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Real-Time Estimation of Airflow Vector based on Lidar Observations for Preview Control

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Abstract. The control technique in a gust alleviation system by using the airborne Doppler Lidar technology is expected to enhance aviation safety to minimize the risks of turbulence-related accidents. Accurate measurement and estimation of the vertical wind velocity are very important in the successful implementation of a gust alleviation system by using the airborne Doppler Lidar technology. An estimation algorithm of airflow vector based on the airborne Lidars is proposed and investigated for preview control to prevent turbulence-induced aircraft accidents in flight. The use of the simple vector conversion method, which is an existing technique, assumes that the wind field between the Lidars is homogeneous. The assumption of a homogeneous field would be wrong when turbulence occurs due to large wind velocity fluctuation. The proposed algorithm stores the line-of-sight (LOS) wind data with each passing moment and uses recent and past LOS wind data in order to estimate the airflow vector. The recent and past LOS wind data are used to extrapolate the wind field between the airborne twin Lidars. Two numerical experiments—ideal vortex model and numerical weather prediction—were conducted to evaluate the estimation performance of the proposed method. The proposed method has much better performance than simple vector conversion in the two numerical experiments, and it can estimate accurate two-dimensional wind field distributions unlike simple vector conversion. The estimation performance and the computational cost of the proposed method can satisfy the performance demand for preview control.

1 Introduction

Atmospheric turbulence poses a potential risk to aircraft operation, and an increase in the rate of accidents related to turbulence has been reported by the Federal Aviation Administration in 2014. Statistics reported by Boeing (2015) show that fatal accidents and onboard fatalities occurred worldwide in commercial jet flights from 2006 through 2015. From these statistics, 23% of accidents were due to Loss of Control-In Flight (LOC-I), which is the largest proportion of accidents by percentage. The International Air Transportation Association (2016) shows that LOC-I frequently occurs when the aircraft speed is well below the stall speed; in conjunction with weather conditions, it is the most common factor for LOC-I accidents, with 42% of LOC-I accidents having occurred under degraded meteorological conditions. The Japan Transport Safety Board has identified that accidents caused by turbulence accounted for 48% of aircraft accidents involving commercial airplanes from 2003-2012 in Japan. The

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accidents caused by convective systems such as cumulonimbus have decreased owing to advances in airborne Radar (Airbus, 2020; Sermi et al. 2015). However, non-cloud atmospheric turbulence, called clear air turbulence (CAT), cannot be detected by Radar, as reported by Soreide et al., 2000, Barny, 2012, and Inokuchi et al., 2009; therefore, airborne observation methods for CAT are needed. CAT observation and prediction systems are essential to aviation safety to minimize risks of turbulence-related accidents.

Recently, airborne Doppler Lidar has been developed by Soreide et al., 2000; Barny, 2012; Inokuchi et al., 2009; Machida, 2017; and Inokuchi and Akiyama, 2019. Lidar can detect wind velocity in clear air, but cannot work during precipitation. Aerosol particles are received instead of laser beams due to a scattering light effect caused by the rain particles. The aerosol particles are much smaller than precipitation droplets in the air (Inokuchi and Akiyama, 2019). Japan Aerospace Exploration Agency (JAXA) is researching and developing a coherent Doppler Lidar capable of remotely detecting air turbulence in clear air conditions, and has conducted the flight demonstration of a Lidar system that includes a provision to provide turbulence information to pilots (Inokuchi et al., 2009, Machida, 2017; Inokuchi and Akiyama, 2019). Inokuchi et al., 2009 showed that airborne Doppler Lidar can detect CAT in front of an aircraft in flight at altitudes of 3,200 m during a flight observation campaign. Based on advance airflow information, flight demonstrations were carried out with the aim of providing pilots with information to judge the need to go around from an approach to avoid wind shear, and the need for seat belt sign lighting during cruise and altitude changes (Inokuchi and Akiyama, 2019). Although Lidar systems are useful for providing wind information to pilots, these systems may be able to provide short-range turbulence information to avoid turbulence tactically, particularly in high altitude (Hamada, 2019) by emitting a laser beam, and by receiving scattered light from aerosol particles that are much smaller than precipitation droplets in the air. Therefore, when the number of aerosol particles that emit scattered light is small, it is difficult to measure wind information at a distance. As altitude increases, the aerosol density decreases, and the observation range tends to decrease accordingly. The maximum observation range and aerosol density measured at each altitude are shown by Inokuchi and Akiyama, 2019. For this reason, automatic control to alleviate aircraft vibration is important, as well as for providing turbulence information.

The automatic control to alleviate aircraft vibration is called the gust alleviation control and has been studied since the 1970s; most of them were based on feedback sensors only, such as inertial measurement units (Regan and Jutte, 2012). Recently, reduced effect of turbulence by preview controlling based on airborne Lidar observation has been reported in the studies by Schmitt et al., 2007; Fezans et al., 2019; and Hamada, 2019. The aim of the Aircraft Wing with Advanced Technology Operation (AWIATOR) is the development of new direct-lift control devices and a Lidar system for turbulence measurement (Schmitt et al., 2007). Another project on Lidar systems was called “Demonstration of Lidar based CAT detection” (DELICAT) by Barny, 2012. This project developed airborne ultraviolet Lidar for gust and turbulence measurements. The test flights were carried out by using an Airbus 340 aircraft with ultraviolet Lidar. In both the AWIATOR and the DELICAT experiments, the measurement range was short, because the Lidar was developed for controlling the aircraft automatically.

In order to successfully implement a gust alleviation system by using the airborne Doppler Lidar technology, it is very important to measure the vertical wind velocity accurately. Both horizontal and vertical winds

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affect the aircraft motion; the effect of changing the vertical wind velocity is greater due to the fact that the angle of attack is relatively larger than the effect of changing the horizontal wind velocity, which affects only the airspeed (Fezans et al., 2019). However, the single Doppler Lidar system can only detect the LOS wind as a one-dimensional piece of information, and for this reason, the vertical wind velocity in front of the aircraft cannot be measured by the single Lidar system (Hamada, 2019). It is necessary to perform Lidar measurements in two directions, upward and downward, in order to obtain the vertical wind velocity. Figure 1 shows a representation of this concept. The vertical wind velocity vector is generated from the differences between the upward and downward LOS winds by using the simple vector conversion. The simple vector conversion is incapable of estimating the vertical wind velocity with high accuracy to control the aircraft automatically because the technique assumes homogeneity between the upward and downward Lidars (Fezans et al., 2019). In this study, a fully turbulent field with atmospheric turbulence and gust was considered; under these conditions, it is difficult to estimate the vertical wind velocity with high accuracy using simple vector conversion. In particular, the estimation accuracy of the vertical wind velocity rapidly worsened when the estimation position was located farther ahead from the aircraft.

In addition, actual Lidar observations have some errors, noise, and loss of data, which lead to negative effects on aircraft control, as reported by Misaka et al. (2015). These errors, noise and loss of data increase at higher altitudes, where aerosol density is smaller than that in the atmosphere. Misaka et al. (2015) proposed a filtering algorithm based on a simple Kalman filter to remove the wind velocity errors with Lidar measurements. It is essential to deal with the Lidar errors, noise and loss of data more carefully for preview control. In this case, an accurate airflow vector estimation method and an efficient real-time filtering algorithm are required to use Lidars accurately for preview control.

