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ORIGINAL ARTICLE

Practical method for evaluating wind influence on autonomous ship operations (2nd report)

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Abstract

Recently, a considerable number of research and development projects have focused on automatic vessels. A highly realistic simulator is needed to validate control algorithms for autonomous vessels. For instance, when considering the automatic berthing/unberthing of a vessel, the effect of wind in such low-speed operations cannot be ignored because of the low rudder performance during slow harbor maneuvers. Therefore, a simulator used to validate an automatic berthing/unberthing control algorithm should be able to reproduce the time histories of wind speed and wind direction realistically. Therefore, in our first report on this topic, to obtain the wind speed distribution, we proposed a simple algorithm to generate the time series and distribution of wind speed only from the mean wind speed. However, for wind direction, the spectral distribution could not be determined based on our literature surveys, and hence, a simple method for estimating the coefficients of the stochastic differential equation (SDE) could not be proposed. In this study, we propose a new methodology for generating the time history of wind direction based on the results of Kuwajima et al.'s work. They proposed a regression equation of the standard deviation of wind direction variation for the mean wind speed. In this study, we assumed that the wind direction distribution can be represented by a linear filter as in our previous paper, and its coefficients are derived from Kuwajima's proposed equation. Then, as in the previous report, the time series of wind speed and wind direction can be calculated easily by analytically solving the one-dimensional SDE. The joint probability density functions of wind speed and wind direction obtained by computing them independently agree well with the measurement results.

Keywords Wind speed and direction · Stochastic differential equation · Liner filter · Estimation of drift and diffusion

1 Introduction

Wind disturbance has a significant impact on vessels operated in harbors under low-speed maneuvering motion, as mentioned in our previous report [1]. When wind speeds exceed a certain level, it becomes difficult for vessels to safely berth by themselves, and a choice has to be made between berthing with the help of anchors or tugboats or suspending the berthing operation altogether. Not only wind speed but also wind direction is a key factor to consider during berthing/unberthing operations. Berthing trajectories are known to vary depending on the wind direction. Further, the threshold values of wind speed can change due to wind direction.

Several recent projects have explored automatic berthing/unberthing control algorithms. To improve the performance of automatic berthing/unberthing control systems, it is necessary to tune and optimize the parameters in the control algorithms. To do so, numerical simulation is essential, but the number of numerical simulations required for optimization is huge when algorithms such as stochastic multipoint search are employed. Therefore, it is desirable to reduce the time required for function evaluation (i.e., simulation for one scenario in this case) as much as possible. In such simulations, it is necessary to consider wind disturbances with the designated wind spectrum, rather than disturbances such as white noise, to increase realism.

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In the research and development field of naval architecture and ocean engineering, the superposition method has been used to achieve the objective of generating irregular signals with specified spectra. The superposition method is as follows. Here, x_{sig}: irregular signal, $S_{\mathrm{sig}}(\omega_{\mathrm{sig}})$: spectrum of the irregular signal, ω_{sig}: frequency, $\epsilon_{\mathrm{sig}} \in [0, 2\pi)$: a uniformly distributed random number. In this case, the irregular signal is expressed as follows.

$$x_{\mathrm{sig}}(t) = \sum_{i=1}^{\infty} \sqrt{2S_{\mathrm{sig}i}(\omega_{\mathrm{sig}i})\mathrm{d}\omega_{\mathrm{sig}i}} \cos(\omega_{\mathrm{sig}i}t + \epsilon_{\mathrm{sig}i}) \quad (1)$$

However, the superposition method, which is conventionally used in the fields of naval architecture and ocean engineering, incurs high computational cost because of the presence of a `for` loop for wave superposition. To avoid the self-repetition of generated signals, the number of superimposed waves must be kept large. From another perspective, the number also must be maintained to some extent to avoid deterioration of statistical properties [2]. For example, Maruyama et al. [2] also shows that when the number of spectral divisions is set to about 10^4, no repetition occurs for almost 9 h. However, with such a large number of divisions, one is faced with the problem of large computational cost required for superposition. To solve this problem, it is necessary to avoid the repetition of time series by other methods instead of the energy equidivision method. On the other hand, another technique that reduces the increase in computational cost is the spectral unequal subdivision method [3]. Even so, however, there may not yet be a unified view on what size of subdivision is appropriate. As described above, so long as the superposition method is employed for long wind-time history, reducing the computational cost drastically remains a challenge. Therefore, there is a need for an alternative method to generate the time series of wind speed and direction without self-repetition.

