation accuracy which can increase the computational cost.

# PROBLEM FORMULATION

The preparatory work of simulation is presented in this section. This simulation demonstrates states and parameters estimation for a vessel's steady turning motion. Both actual vessel navigational data and sensor measurement are generated artificially with certain statistical behavior. Despite the gap compared with real data, the simulated data can be used as the first trial to validate the algorithm. The vessel is assumed as a small size container whose water plane has 100 meters in length and 20 meters in width. The center of gravity is centrally located. It also assumes that the vessel equips with a typical rudder-propeller-thrust system, hence it is underactuated.

## Kinematic Curvilinear Motion Model

Fig.2 demonstrates a vessel turning maneuvering. A North-East-Down inertial frame is defined. The vessel's position is shown in 3 consecutive time steps. The vessel's related states and parameters are shown in the current step $T(t)$. The green dots represent the vessels' gravity center $P_{CG}$ where the red dots are the vessel's pivot points $P_P$. According to the proposed pivot point equation (Seo. S.G, 2016), the distance between $P_{CG}$ and $P_P$ is proportional to the sway velocity $v(t)$. As the vessel keeps turning, the increment of the sway velocity component can cause the pivot point to move to the bow side gradually. This phenomenon is also demonstrated in Fig.2.

The ship's states and parameters can be classified into 3 types based on the reference coordinates:

- inertial frame:

$P_{CG}$, $P_P$, course speed vector $V(t)$ and its component $v_{xg}(t)$ and $v_{yg}(t)$, acceleration $a_{xg}(t)$ and $a_{yg}(t)$, heading $\psi(t)$ and yaw rate $r(t)$;

- vessel body-fixed frame:

Surge $u(t)$ and sway velocity $v(t)$, acceleration $a_u(t)$ and $a_v(t)$

- tangent and normal to course speed vector $V(t)$:

tangent acceleration component: $a_{tg}(t)$,
normal acceleration component: $a_{ng}(t)$.

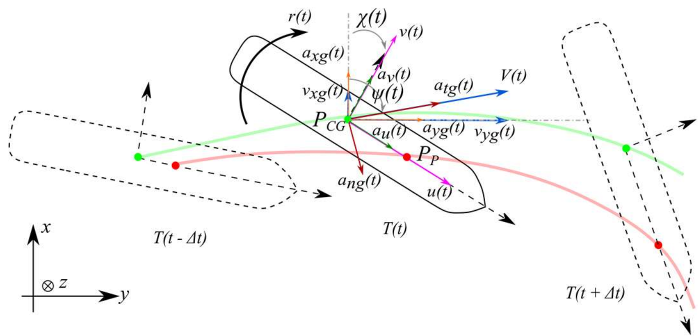


Fig. 2. Kinematic curvilinear motion model for vessels.

The curvilinear motion model for ship maneuvering can be written as:

$$\dot{\chi}(t) = \frac{a_{ng}(t)}{V(t)}$$
$$\dot{V}(t) = a_{tg}(t)$$
$$v_{xg}(t) = V(t)\cos\big(\chi(t)\big)$$
$$v_{yg}(t) = V(t)\sin\big(\chi(t)\big) \tag{1}$$

The surge $u(t)$ and sway velocity $v(t)$ can be expressed as:

$$u(t) = v_{xg}(t)\cos(\psi(t)) + v_{yg}(t)\sin(\psi(t))$$
$$v(t) = v_{yg}(t)\cos(\psi(t)) - v_{xg}(t)\sin(\psi(t)) \tag{2}$$

The accelerations in the inertial frame can thus be represented as:

$$a_{xg}(t) = \dot{v}_{xg}(t) = a_{tg}(t)f^{vxg} - a_{ng}(t)f^{vyg}$$
$$a_{yg}(t) = \dot{v}_{yg}(t) = a_{tg}(t)f^{vyg} + a_{ng}(t)f^{vxg} \tag{3}$$