In this study, an estimation method and an airflow vector filtering algorithm, for both horizontal and vertical wind directions, based on upward and downward Lidars, is proposed for preview control to prevent turbulence-induced aircraft accidents. The Lidars system in this paper is also used by JAXA in its ongoing “Lidar-based gust alleviation control” research project. The Lidars are assumed to compliant with the specifications for preview control currently under development by the JAXA. The proposed algorithm stores the LOS wind data continuously, and uses recent and past LOS wind data to estimate the airflow vector, although the simple vector conversion utilizes recent LOS wind data. The recent and past LOS wind data are used to extrapolate the wind field between Lidars. The airflow vector is calculated by using the extrapolated wind data from its horizontal and vertical components. The estimation accuracy of the airflow vector in front of the aircraft is improved by using the extrapolated wind data because the area between the Lidars represents a more homogeneous area. A polynomial expression is used to extrapolate the wind field by using the recent and past LOS wind data. In addition, the proposed method can estimate the two-dimensional distribution of the wind field between the Lidars unlike the simple vector conversion.

Two test configurations, an ideal vortex flow field and a weather field, were calculated by numerical weather prediction (NWP) system, were utilized to evaluate the performance of the airflow vector. The experiment generates a large amount of pseudo-Lidars measurements along flight routes from the reference wind field for

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evaluation of the estimated performance. The experiment can compare the prediction results with the reference wind field in order to confirm the entire wind field values.

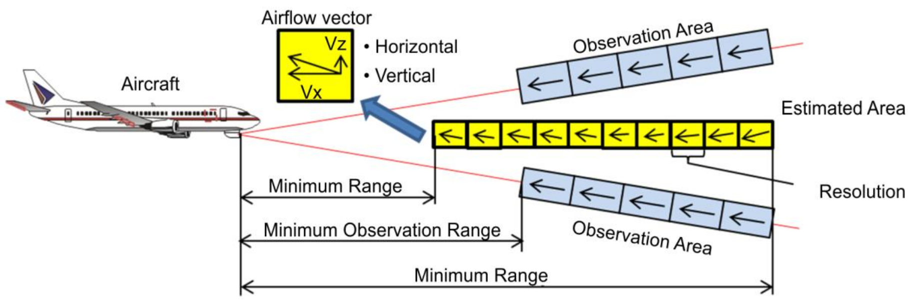

Fig. 1 Concept of the airborne Lidars observation system

2 Methods

2.1 Airborne Lidar specifications

The airborne Lidar observation system for preview control to prevent turbulence-induced aircraft accidents currently under development by JAXA is shown in this section. This system has airborne Lidars that are aiming upwards and downwards. The angle between airborne Lidars that are aimed in the upward and downward direction is 20 degrees, that is, 10 degrees between the horizontal line and each Lidar. Each Lidar measures the LOS wind velocity, and a couple of LOS wind velocity values are used to estimate the airflow vector in the area between the Lidars. There are additional performance requirements for preview control, namely, the estimation frequency and estimation accuracy of vertical wind velocity. The frequency of estimation is required to be more than 5 Hz, and the estimation accuracy of the vertical wind velocity is required to be lower than 2.6 ms^{-1} in the LOS distance of 500 m. In addition, the observation accuracy of LOS wind is $\pm 0.9ms^{-1}$ and the observation resolution of a Lidar is approximately 25 m.
Next, an existing technique to estimate the airflow vector, by using a couple of LOS wind values, is shown. The airflow vector in the area between upward and downward Lidars has been estimated by simple vector conversion. This procedure is a similar concept as the vertical azimuth display approach in general ground Lidar systems (Newsom et al., 2017). This simple vector conversion is given as

$$u_x{}^T = \frac{\left(W_1{}^T + W_2{}^T\right)}{2cos\,\theta},$$
$$u_z{}^T = \frac{\left(W_1{}^T - W_2{}^T\right)}{2sin\,\theta}, \tag{1}$$

where $u_x{}^T$ and $u_z{}^T$ are the horizontal and vertical wind velocity measurements at the observation time T, $W_1{}^T$ and $W_2{}^T$ are the LOS wind velocities of the upward and downward directed Lidars at the observation time T, and θ is the angle between the horizontal line and each Lidar, which is 10 degrees in this study. The simple vector conversion assumes that the wind field area between the Lidars is homogeneous (Newsom et al., 2017). Figure 2 shows the explanation of the assumption. The areas between the Lidars are 69.5 m and 173.6 m at the LOS distances of 200 m

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and 500 m ahead of the aircraft; therefore, the areas between the Lidars are assumed to be homogeneous. However, the assumption of a homogeneous field would be wrong when a large fluctuation in wind velocity occurs, creating turbulence. In homogenous conditions, a simple vector conversion can estimate the airflow vector accurately; however, in non-homogenous conditions, the estimation is expected to have poor accuracy.

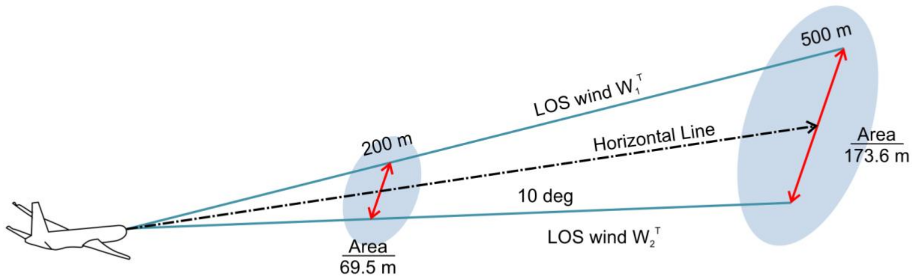

Fig. 2 The explanation of the assumption

2.2 Estimation Algorithm based on Extrapolation

The proposed method stores the LOS wind data continuously, and uses recent and past LOS wind data values in order to estimate the airflow vector, although the simple vector conversion utilizes recent LOS wind data. The recent and past LOS wind data are used to extrapolate the wind field between the Lidars, and this area between the Lidars has not been measured directly by the Lidars. The airflow vector is calculated by using Eq. (1) and the extrapolated wind data of its horizontal and vertical components. The airflow vector estimation accuracy far ahead of the aircraft is improved by using the extrapolated wind data because it is valid to assume that the area between upward and downward Lidars is non-homogeneous. The simple vector conversion only can be applied to homogenous wind field conditions, but the algorithm can extrapolate data points by using past measurements so that it can be used in non-homogenous wind field conditions. A polynomial expression is used to extrapolate the wind field values by using the recent and past LOS wind data. In addition, the proposed method can estimate the two-dimensional distribution of the wind field between the Lidars unlike the simple vector conversion.

Figure 3 shows the overview of the proposed method estimation method when an actual data point and two-past LOS wind data points are used. When the aircraft speed is V and the time span of observation is dt, the airflow moves backwards at $V\times dt$ because the aircraft is advancing. Actual observation times are denoted as T and past observation times are T-1 and T-2. The proposed method uses the actual LOS wind values (W_1^T and W_2^T) and the past LOS wind values ($W_1^{T\text{-}1}$, $W_2^{T\text{-}1}$ and $W_1^{T\text{-}2}$, $W_2^{T\text{-}2}$). The distances between the horizontal line and each Lidar are denoted as z^T, $z^{T\text{-}1}$ and $z^{T\text{-}2}$, respectively. A first-degree polynomial expression of the least-squares method (LSM) is applied and using some LOS wind data values, the wind field values are extrapolated according to Eqs. (2) and (3). The calculated polynomial expression is used to obtain the extrapolated LOS wind at the horizontal line, and the airflow vector is calculated by Eq. (1) and the extrapolated LOS wind.