Several studies explored the horizontal component of gustiness, and several wind spectrum forms have been proposed by Kármánn [4], Hino [5], Davenport [6], and others. Many attempts have been made to find probability distributions and statistics of speed and wind direction (e.g. [7–9]). Among them, Carta et al. studied the joint probability of wind velocity and direction [10]. The stochastic behavior of wind disturbance too has been investigated [11–15]. Li and Kareem [16] used the autoregressive and moving average (ARMA) recursive models to generate wind time history. Further, Benth et al. [17] used an Ornstein–Uhlenbeck process to model the power production of wind farms. Their study is somewhat similar to our previous study [1] in terms of direction and approach. Among the aforementioned studies, Nichita et al. [12] approximated the wind spectra with a two-dimensional filter, and calculated the wind-time series. Dostal et al. [18] approximated the wave with a two-dimensional stochastic differential equation (SDE) using the continuous autoregressive moving average (CARMA) process. Although these studies used two-dimensional SDEs, as described in a previous paper [1], wind velocity variations can possibly be approximated using a lower-order filter, i.e., a one-dimensional (1D) filter of the lowest possible dimension. To achieve such an objective, the authors attempted in the first part of their paper to model the wind velocity variation.

The system approximated by the one-dimensional filter having a form of the following SDE:

$$\mathrm{d}u_{\mathrm{w}}(t) = m_{\mathrm{WS}}(u_{\mathrm{w}}(t) - \bar{u})\mathrm{d}t + \sigma_{\mathrm{WS}}\mathrm{d}W(t) \quad (2)$$

Here, $u_{\mathrm{w}}(t) \in \mathbb{R}$: wind velocity, $\bar{u} \in \mathbb{R}$: mean wind velocity, $m_{\mathrm{WS}} \in \mathbb{R}$: drift coefficient, $\sigma_{\mathrm{WS}} \in \mathbb{R}$: diffusion coefficient. For the case where $\bar{u} = 0$, the stochastic differential equation (SDE) in Eq. 2 is also known as the Ornstein–Uhlenbeck process. It is a linear SDE with drift coefficient m_{WS} and standard deviation σ_{WS}. In this study, the set of real numbers is denoted by $\mathbb{R}$. The expectation operation is denoted by $\mathbb{E}$, and t represents time.

Further, $W(t)$: one-dimensional standard Wiener process that satisfies the relation

$$\begin{cases} \mathbb{E}[W(s) - W(t)] = 0 \\ \mathbb{E}[(W(s) - W(t))^2] = |t - s| \\ \qquad \text{and} \\ \begin{cases} \mathbb{E}[W(s)W(t)] = \min(s, t) \\ \qquad \text{or} \\ \mathbb{E}[\mathrm{d}W(s)\mathrm{d}W(t)] = \delta_{\mathrm{D}}(t - s) \end{cases} \end{cases} \quad (3)$$

and $\mathrm{d}W(t)$ is the increment of the Wiener process. Here, $\delta_{\mathrm{D}}(t)$ means the Dirac's delta function.

The system is approximated by the well-known Ornstein–Uhlenbeck process, which allows the use of known analytical solutions and the generation of a time series. It should also be noted that, as long as the random numbers are not repeated, this method does not cause self-repetition.

In fact, this method has been used in research on the automatic berthing control algorithm by reinforcement learning [19] (Fig. 1).

The SDE had two unknown terms, namely, drift term m_{WS} and diffusion terms σ_{WS} in Eq. 2. In our previous study [1], when examining wind speed fluctuations, we approximated the drift and diffusion from the values of the Davenport spectral [6] and Hino spectral [5]. However, we could not determine the drift and diffusion terms for wind direction at that time because of the lack of sufficient literature on the subject.

Although the randomness of wind direction has not been extensively researched, the reports of Kuwajima et al. [20,

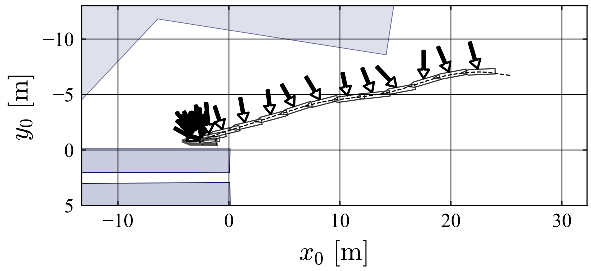

Fig. 1 Generated wind used in reinforcement learning on automatic berthing Controller [19]

Table 1 Used data for analysis

Item	Measurer	Approx. position	Term
Sample 1	K. Sasa	50.01833 N 5.01090 W	2018/12/11–15
Sample 2	K. Sasa	53.50333 N 9.96158 E	2018/12/17–31
Sample 3	R. Sawada	34.34829 N 133.14667 E	2021/11/25
			2022/1/15

21] are available. Based on these studies, we propose a methodology for determining the unknown coefficients of SDEs based on the relationship between mean wind speed and standard deviation of wind direction variation.

The initial results of our investigation were reported previously by Maki et al. [22]. The present paper reports the results more extensively and with some revisions.

2 Notations

Some symbols have already been defined and used in the preface. The meanings of some symbols, including duplications, are given here. In this study, the n-dimensional Euclidean space is denoted by $\mathbb{R}^n$, and the set of real numbers for $n = 1$ is denoted by $\mathbb{R}$. Vectors are defined by column vectors. The expectation operation is denoted by $\mathbb{E}$, and t and s represent time.