The accelerations in surge and sway directions are:

$$a_u(t) = \dot{u}(t) = \big(a_{xg}(t) + r(t)v_{yg}(t)\big)\cos\big(\psi(t)\big) + \big(a_{yg}(t) - r(t)v_{xg}(t)\big)\sin(\psi(t))$$
$$a_v(t) = \dot{v}(t) = \big(a_{yg}(t) - r(t)v_{xg}(t)\big)\cos(\psi(t)) - \big(a_{xg}(t) + r(t)v_{yg}(t)\big)\sin\big(\psi(t)\big) \tag{4}$$

with:

$$f^{vxg} = \cos\big(\chi(t)\big) = v_{xg}(t)/\sqrt{v_{xg}(t)^2 + v_{yg}(t)^2}$$
$$f^{vyg} = \sin\big(\chi(t)\big) = v_{yg}(t)/\sqrt{v_{xg}(t)^2 + v_{yg}(t)^2} \tag{5}$$

## System Model & Discretization

The above-mentioned model is used to generate a continuous-time system model in (Perera, 2015). To implement the PF algorithm, this continuous-time system needs to be discretized.

The continuous-time system model is given by:

$$\dot{X}_g(t) = f\left(X_g(t)\right) + w_g(t)$$
$$E\left(w_g(t)\right) = 0; E\left(w_g(t) \cdot w_g(t)\right) = Q(t) \tag{6}$$

with:

$$X_g(t) = \left[x_g(t)\ v_{xg}(t)\ y_g(t)\ v_{yg}(t)\ u(t)\ v(t)\ \psi(t)\ r(t)\ a_{tg}(t)\ a_{ng}(t)\right]^T$$

$$f\left(X_g(t)\right) = \left[v_{xg}(t)\ a_{xg}(t)\ v_{yg}(t)\ a_{yg}(t)\ a_u(t)\ a_v(t)\ r(t)\ 0\ 0\ 0\right]^T \tag{7}$$

System process noise $w_g(t)$ is a white Gaussian noise with 0 mean value and covariance matrix $Q(t)$. Estimating the element values in covariance matrix is another engineering topic and is also crucial for motion prediction and decision making. A typical method can be found in (Stellet et al., 2015) ground vehicle motion models. The estimation accuracy can become higher with a well-investigated system process noise. As the first try, covariance matrix $Q(t)$ is set to be a diagonal and time-invariant matrix (citation the equation) in this study.

$$Q = diag[Q_x\ Q_{v_x}\ Q_y\ Q_{v_y}\ Q_u\ Q_v\ Q_\psi\ Q_r\ Q_{a_{tg}}\ Q_{a_{ng}}] \tag{8}$$

For the stochastic differential equations (5), the Euler-Maruyama method is a popular method for the discretization process (Murray and Storkey, 2011). The discretized system model can be represented as:

$$X_g(k) = X_g(k-1) + \Delta t \cdot f\left(X_g(k-1)\right) + \sqrt{\Delta t} \cdot w_g(k) \tag{9}$$

with $w_g(k) \sim N(0, Q)$

### Measurement Model

The measurement model is a discrete-time model. The observable measures are the ship position, heading, yaw rate, and surge & sway acceleration. These data sets can be easily obtained from the GNSS system and onboard sensors. The measure model can be written as:

$$Z_g(k) = h\left(X_g(k)\right) + w_z(k), \qquad k = 0, \Delta t, 2\Delta t, \ldots$$

with:

$$E\left(w_z(k)\right) = 0; E\left(w_z(k) \cdot w_z(k)\right) = [R(k)]; \tag{10}$$

$$h\left(X_g(k)\right) = \left[x_g(k)\ y_g(k)\ \psi(k)\ r(k)\ a_u(k)\ a_v(k)\right] \tag{11}$$

measurement noise $w_z(k)$ is also set to be Gaussian-distributed and covariance $R(k)$ is a diagonal matrix since the sensors are assumed to work separately. Finally, it is assumed that system and measurement noise processes are uncorrelated, i.e. $E\left[w_g(k), w_z(k)\right] = 0$ for all $k$.