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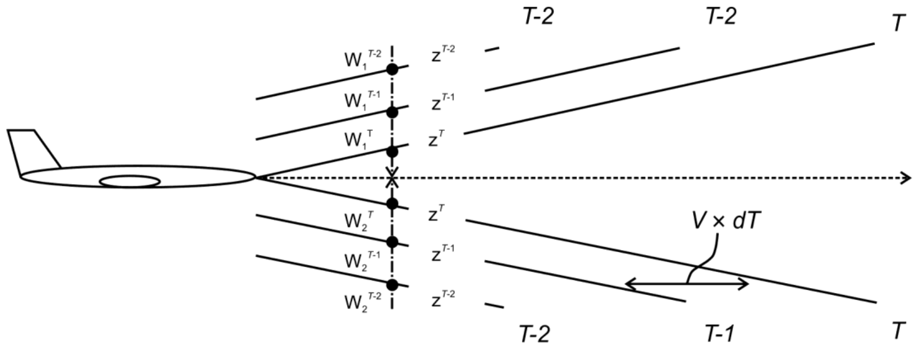

Fig. 3 **Overview of estimation by proposed method when the recent and two-past LOS wind data are used**

$$W_j'(z) = a_j z + b_j \tag{2}$$

$$a_j = \frac{N\sum_{i=T-(N-1)}^{T} z^i\, W_j^{\,i} - \sum_{i=T-(N-1)}^{T} z^i\ \sum_{i=T-(N-1)}^{T} W_j^{\,i}}{N\sum_{i=T-(N-1)}^{T}(z^i)^2 - \left(\sum_{i=T-(N-1)}^{T} z^i\right)^2},$$

$$b_j = \frac{\sum_{i=T-(N-1)}^{T} z^i\ \sum_{i=T-(N-1)}^{T} W_j^{\,i} - \sum_{i=T-(N-1)}^{T} z^i\, W_j^{\,i} \sum_{i=T-(N-1)}^{T} z^i}{N\sum_{i=T-(N-1)}^{T}(z^i)^2 - \left(\sum_{i=T-(N-1)}^{T} z^i\right)^2}. \tag{3}$$

2.3 Filtering error and the lack of wind velocity data

In this study, two filtering algorithms are used to remove the error and the loss of data of LOS wind velocity in airborne Lidars. Firstly, we use a filtering algorithm that is a simple representation of the Kalman filter with simplified Kalman gain (Misaka et al., 2015). The algorithm assumes that infinite variance is used to exclude outliers and loss of data. This method uses the Lidar spectrum data at each range-bin, and the algorithm defines the validity of the measurements during the Lidar data peak detection process. To identify the correct and non-correct LOS wind velocity values, two spectrum thresholds are defined. Firstly, the largest and second-largest spectrum values, k_{1st} and k_{2nd}, are adjacent to each other, i.e., the distance between the largest and second-largest spectrum values in the Fast Fourier Transform is equal to one. Secondly, the distance from the averaged spectrum peak k_{ave} is less than a certain allowance k_{dif}, which represents the only hyper-parameter in this algorithm as well as a parameter related to smoothness. In this study, the filtering algorithm is carried out first when the observation data is obtained.

$$K_{i,j} = \begin{Bmatrix} 1 & |k_{1st} - k_{2nd}| = 1\ and\ |k_{1st} - k_{ave}| < k_{dif} \\ & 0 \quad Others \end{Bmatrix} \tag{4}$$

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Secondly, a robust LSM estimation, based on Tuckey's biweight methodology (Huber, 2008), is carried out to reduce the impact of the error in the LOS wind velocity. This method is based on the LOS wind data unlike the spectrum data of Lidar observation at the first method. Although the filtering algorithm based on a simple Kalman filter can remove the error, it is essential to deal with the error and the loss of data of the Lidars more carefully when the filtering algorithm is used for the preview control. Therefore, the robustness of the estimated airflow vector is secured by using the filtering algorithm based on a simple Kalman filter together with robust LSM. In addition, the robust LSM estimation can make use of the extrapolation algorithm effectively as per Eqs. (2) and (3). Therefore, the robust LSM estimation provides a simpler and more robust algorithm. The concept of a robust LSM is validated by analyzing the difference between the observed LOS wind values and those LOS wind values estimated by the polynomial expression. Weights are defined to each LOS wind velocity value, and the weights are changed depending on the validation numbers. The difference d_j^T between the observed LOS wind values and estimated LOS wind values from the polynomial expression is defined by Eq. (5) with Eq. (2). The permissible difference range L is defined and the weights w_j^T (d_j^T) are calculated depending on d_j^T. Three thresholds for defining w_j^T (d_j^T) from L are used as shown in Eq. (6). Equation 7 shows the calculation of the polynomial expression of the first degree with LSM and weights w_j^T (d_j^T).

$$d_j{}^T = W_j{}^T - \left(a_j z + b_j\right) \tag{5}$$

$$\begin{gathered} w_j{}^T\left(d_j{}^T\right) = 0 \ \left(d_j{}^T < -L\right) \\ w_j{}^T\left(d_j{}^T\right) = \left(1 - \left(\frac{d_j{}^T}{w_j{}^T}\right)^2\right)^2 \left(-L \le d_j{}^T \le L\right) \\ w_j{}^T\left(d_j{}^T\right) = 0 \ \left(d_j{}^T > L\right) \end{gathered} \tag{6}$$

$$\begin{gathered} a_j{}' = \frac{\sum_{i=T-(N-1)}^{T} w_j{}^i \sum_{i=T-(N-1)}^{T} w_j{}^i z^i \ W_j{}^i - \sum_{i=T-(N-1)}^{T} w_j{}^i z^i \ \sum_{i=T-(N-1)}^{T} w_j{}^i W_j{}^i}{\sum_{i=T-(N-1)}^{T} w_j{}^i \sum_{i=T-(N-1)}^{T} w_j{}^i (z^i)^2 - \left(\sum_{i=T-(N-1)}^{T} w_j{}^i z^i\ \right)^2} \\ b_j{}' = \frac{\sum_{i=T-(N-1)}^{T} w_j{}^i z^i \ \sum_{i=T-(N-1)}^{T} w_j{}^i W_j{}^i - \sum_{i=T-(N-1)}^{T} w_j{}^i z^i \ W_j{}^i \sum_{i=T-(N-1)}^{T} w_j{}^i z^i}{\sum_{i=T-(N-1)}^{T} w_j{}^i \sum_{i=T-(N-1)}^{T} w_j{}^i (z^i)^2 - \left(\sum_{i=T-(N-1)}^{T} w_j{}^i z^i\ \right)^2} \end{gathered} \tag{7}$$

2.4 Filtering wind velocity noise

The Lidar observation is subject to not only measuring errors and loss of LOS data values but also random noise; this type of noise also leads to a poor estimation of the airflow vector. A simple spline algorithm generates a curve that passes through all sample points; therefore, the simple spline algorithm is not able to generate a smooth curve when the sample points have random noise, and a smoothing spline algorithm is applied to remove the random noise of the Lidar LOS wind values, as in the study by Woltring, 1986. The generated smoothing spline algorithm

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curve does not pass through all sample points, and because of that, it can produce a smoother curve, even if it has random noise from Lidar LOS wind measurements. The smoothing spline model minimizes the criterion function C_p, per Eq. (8) where y_i is a sample point value, $s_p(x)$ is the value generated by a simple spline algorithm, v_i is a weighted factor and p is regularization parameter. The smoothest curve is generated when the criterion function Cp is minimized.

$$C_p = \sum_{i=1}^{n} v_i\{y_i - s_p(x)\}^2 + p \int \left(\frac{d^2 s_p}{dx^2}\right)^2 dx \tag{8}$$

2.5 System flowchart

The airflow vector estimation algorithm is a sequence of five different processes, which are summarized below. The system flowchart is shown in Fig. 4.

1) The filtering algorithm based on simple Kalman filter is carried out to remove the error of LOS wind data when the Lidar measures LOS wind data values.