3 One-dimensional filter of wind direction

We analyzed the data measured on board a ship (see Table 1). The sampling frequency of wind speed for all the data was 1 [Hz].

Figure 2 shows a picture of the anemometer used to measure Sample 3.

Kuwajima et al. [20] obtained the following regression formula for the relationship between the standard deviation of wind direction σ_γ [deg.] and the mean wind velocity $\bar{u}$ [m/s].

Fig. 2 Anemometer used in Sample 3 acquisition

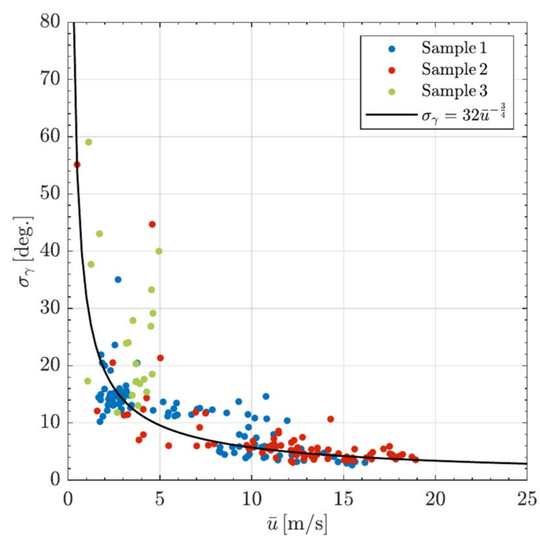

Fig. 3 Standard deviation of wind direction

$$\sigma_\gamma = 32\bar{u}^{-\frac{3}{4}}. \tag{4}$$

To verify the validity of the regression in equation (Eq. 4), statistical analysis was performed on the time-series data sample shown in Table 1. Figure 3 shows the corresponding comparison.

From this figure, we can understand that Kuwajima's regression equation estimates the statistics of wind direction from only wind speed information with practical accuracy. The final goal of this research is to obtain an SDE that describes well the stochastic property of wind direction using Kuwajima's regression equation.

First, the wind direction $\gamma(t)$ is separated into an average component $\bar{\gamma}$ and a variable component $\tilde{\gamma}(t)$ as follows. Note that t is time.

$$\gamma(t) = \bar{\gamma} + \tilde{\gamma}(t). \tag{5}$$

Further, suppose that the variation component $\tilde{\gamma}$ can be approximated by the following one-dimensional SDE where $W(t)$ is a one-dimensional Wiener process.

$$\mathrm{d}\tilde{\gamma} = m(t, \tilde{\gamma})\mathrm{d}t + \sigma(t, \tilde{\gamma})\mathrm{d}W(t). \tag{6}$$

Here, $m(t, \tilde{\gamma})$ is the drift term, and $\sigma(t, \tilde{\gamma})$ is the diffusion term. Now, consider the following case:

$$\begin{cases} m(t, \tilde{\gamma}) = \alpha\tilde{\gamma} \\ \sigma(t, \tilde{\gamma}) = \varsigma \end{cases} \tag{7}$$

This equation assumes that the drift term linearly varies with slope α with respect to the change from the mean wind direction and that diffusion is constant in ς.

Then, the SDE becomes:

$$\mathrm{d}\tilde{\gamma}(t) = \alpha\tilde{\gamma}\mathrm{d}t + \varsigma\mathrm{d}W(t). \tag{8}$$

For systems where only additive noise is present, the stability of the system is determined only by the stability of the deterministic part. In the case of a simple one-dimensional system such as the present one, $\alpha < 0$ is the condition for the system stability, as stated in the previous work by Maki et al. [1]

Now, we have established the form of the SDE. Next, we explain how to determine the drift term m and the diffusion term σ in the SDE. As mentioned in the previous paper[1], these terms can be estimated from the time series data using Eq. 9 with a conditional expectation [23].

$$\begin{cases} m(t, \tilde{\gamma}) = \lim\limits_{\mathrm{d}t \to +0} \dfrac{\mathbb{E}[\mathrm{d}\tilde{\gamma}(t) \mid \tilde{\gamma}(t) = \tilde{\gamma}]}{\mathrm{d}t} \\ \sigma^2(t, \tilde{\gamma}) = \lim\limits_{\mathrm{d}t \to +0} \dfrac{\mathbb{E}\left[(\mathrm{d}\tilde{\gamma}(t))^2 \mid \tilde{\gamma}(t) = \tilde{\gamma}\right]}{\mathrm{d}t} \end{cases} \tag{9}$$

Many studies dealt with obtaining the drift term $m(t, \tilde{\gamma})$ and diffusion term $\sigma(t, \tilde{\gamma})$ from time series data [11, 13, 24–30].

As reported in our previous paper[1], when the wind direction varies, the drift seems to have a linear relation over a wide range, while the diffusion σ seems to have a slightly parabolic shape. Therefore, it may be unreasonable to assume that diffusion σ is constant, and this is one of the issues to be addressed in the future.