### Bootstrap Filter Algorithm

The PF used in this study is the standard bootstrap filter. The general algorithm is shown as follows (Sarkka, 2013):

Boostrap filter algorithm

- Draw $N$ particles ${X_g}_0^{(i)}$ from a prior guess
  $${X_g}_0^{(i)} \sim p\left(X_{g0}\right)\ (i = 1, \ldots, N)$$
  and set particles' weights $w_0^{(i)} = 1/N\ \ (i = 1, \ldots, N)$
- For each step $k = 1, \ldots, T$
  (i) Draw new particles ${X_g}_k^{(i)}$ from the discretized system model (8)
  $${X_g}_k^{(i)} \sim p\left({X_g}_k \middle| {X_g}_{k-1}^{(i)}\right)\ \ (i = 1, \ldots, N)$$
  (ii) Calculate each particle's weights
  $$w_k^{(i)} = p\left(Z_g(k) \middle| {X_g}_k^{(i)}\right) w_{k-1}^{(i)}\ \ (i = 1, \ldots, N)$$
  and normalize $w_k^{(i)}$ to sum to unity
  (iii) Resampling process

The resampling process is used to solve the degeneracy problem. After this process, the particles with very small weights will be replaced by the particles with large weights. A more completed research about the resampling process can be seen in the literature (Kitagawa, 1996).

## COMPUTATIONAL SIMULATION

The simulation result is presented in this section. The actual vessel states and parameters are simulated data sets. The measurement is generated by adding reasonable sensor noises to the simulated data sets (Alessandro et al., 2017). Though PF is capable of treating the non-Gaussian noise, the measurement noises are assumed to be Gaussian-distributed in this study as the general case. The discretized time step $\Delta t$ is set to 1 second which is a practical sampling time of GNSS systems in the open sea. The estimated vessel states and parameters are calculated by the Bootstrap Filter algorithm.

### Actual Vessel Data

The simulated actual vessel positions and orientations along with its trajectory are shown in Fig.3. It is a steady turning motion with the impact from external disturbances. The trajectory is hence not a perfect circle. The total simulation time is 120 seconds. The vessel is represented by the grey icon every 5 seconds. The green spots record the vessel's center of gravity. Blue arrows stand for the vessel's course speed vectors and the red solid line is the true trajectory. This trajectory is similar to the one shown in Fig.2. This can be considered as an example of a vessel's turning motions with external disturbances during a short operation time. The initial states and parameters are listed as follows:
$x_g = 0, v_{xg} = 10\ [m/s], y_g = 0, v_{yg} = 0[m/s], u = 10[m/s]$,
$v = 0, \psi = 0, r = 2[°/s], a_{tg} = -0.1[m/s^2], a_{ng} = 0.3[m/s^2]$.

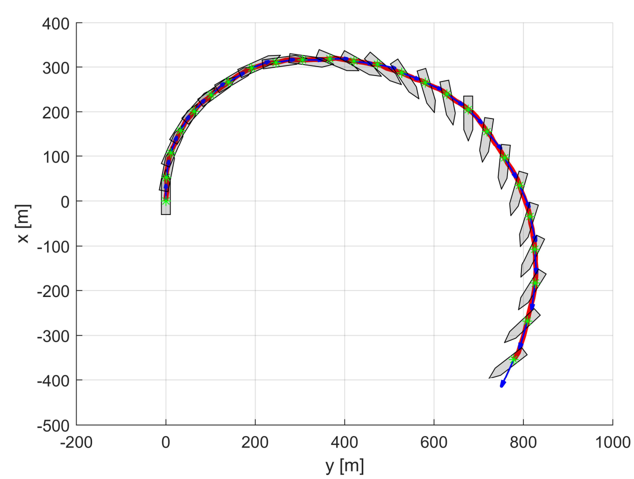


Fig. 3. Ship's actual position, orientation, course speed vector, and trajectory.

### Initialization of Bootstrap Filter

The algorithm starts with drawing particles from a prior guess $p(X_{g0})$. As the preparation work for simulation, the prior guess is also assumed to be Gaussian distributed, i.e. $p(X_{g0}) = N\left(X_{g0}\middle|Q(t)\right)$ with:

$$X_{g0} = \left[x_{g_0}\ v_{xg_0}\ y_{g_0}\ v_{yg_0}\ u_0\ v_0\ \psi_0\ r_0\ a_{tg_0}\ a_{ng_0}\right] \tag{12}$$

Since position, heading, and yaw rate can be directly obtained from the sensors, these measurement data can be used as the expectation values for prior guess (12). For the velocity $v_{xg_0}$ and $v_{yg_0}$, a reasonable initial guess can be obtained by the differentiation of historical GNSS data or from the ship's design performance data. In this simulation, $v_{xg}$ is set to be uniformly distributed between 5 and 15 $[m/s]$ and $v_{yg0}$ is set uniformly distributed between $-2$ and 2 $[m/s]$. Once the $v_{xg_0}$ and $v_{yg_0}$ are obtained, according to (2) and (3), the responsible $u_0$, $v_0$, $a_{tg_0}$, and $a_{ng_0}$ can also be calculated. Particle number $N$ is set to 1000.