2) The smoothing spline method is applied to reduce the negative effect of the random noise of LOS wind data values and extrapolates the value at the position for which no measurements can be read. . This is identified as the first step error.

3) The extrapolation, based on the polynomial expression, is carried out to estimate the wind field values by using current and past LOS wind data.

4) A robust LSM model is applied to obtain a more accurate polynomial expression, and repeats the calculation until the parameter converges.

5) The airflow vector is calculated by Eq. (1) and the extrapolated LOS wind.

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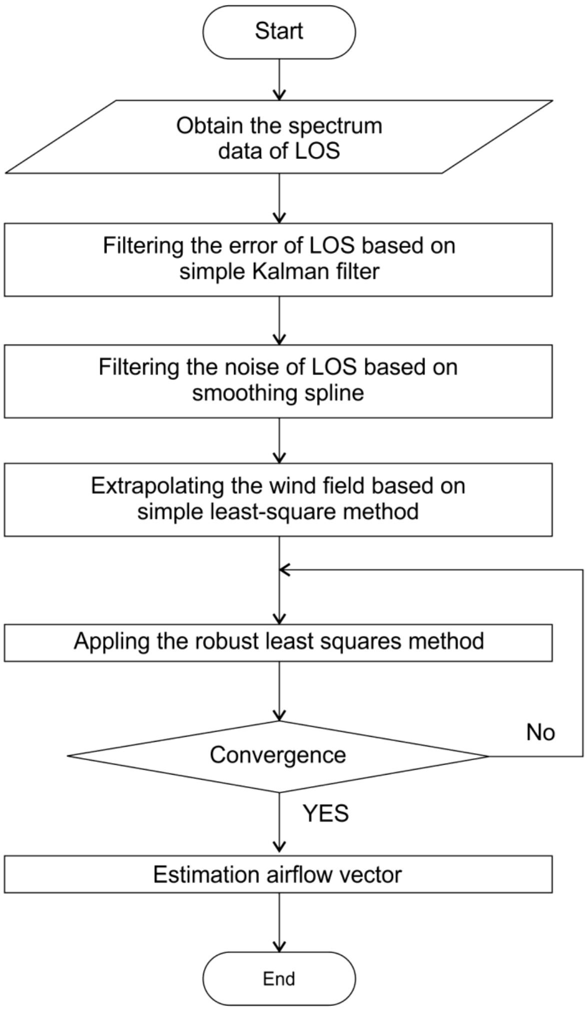

Fig. 4 System flowchart for the airflow vector estimation algorithm

3 Test Configurations

3.1 Ideal vortex model

Numerical experiments are used to evaluate the performance of actual airborne Lidars. The ideal vortex model is defined and used to evaluate the estimated performance of the airflow vector. In this study, the Hallock-Burnham vortex model (Hinton et al., 1997) is used as the ideal vortex model. The experiment generates a large amount of pseudo Lidars values along flight routes by the ideal vortex model. The airflow vector is estimated by using the pseudo-Lidars readings, and the estimated airflow vector is compared with the reference field of the ideal vortex model. The experiment can compare the estimation results with the reference wind field values to confirm the entire

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wind field. Figure 5 shows the distribution of vertical wind velocity generated by the Hallock-Burnham vortex model.

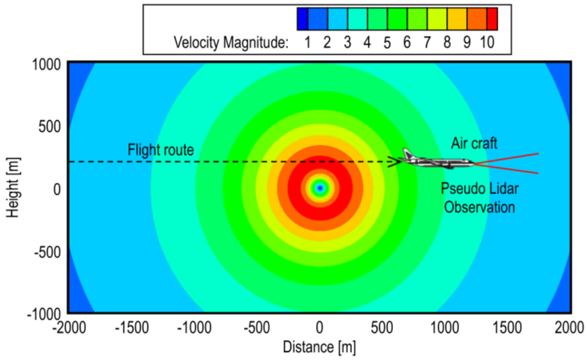

Fig. 5 The distribution of vertical wind velocity generated by the vortex model

3.2 NWP model

The results predicted by the numerical weather model, that is, the Japan Meteorological Agency Non-Hydrostatic Model (JMA-NHM), are used to evaluate the airflow vector estimation performance. In this study, JMA-NHM is employed to obtain the wind field for the evaluation (Saito et al., 2007 and Kikuchi et al., 2015). To obtain the high-resolution weather prediction, a one-way multi-nesting technique (Kikuchi et al. 2015) is conducted for downscaling purposes. The computational domain is nested four times to increase grid resolutions from 5.0 to 0.05 km gradually (as follows: 5.0, 1.5, 0.5, 0.15, and 0.05 km).

A three-hour mesoscale objective analysis data, collected using a mesoscale four-dimensional variational data assimilation system at the Japan Meteorological Agency (Saito et al., 2007), are used for the initial condition of 5.0-km grid resolution. The experiment used the JMA-NHM wind field, which can provide more realistic test results than the ideal vortex model for the performance evaluation. The experiment generates a large amount of pseudo twin Lidar observation values along flight routes from the wind field data generated by JMA-NHM. The airflow vector is estimated by using the pseudo-Lidar observation, and the estimated airflow vector is compared with the reference field of JMA-NHM. Figures 6 and 7 show the experiment concept used by JMA-NHM and the distribution of the vertical wind velocity values generated by JMA-NHM.

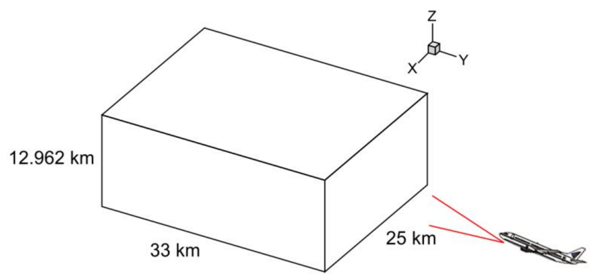

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Fig. 6 The concept of the experiment used by JMA-NHM.

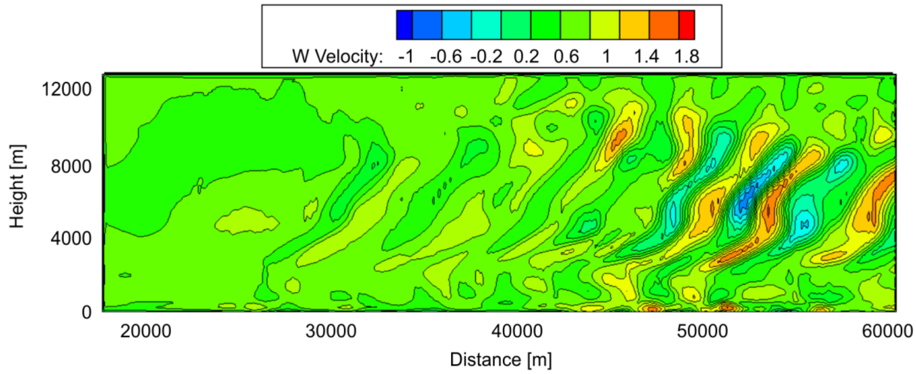

Fig. 7 Vertical wind velocity distribution map generated by JMA-NHM

3.3 Generation of pseudo errors and noise

Errors and noise were generated artificially to confirm the effect of the proposed filtering algorithms. Errors and noise are generated by using the parameter of the backscattering coefficient in the atmosphere and the statistics-based coherent Lidar equation (Kameyama et al., 2007). The backscattering coefficient that is strongly related to the aerosol density in the atmosphere has an impact on the Lidar measurements and estimation performance. When the backscattering coefficient is very low, the measurement performance is worse, and the LOS wind data show errors and noise. In addition, the measurement performance is related to the focal distance, pulse width and Lidar power (Kameyama et al., 2007). The signal-noise ratio (SNR) at the receiver, at each LOS distance, is calculated by using the coherent Lidar equation and the detailed operating condition of JAXA's Lidar [7-9].