The FPK equation for wind directional variation is as follows:

$$0 = -\frac{\mathrm{d}}{\mathrm{d}\tilde{\gamma}}\alpha\tilde{\gamma}\mathscr{P}(\tilde{\gamma}) + \frac{1}{2}\frac{\mathrm{d}^2}{\mathrm{d}\tilde{\gamma}^2}\varsigma^2\mathscr{P}(\tilde{\gamma}). \tag{10}$$

By solving the above equation, we can obtain the stationary probability density function as a Gaussian distribution with variance $\varsigma^2/2\alpha$:

$$\mathscr{P}(\tilde{\gamma}) = \sqrt{\frac{\alpha}{\varsigma^2\pi}} \exp\left(-\frac{\alpha}{\varsigma^2}\tilde{\gamma}^2\right). \tag{11}$$

Therefore, considering that the standard deviation of this normal distribution, that is:

$$\sigma_\gamma^2 = \frac{1}{2}\frac{\varsigma^2}{\alpha} \tag{12}$$

is equal to the regression equation (Eq. 4) for the standard deviation obtained by Kuwajima et al. [20], the following relationship can be obtained.

$$\alpha = \frac{\varsigma^2}{2 \cdot 32^2}\bar{u}^{\frac{3}{2}}. \tag{13}$$

Here, σ_γ, ς, and α are related to each other, and one of the parameters must be specified. Therefore, first, we plotted $\tilde{\sigma}$ and α as calculated from the measurement data (see Fig. 4).

In the right figure, ς appears to be constant in the range of $\bar{u} > 10\,[\mathrm{m/s}]$, so hereafter we represent this ς value as $\hat{\varsigma}$ as follows:

$$\hat{\varsigma} = 2.3. \tag{14}$$

By substituting this into Eq. 13, we determine α. Hereafter, the α determined by the following equation is represented as $\hat{\alpha}$:

$$\hat{\alpha} = \frac{\hat{\varsigma}^2}{2 \cdot 32^2}\bar{u}^{\frac{3}{2}}. \tag{15}$$

Using these values, it is therefore possible to compute a time series of the variations in wind direction. Here, $\bar{\gamma}$ represents the average wind speed. This solution can be expressed as follows when the initial value is $\gamma(0) = \gamma_0$.

$$\gamma(t) = e^{-\hat{\alpha}t}\gamma_0 + \bar{\gamma}(1 - e^{-\hat{\alpha}t}) + I(t). \tag{16}$$

Here, The Itô integral $I(t)$ is defined as follows:

$$I(t) \equiv \hat{\varsigma}_\mathrm{C} \int_0^t e^{-\hat{\alpha}(t-s)}\mathrm{d}W(s). \tag{17}$$

$I(t)$ should be evaluated as left-hand Riemann sums (e.g., [31]). See Maki et al. [1] for more information on this section.

For convenience, we write $I(t)$ as I_{N_t} and t as t_{N_t}. Let $\mathrm{d}t$ be defined as follows.

$$\mathrm{d}t \equiv t_{N_t+1} - t_{N_t}. \tag{18}$$

Then, the relationship between I_{N_t+1} and I_{N_t} can be expressed by the following recurrence formula:

$$I_{N_t+1} = e^{-\hat{\alpha}\mathrm{d}t}\left[I_{N_t} + \hat{\varsigma}\{W(t_{N_t+1}) - W(t_{N_t})\}\right]. \tag{19}$$