## Simulation Result

The estimation result of vessel position is shown in Fig.4. The actual vessel position is presented in a solid blue line and the measurement position data are labeled as the green cross. The red dots are the estimation values. The position error is plotted in Fig.5. Position estimation error in both x- and y-axes becomes less than 2 meters in a fast time.

Fig.6 ~ 7 are the simulation result of heading and yaw rate. The result also shows a good converge property. For the unobservable velocity and acceleration states, the estimated values have a deviation at the beginning, but also converge as the filter executes further (Fig.8 ~ 9). The simulations with different prior guess values also show that if the initial value of $v_{xg_0}$ and $v_{yg_0}$ (12) have a large aberration from the actual value, the estimation results can diverge quickly. This problem cannot be solved by purely increasing particle numbers. Consequently, a reasonable initialization of PF is vital for the filtering performance of this kind of PF.

The estimation result of surge $u(t)$ and sway velocity $v(t)$ does not show a good convergency (Fig. 10). The estimated value shows a sudden discontinuous gap at some time step or a constant drift. The purely increasing of the particle number cannot solve this problem. The simulation result by EKF algorithm using this same model shows that the convergence rates of $u$ & $v$ are relatively slow compared with other's (Perera, 2017), therefore a more detail study for the estimation of these 2 states is necessary.

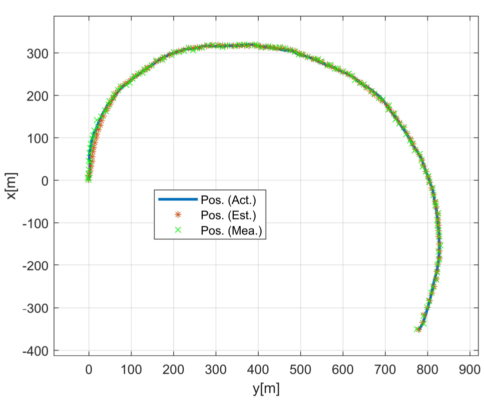

Fig. 4. Ship's position simulation result

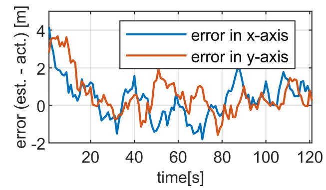

Fig.5. Estimated position error

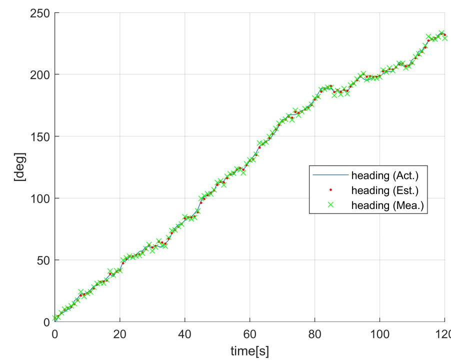

Fig. 6. Ship's heading simulation result

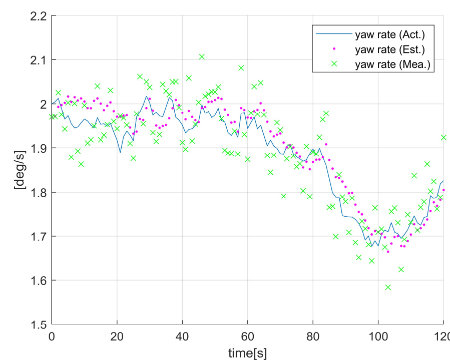

Fig. 7. Ship's yaw rate simulation result

## CONCLUSION

States and parameters estimation is an essential job to support SA module for both conventional navigation and future's autonomous shipping. The estimated various datasets can be further used to predict the vessel's trajectory with higher accuracy. This can provide navigator or onboard AI more dedicated information, hence an action against the collision can be implemented earlier. This study uses PF approach (Bootstrap Filter Algorithm) combined with a curvilinear kinematic model. Kinematic motion model is a better solution to predict ship maneuvers during a short operation time if the vessel dynamic conditions are too complex.