$$SNR(R) = \frac{\eta\, P_t\, \Delta R\, \beta\, K^{2R}\, \frac{\pi D^2}{4R^2}}{h\, f\, B\, SRF(R)} \tag{9}$$

$$SRF(R) = 1 + \left\{1 - \frac{R}{F}\right\}^2 \left\{\frac{k(A_c\, D)^2}{8R}\right\}^2 + \left\{\frac{A_c\, D}{2S_0(R)}\right\}^2 \tag{10}$$

$$S_o(R) = (1.1\, k^2\, R\, C_n^2)^{-\frac{3}{5}} \tag{11}$$

R is the observation distance, η is system efficiency, P_t is light transmission power, ΔR is the resolution range, β is backscattering coefficient, K is atmospheric transmittance, D is the opening size of optical antenna, h is Planck constant, f is optical frequency, B is received bandwidth, F is focal distance, k is wave number, A_c is vignetting factor of optical antenna and C_n^2 is atmospheric structure constant. In this study, the conditions are set according to the design specification for airborne Lidars. In this study, six atmospheric conditions are prepared in order to evaluate the filtering performance. The backscattering coefficients are (Standard case) 1.8×10^{-8} $sr^{-1}m^{-1}$, (a) 1.8×10^{-11}

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sr^{-1}m^{-1}, (b) 1.35×10^{-11} sr^{-1}m^{-1}, (c) 0.9×10^{-11} sr^{-1}m^{-1}, (d) 0.45×10^{-11} sr^{-1}m^{-1}, and (e) 0.18×10^{-11} sr^{-1}m^{-1}. Figure 8 shows the statistics for the error and noise depending on the SNR bandwidth.

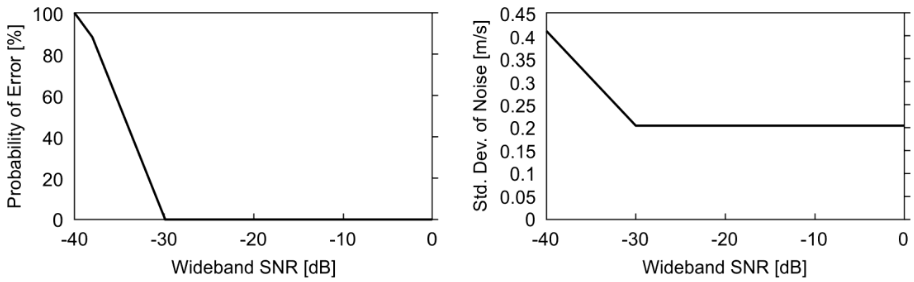

Fig. 8 Probability of error and standard deviation of noise

4 Results

4.1 Ideal Vortex Model without Error and Noise

The numerical experiments of the ideal vortex model are carried out, and Figs. 9 and 10 show the distributions of the horizontal and vertical wind components that are estimated by the simple vector conversion and the proposed method. The upper figures show the wind field values generated by the ideal vortex model; the middle figures represent the wind field values estimated by the simple vector conversion method, and the lower figures are the wind field values estimated by the proposed method with five-past LOS wind datasets. Figures to the left represent the horizontal wind values, and figures to the right represent the vertical wind values. Figure 9 shows the results after 10 s and Fig. 10 after 15 s.

As shown in Figs. 9 and 10, the results of the simple vector conversion method cannot be shown in a two-dimensional distribution between the Lidars, as the assumption is that the wind field of the area between the Lidars is homogeneous. On the other hand, it is confirmed that the proposed method can estimate the two-dimensional distribution of wind field values between the Lidars. Figure 9 shows that the two-dimensional distribution obtained with the proposed method are very similar to that of the reference field. In addition, the results show that the horizontal wind velocity with the simple vector conversion is approximately -7 m/s, whereas that with the proposed method is -9.5 ms^{-1}; the horizontal wind velocity of the reference field is -9.0 ms^{-1} at LOS distance of 450-500 m. Figure 10 shows that the results of the horizontal wind and vertical wind with simple vector conversion are considerably lower than those of the reference field. The horizontal wind results show that the value obtained with the simple vector conversion is approximately -9.5 ms^{-1}, whereas that with the proposed method is approximately -3.5 ms^{-1}; the horizontal wind velocity of the reference field is approximately -4.5 ms^{-1} at LOS distance of 450-500 m. The vertical wind results show that the value obtained with simple vector conversion is approximately -1.0 m/s, whereas that obtained with the proposed method is approximately 8.5 ms^{-1}; the vertical wind velocity of the reference field is approximately 7.0 ms^{-1} at LOS distance of 450-500 m. Therefore, simple vector conversion has significantly large errors between the reference and estimated values. The errors in both the horizontal and vertical wind values estimated by the proposed method are much smaller than those estimated with simple vector conversion.

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Although the two-dimensional distribution of the horizontal wind field values of the proposed method is larger than that of the reference field at LOS distance of 450-500 m, the two-dimensional distribution of the vertical wind field values of the proposed method can provide a good assessment of the reference field shown in Fig. 10. The 15-s timing in Fig. 10 is a more challenging case than others because the aircraft is positioned very close to the center of the vortex, and the wind direction changes abruptly. Although it is difficult to estimate the perfect wind field value at this time by using the proposed method, it is confirmed that the proposed estimation method has much higher accuracy than simple vector conversion. From the above, the proposed method has much better performance than the simple vector conversion method, and it can estimate the two-dimensional distribution of wind field values accurately unlike the simple vector conversion method.

Next, a statistical estimation performance is conducted by using 100-pseudo routes; Fig. 11 shows the results for the vertical wind values along with the performance demand for automatic control. The root mean square error (RMSE) between the reference field value and the estimated wind field value is used for evaluating the estimation performance. In addition, the difference in the number of past Lidar observations used to determine the wind field, that is the past LOS wind, is checked. The simple vector conversion cannot satisfy the performance demand at LOS distance farther than 350 m. This means that it might be difficult to achieve preview control using the simple vector conversion method. At the LOS distance of 500 m, the RMSEs of the vertical wind values of the simple vector conversion and proposed method is approximately 4.0 ms^{-1} and 1.2 ms^{-1}, respectively, and the RMSE can be reduced to 30%. The proposed method can satisfy the performance demand even if the number of using the past LOS wind values is different. In this case, a lower number of using the past LOS wind leads to better estimation performance.

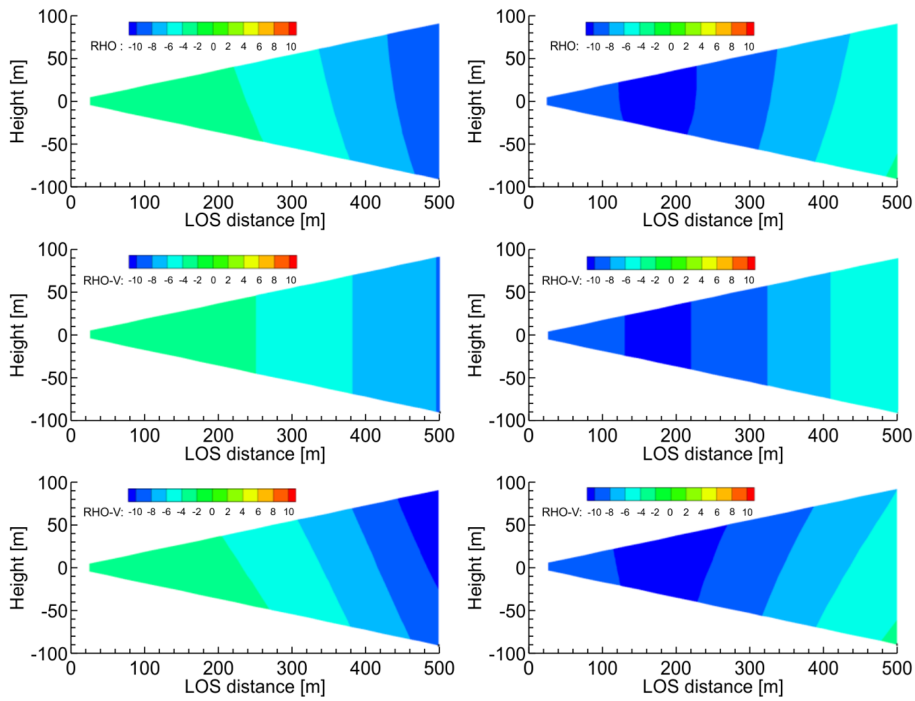

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Fig. 9 **Distributions of the horizontal and vertical wind components estimated by the simple vector conversion method vs. the proposed method (10 s)**