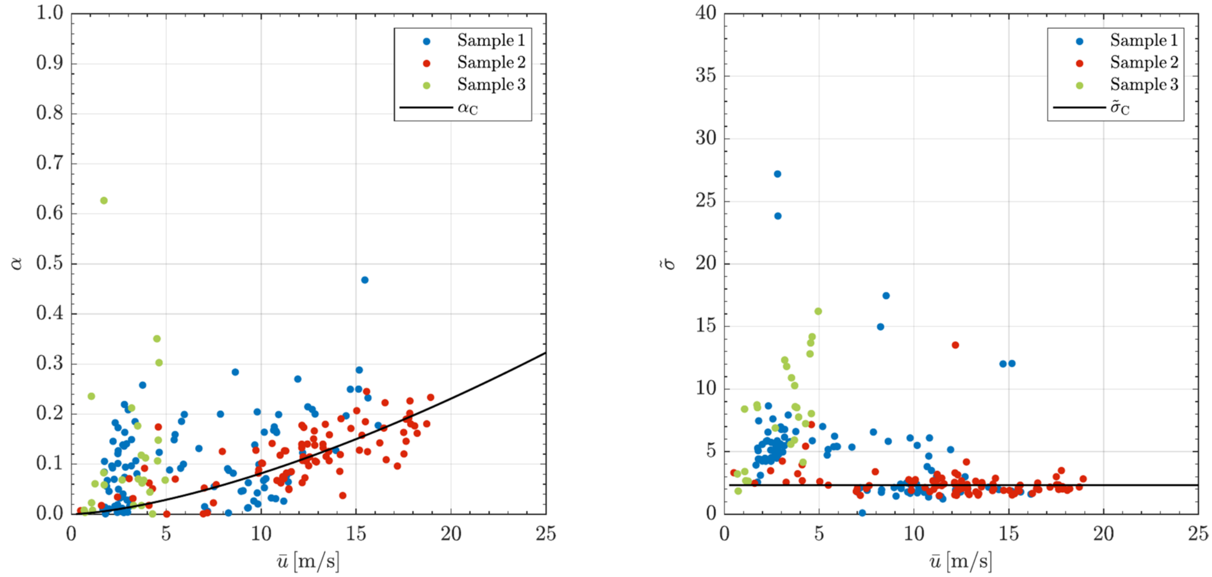

Fig. 4 α and σ obtained from each Sample

As shown in our previous paper [1], the drift term $m(\tilde{\gamma})$ and diffusion term $\sigma(\tilde{\gamma})$ can be estimated from the time series data as a function of $\tilde{\gamma}$. From Eq. 11, we can see that $\mathscr{P}(\gamma)$, drift term m, and diffusion term σ are related to each other. Even if one of them cannot be determined exactly, it can be estimated from another term, as shown by Minano et al.[15]. In this case, there may be a slight problem in estimating the Diffusion σ. Meanwhile, the wind direction generally follows a normal distribution. Therefore, improving the estimation accuracy rather than imposing Minano's condition as a constraint condition may be a research direction. This is one of the author's future works.

4 Algorithm

The algorithm of the present method is shown in Alg. 1.

Algorithm 1 $\gamma(t)$ generation

1: Step 1 Set winds mean speed $\bar{u}$ and $f_{ref} = 0.5$
2: Step 2 Set $s_C = 2.3$ and compute α_C by Eq.15.
3: Step 3 Generate the time-varying component of wind direction $\tilde{\gamma}(t)$ by using Eq.19.
4: Step 4 Generate the wind time history by Eq. 5.

Notice that in the case of simultaneous generation of wind velocity and direction, the user has to use different Wiener processes for velocity and direction time series generation. Otherwise, both time series will have a correlation.

5 Results and discussion

The results of the wind direction variation distribution as calculated using the obtained $\tilde{\sigma}_C$ and α_C are shown in Figs. 5 and 6. The time series are also shown in Figs. 7 and 8. The time series data of wind direction is pre-shifted so that the mean value is 180°. Note that the method proposed in this paper for calculating the variation of wind direction requires the average wind speed as the only input value. In the following calculations, the mean value of the time series of wind velocity for one hour of the measured data was obta ined.

In these four figures, three results from the analysis of real ship measurements data, the orange line (denoted as "Lin. filter anal. solution from obs. data") and the purple line (denoted as "Lin. filter anal. solution from theor. data") are compared. The three results are compared. In the calculation of the orange line, first the drift and diffusion are calculated from the measured values based on Eq. 9. Then, the time series of wind direction is calculated using these properties, and the obtained data is statistically analyzed. The drift was extracted from the slope near the origin (180°), and the diffusion was extracted from the value at the origin. The purple line is the result based on the proposed calculation method.

As shown in Figs. 5 and 6, the spectral analysis results of the time series generated by the present algorithm are generally consistent with the results of the spectral analysis of the time series measured on board. In addition, the trend of the drift obtained from the actual ship measurements seems to be generally consistent with the values proposed in this paper (see purple line). On the other hand, as already pointed out in the previous paper [1], the diffusion obtained from