As a solution for nonlinear systems, the bootstrap filter is a simple and straightforward method compared with other types of PF. The simulation results show that the bootstrap filter can be applied simply for the proposed nonlinear motion model and generate good estimation result for most of the states and parameters. The simulation result shows that the convergence is not guaranteed for all states and parameters. However, the estimation of surge and sway velocity does not show the same convergence properties compared with others. The estimated values

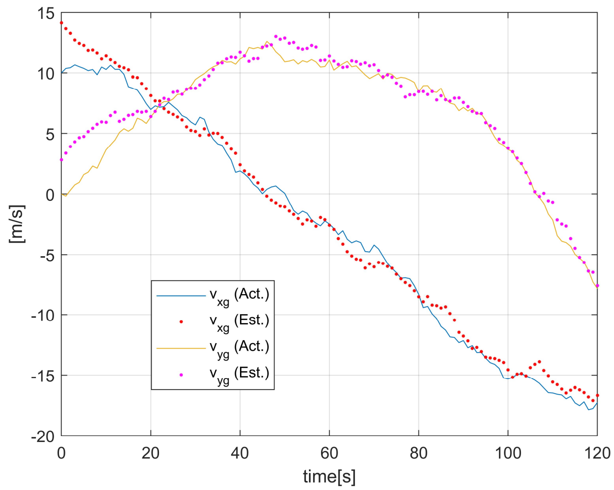


Fig. 8. Simulation result of $v_{xg}$ and $v_{yg}$

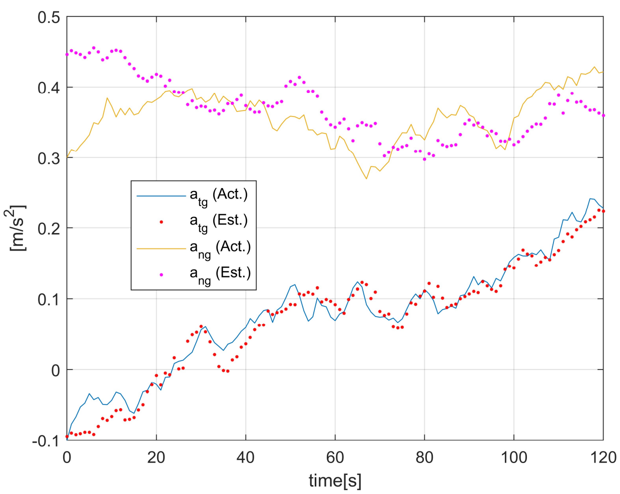


Fig. 9. Simulation result of $a_{tg}$ and $a_{ng}$

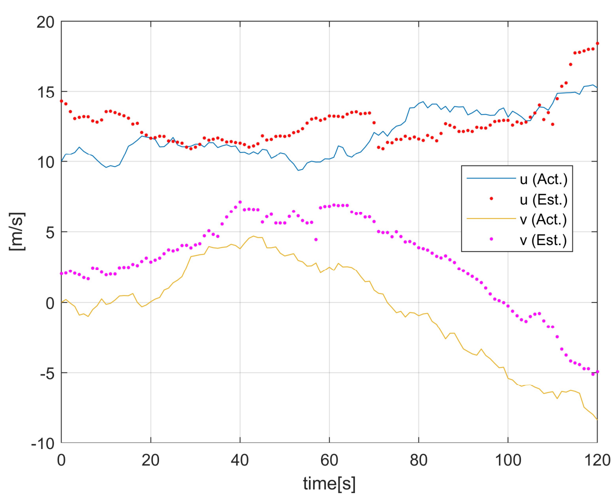


Fig. 10. Simulation result of $u$ and $v$

jump suddenly in some time step and can have a long-term drift against the actual values. A possible reason for this is related to the system model structure or the obstacles for PF in high-dimensional systems (Snyder et al., 2008). This problem needs to be further studied in later research.

One of the possible solutions is the combination of both EKF (or UKF) and PF. Referring to the research in (Rigatos, 2010), it is possible to estimate a part of states and parameters with EKF (or UKF) where the rest states with PF. This operation can reduce the computational cost and states' dimensions that are considered as the major drawbacks of PF. It is expected that the combination of filters can make the estimation more robust and reliable. The future research will also cover a sea-trial experiment. By collecting and analyzing the real navigation data, validation process can be executed by the comparison between experiment and simulation.

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