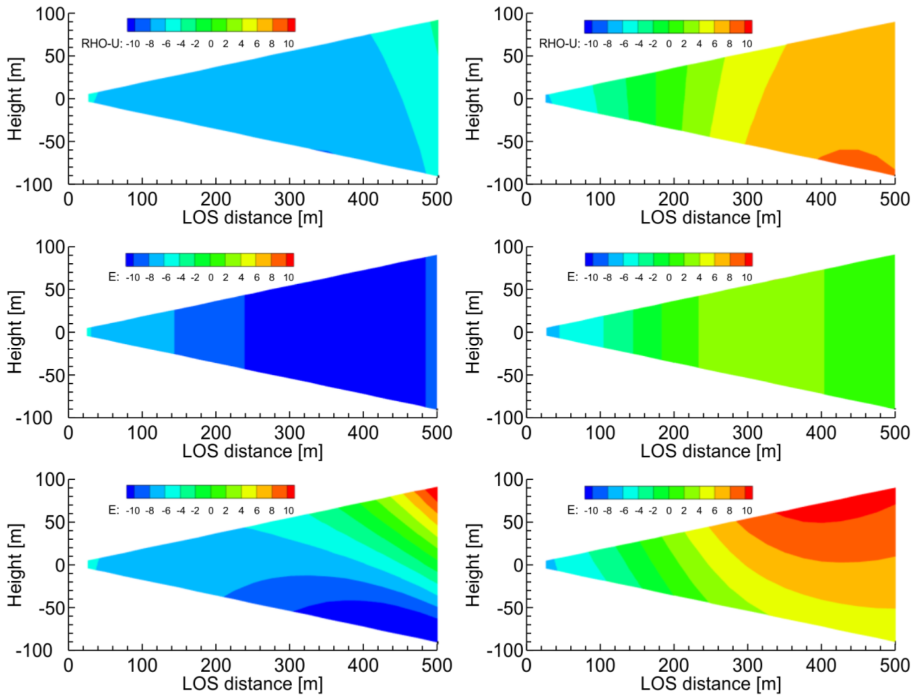

Fig. 10 **Distributions of the horizontal and vertical wind components estimated by the simple vector conversion method vs. the proposed method (15 s)**

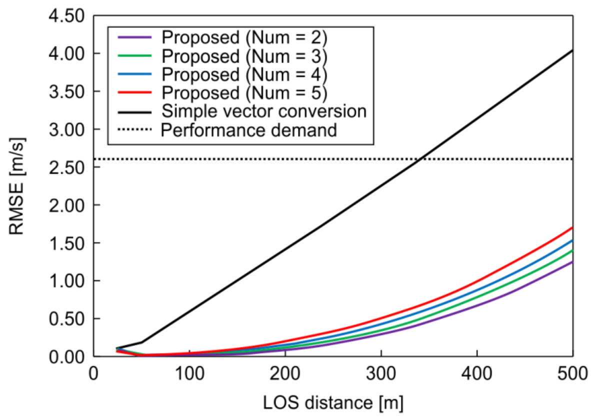

Fig. 11 **Statistical estimation performance of vertical wind values (Ideal vortex model)**

4.1 NWP without Error and Noise

The numerical experiments with NWP values were carried out, and Figs. 12 and 13 show the distributions of the horizontal and vertical wind components that are estimated by the simple vector conversion and the proposed method. Upper figures are reference wind field values generated by NWP; middle figures are the wind fields

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estimated by the simple vector conversion method; lower figures are the wind fields estimated by the proposed method with five-past LOS wind. Left figures correspond to horizontal wind, and right figures correspond to vertical wind. Figure 12 shows the results after 10 s and Fig. 13 after 15 s. As shown in Figs. 12 and 13, the results of the simple vector conversion method cannot show the two-dimensional distribution of the wind field between the Lidars. On the other hand, the proposed method can estimate the two-dimensional distribution of the wind field between the Lidars. Figure 13 shows that the wind velocity of the simple vector conversion method is higher than the reference fields at 300-500 m of LOS distance. From the above, the proposed method has much better performance than simple vector conversions.

Next, the statistical estimation performance is conducted by using 100-pseudo routes, and Fig. 14 shows the results of the statistical estimation performance with the performance demand to control automatically. In addition, the difference of the number of using past LOS wind is also checked. In this case, both simple vector conversion and the proposed method can satisfy the performance demand to preview control; however, the simple vector conversion performance results are much worse than those of the proposed method. The proposed method can estimate quite accurate wind field values. In this case, the use of past LOS wind numbers, higher leads to a better estimation performance.

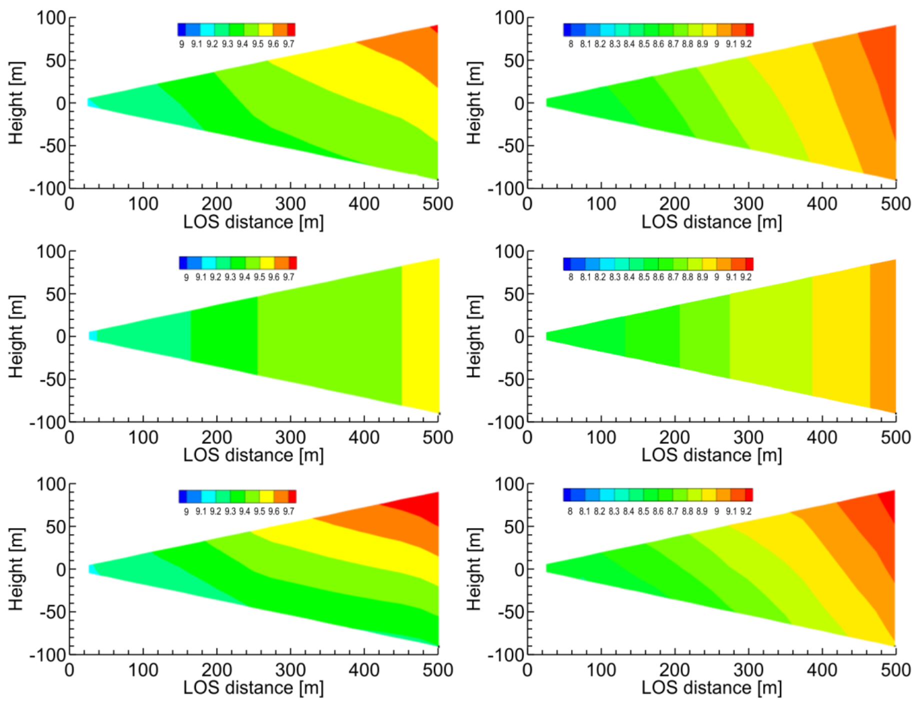

Fig. 12 Distributions of the horizontal and vertical wind components that are estimated by simple vector conversion and the proposed method (10 s)