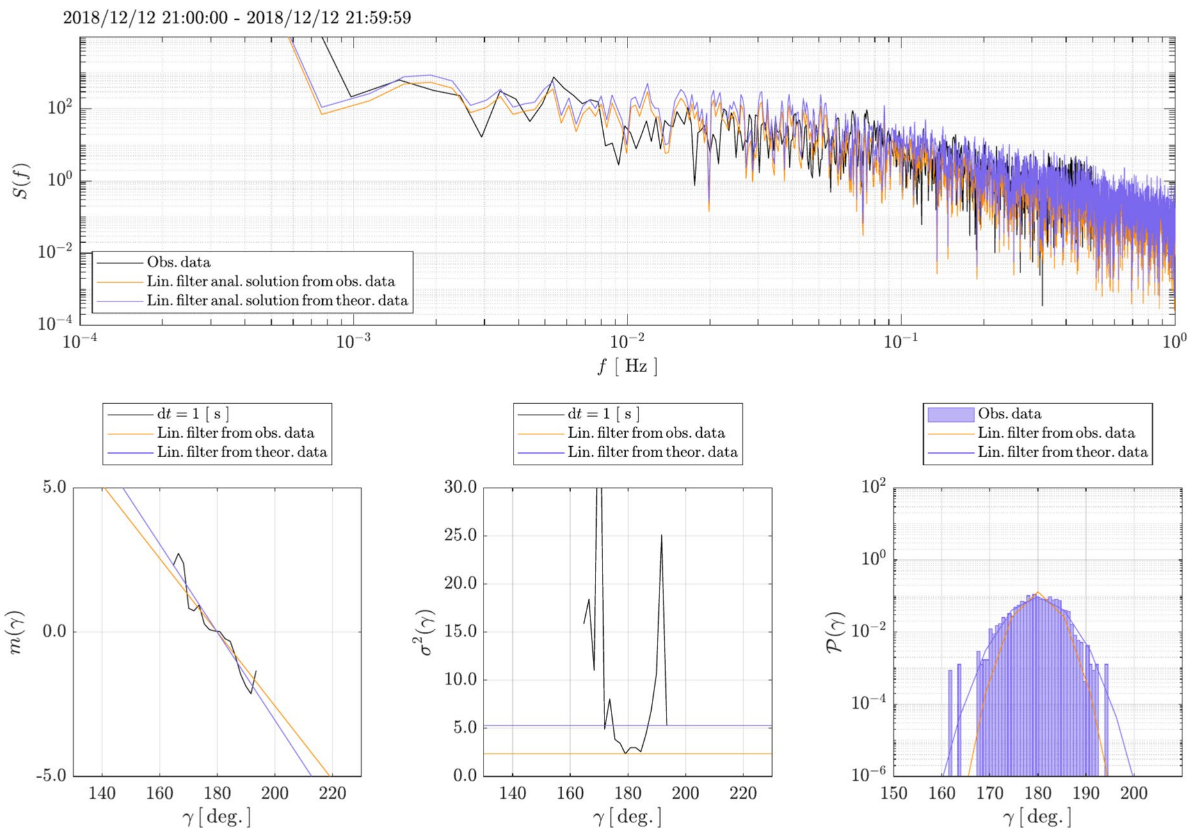

Fig. 5 Analyzed results of wind direction (case1)

the actual ship measurements has a quadratic function-like shape and cannot be said to be a constant. However, it can also be seen that the value proposed in this paper (see the purple line), unlike the orange line, is not a minimum value but a generally larger value. Further, looking at the PDF, it appears that the proposed method generally agrees in trend with the results obtained by analyzing time series measured on board. Figures 7 and 8 compare the time series data themselves, and the trends seem to generally match the onboard measurement data. This result implies that the aforementioned method allows modeling of the variation of wind direction in a form of a time series using only the estimate of mean wind velocity $\bar{u}$.

On the other hand, the time series of wind speed can also be calculated by the method described in our previous paper [1]. Therefore, we simultaneously calculated the time series of wind velocity and direction. As noted in the previous section, the Wiener processes were obtained using different random numbers to avoid numerically derived correlations.

Figures 9 and 10 show the combined probability density function (PDF: Probability Density Function). However, there is no strong correlation between wind speed and wind direction from the viewpoint of the observed values (OBSR) shown in the left figure. Therefore, wind speed and wind direction can be calculated separately. This fact was already pointed out by [20, 21]. Figures 9 and 10 on the right (SIM: numerical results) show the results of numerical calculations based on this idea, and they agree well with the results shown in the left figure. Therefore, the correlation between the two can be ignored from a practical viewpoint.

As we have mentioned, the method proposed in this paper allows us to easily compute time series of wind direction from average wind speed alone. On the other hand, however, there are some issues. As we have pointed out before, the measured values of diffusion are not constant, but have the shape of a quadratic function. Therefore, it is necessary to consider how to make the shape of the diffusion more realistic. Furthermore, the data used to obtain this regression equation are not very large. Updating the coefficients of the regression equation by acquiring more data in the future is one of the research themes to be explored by the authors.

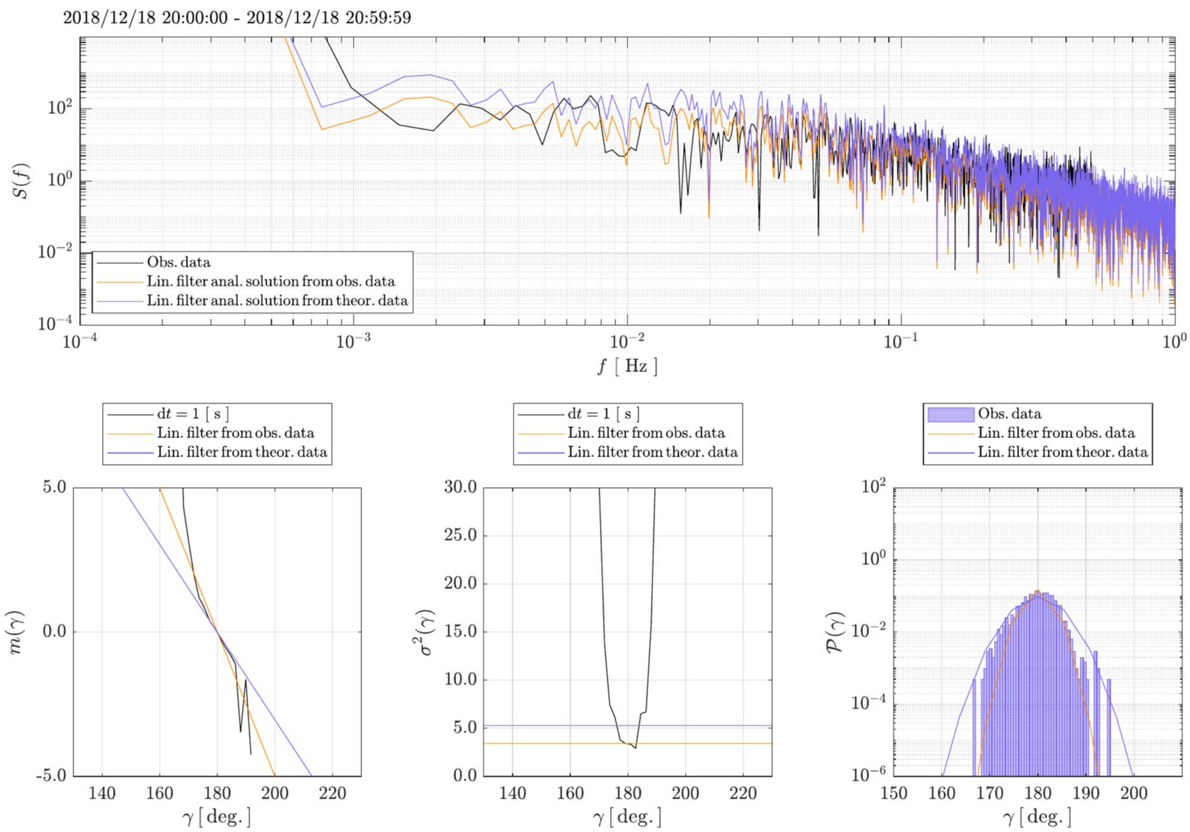

Fig. 6 Analyzed results of wind direction (case2)

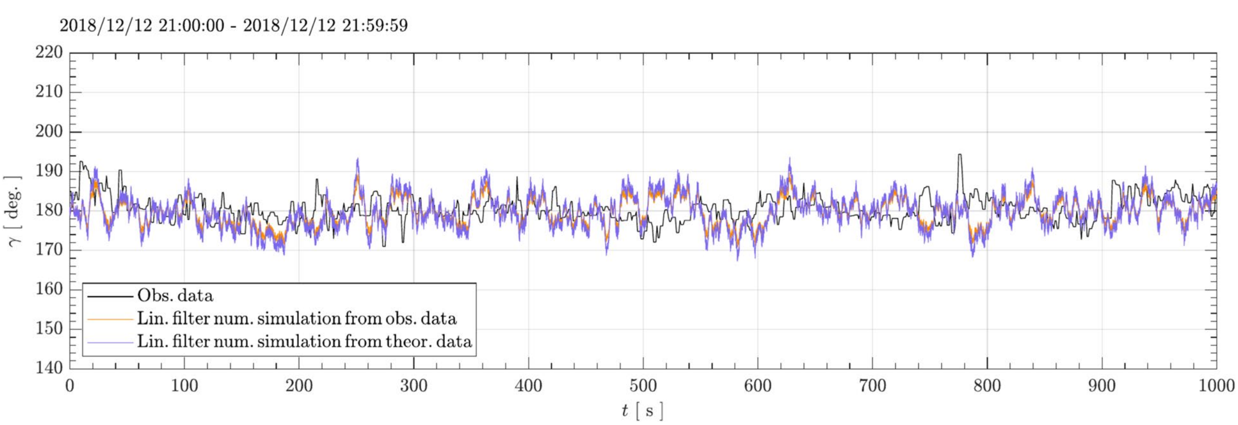

Fig. 7 Time histories of wind direction (case1)

6 Conclusion

In this study, we proposed a new algorithm for generating the time history of wind direction based on the regression equation of the standard deviation of the variations in the wind direction from the mean wind speed obtained in the study of Kuwajima et al. As done in our previous work [1], the one-dimensional SDE was solved analytically to compute the time series of wind speed and direction and that of wind speed. The joint PDFs for wind speed and wind direction obtained by computing them independently were in good agreement with the measurement results. However, the data used to obtain the regression equation were not large. As the next steps in our research, we will update