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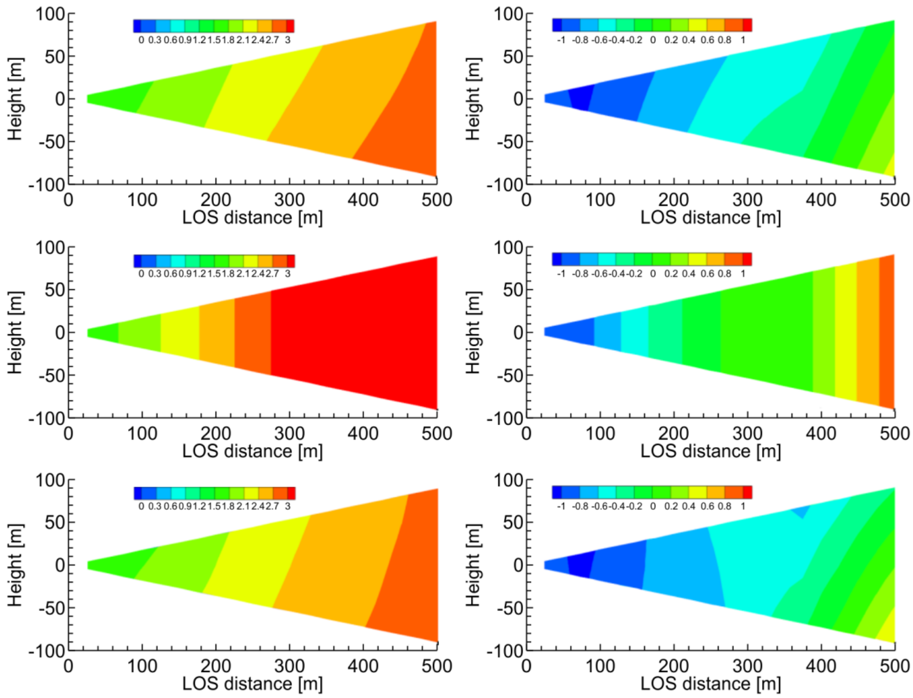

Fig. 13 Distributions of the horizontal and vertical wind components that are estimated by simple vector conversion and the proposed method (15 s)

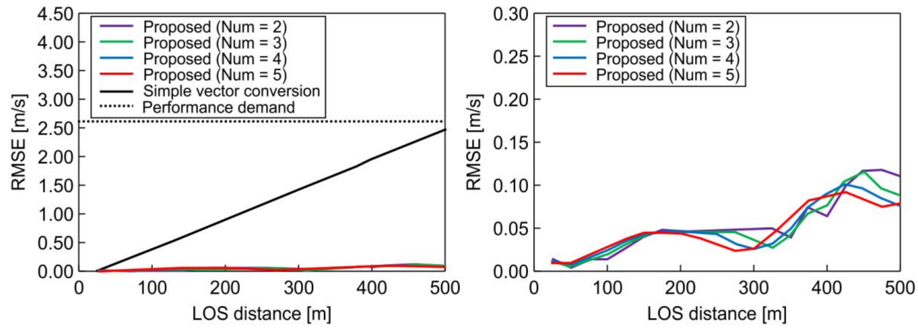

Fig. 14 Statistical estimation performance (NWP) results

4.2 Ideal vortex model with error and noise

In this section, the numerical experiments with error and noise of LOS wind values are conducted to evaluate the estimation performance of the proposed method. This numerical experiment shows the error/noise-filtering performance difference between simple vector conversion and the proposed method with extrapolation by using the past LOS wind. In this study, the atmospheric conditions are used to evaluate six different cases, to generate error and noise data in the LOS wind values. In this study, six atmospheric conditions are prepared in order to evaluate the filtering performance. The backscattering coefficients are (Standard case) 1.8×10^{-8} $sr^{-1}m^{-1}$, (a) $1.8\times10^{-11}sr^{-1}m^{-1}$, (b) 1.35×10^{-11} $sr^{-1}m^{-1}$, (c) 0.9×10^{-11} $sr^{-1}m^{-1}$, (d) 0.45×10^{-11} $sr^{-1}m^{-1}$, and (e) 0.18×10^{-11} $sr^{-1}m^{-1}$.

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The numerical experiments with the ideal vortex model were carried out. Figure 15 shows the LOS wind values, which include the measured data with error and noise, reference wind, the smoothing spline, and the general spline model results. Figure 15 shows that the smoothing spline can filter the error and noise data of LOS wind values. When the general spline is used, the error can be filtered correctly by using a simple Kalman filter and a robust LSM; however, the noise cannot be filtered. Next, a statistical estimation performance is conducted by using 100-pseudo routes, and Fig. 16 shows the results of the statistical estimation performance with error and noise. In addition, the difference of the atmospheric condition in six-case (standard, (a), (b), (c), (d), (e) in the backscattering coefficients) is also checked. The figure to the left is the simple vector conversion results, and the figure to the right shows the proposed method results. The simple vector conversion cannot satisfy the performance demand at a distance farther than 350 m LOS, and cannot work correctly at atmospheric condition (e). The proposed method can satisfy the performance demand except at atmospheric conditions (e). The proposed method shows much better performance than the simple vector conversion, even though it is difficult to estimate the wind field values for atmospheric condition (e) by using both the simple vector conversion and the proposed method, due to the fact, that atmospheric condition (e) contains much larger noise levels than other conditions.

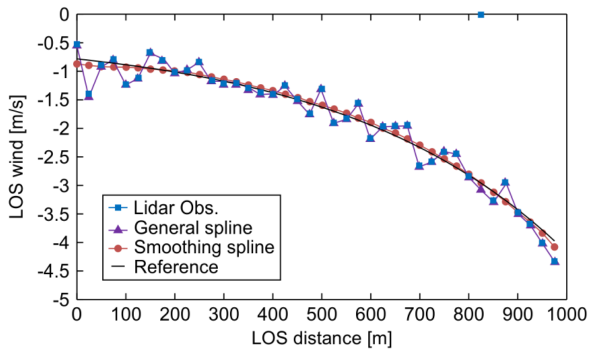

Fig. 15 LOS wind values with measured data with error and noise, reference wind, the smoothing spline and general spline

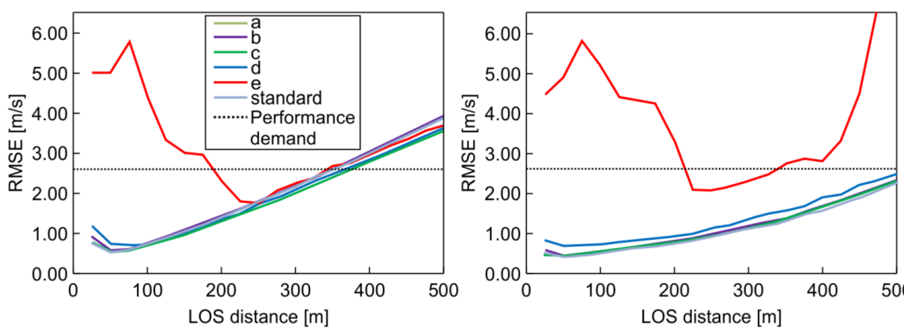

Fig. 16 Statistical estimation performance results with the error and noise (Ideal vortex model)

In addition, the cross-plots of the reference and the estimated vertical wind are shown as Fig. 17. In Fig. 17 (a), (b) the results of the simple vector conversion are presented, (c), (d) show the results of the proposed method, (a) and (c) are the cases without error and noise, and the (b) and (d) are the cases with error and noise. The left figures are

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the wind data at 100 m LOS distance, middle figures are the wind data at 300 m LOS distance, and the right figures are the wind data at 500 m LOS distance. The dots indicate the wind speed estimated at 5 Hz, and the dotted lines indicate the performance demand of the control. By comparing (a) and (c), we can deduct that the proposed method provides a much better estimation than the simple vector conversion. The results in (b) and (d) are spread wider than those in (a) and (c), because of the noise data of LOS wind values. It is worth mentioning that the noise data have more negative effects on the result at 500-m LOS distance than at 100 m and 300 m LOS. A comparison of (b) and (d) shows that the proposed method can provide more accurate estimations than the simple vector conversion method.