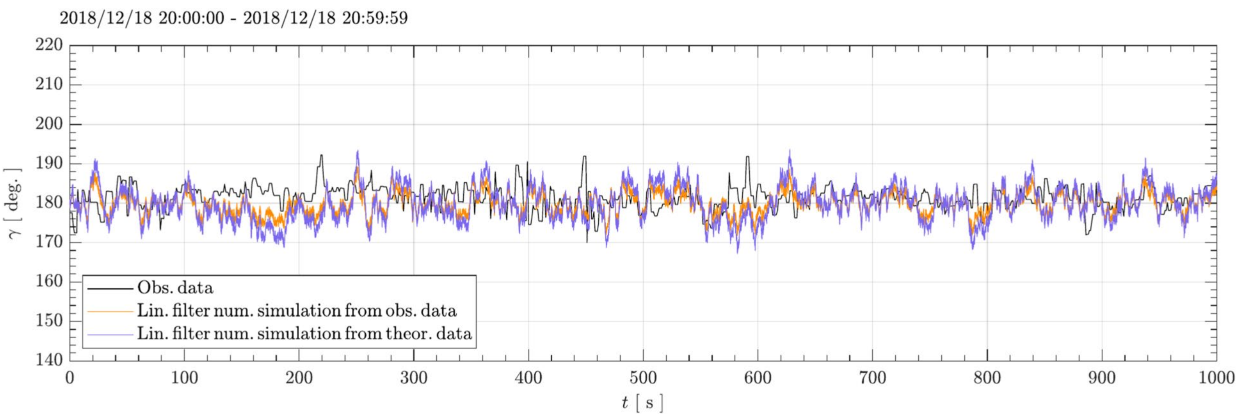

Fig. 8 Time histories of wind direction (case2)

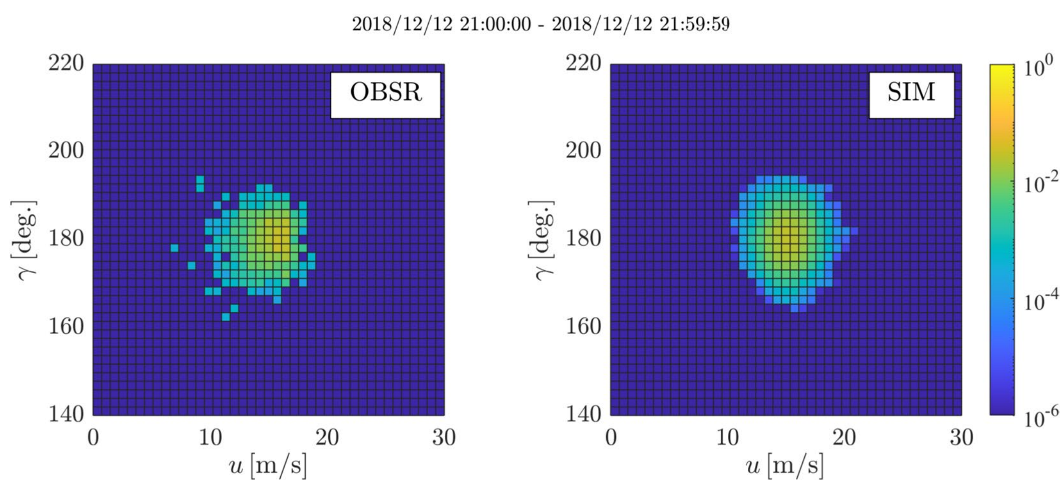

Fig. 9 Joint PDF of wind direction and speed (case1)

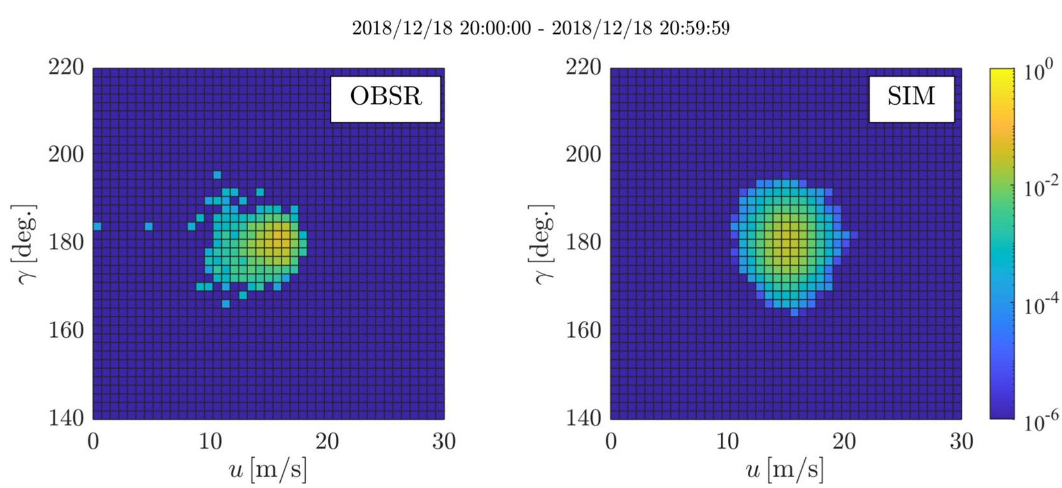

Fig. 10 Joint PDF of wind direction and speed (case1)

the coefficients of the regression equation by acquiring more data in the future.

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Data availability There is no data availability on this work.

Conflict of interest The authors declare that they have no conflict of interest.

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