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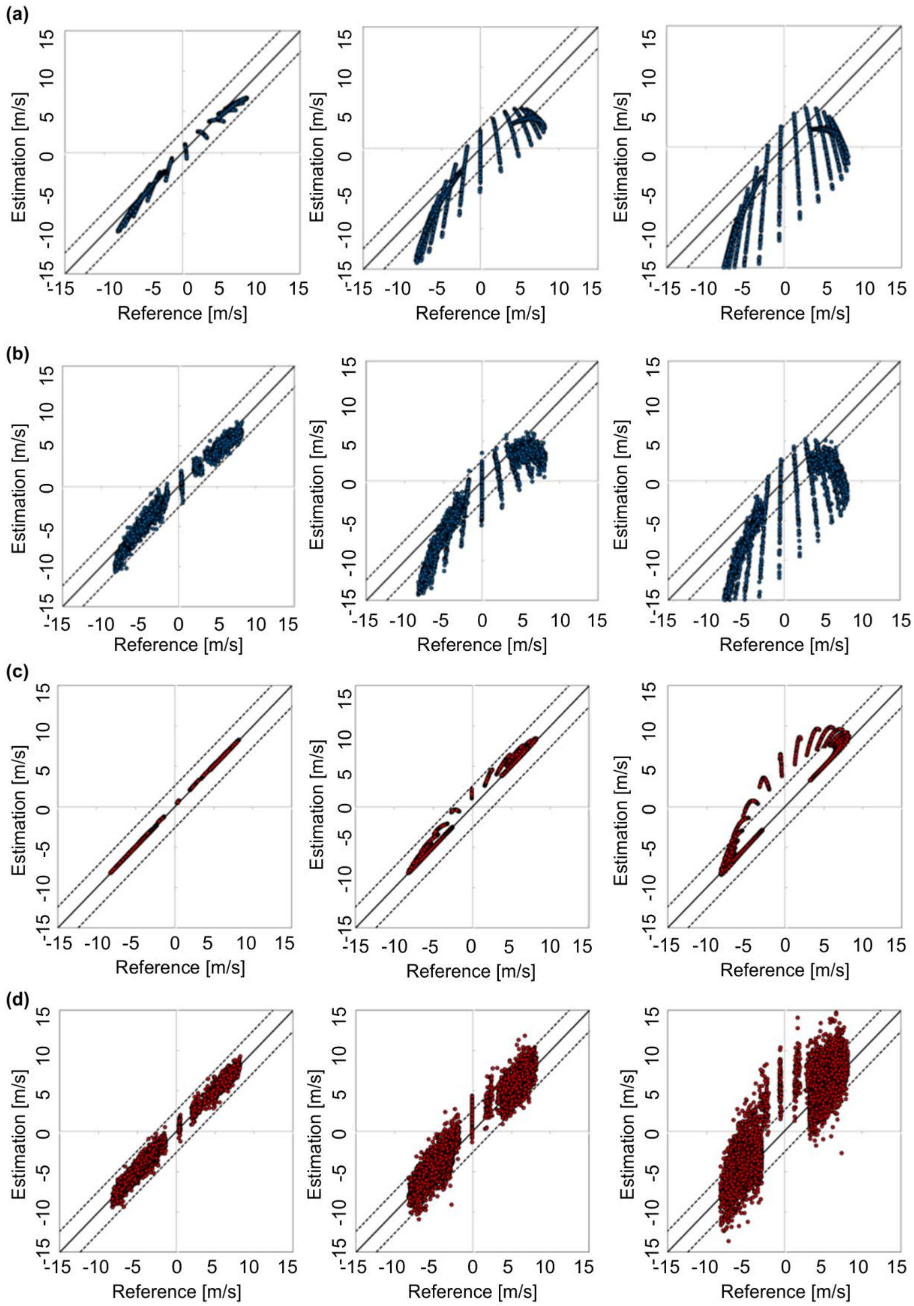

Fig. 17 Cross-plots of the reference and the estimated vertical wind

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4.3 NWP with error and noise

The numerical experiments with NWP were carried out. The statistical estimation performance is conducted by using 100-pseudo routes, and Fig. 18 shows the results of the statistical estimation performance with error and noise. In addition, six different atmospheric condition cases (standard, (a), (b), (c), (d), and (e) in the backscattering coefficients) were used. Figures to the left show simple vector conversion results and figures to the right show results with the proposed method. In this case, both the simple vector conversion and the proposed method can satisfy the performance demand to preview control; however, the simple vector conversion shows worse performance compared to the proposed method. The proposed method can estimate quite accurately wind field values. In addition, the proposed method displays better performance than the simple vector conversion method, and similar to the previous experiment, it is difficult to estimate the wind field values for atmospheric condition (e) by using both the simple vector conversion and the proposed method.

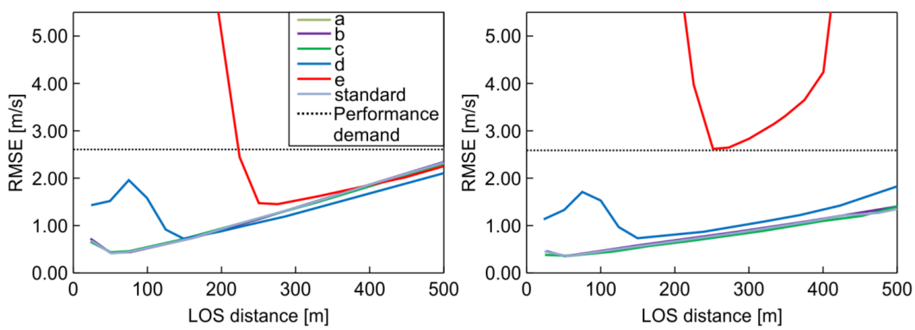

Fig. 18 The results of the statistical estimation performance with the error and noise (NWP)

5. Conclusion

In this study, an airflow vector estimation algorithm based on upward and downward airborne Lidars has been proposed for preview control to prevent turbulence-induced aircraft accidents. This estimation algorithm uses the technique of extrapolating the wind field values by using the LSM and the current and past LOS wind datasets to improve the accuracy of estimated wind values. Two test configurations of numerical experiments, 1) ideal vortex flow field and 2) realistic weather field values with calculated NWP numbers, were used to evaluate the estimated performance of the airflow vector.

The numerical experiments of LOS wind were conducted to evaluate the estimation performance of the proposed method. These numerical experiments showed the difference in performance between simple vector conversion methods and the proposed extrapolation method. The proposed method has much better performance than the simple vector conversion methods, and it can estimate the two-dimensional distribution of wind field values accurately, unlike the simple vector conversion method. The estimation performance and the computational cost of the proposed method can satisfy the performance demand for preview control.

The numerical experiments with error and noise of LOS wind were conducted to evaluate the performance of the proposed estimation method. These numerical experiments showed the error/noise-filtering performance difference between the simple vector conversion method and the proposed extrapolation method. It was also shown that the smoothing spline model could filter noise correctly and reduce its negative effects. Therefore, the proposed method has shown a much better performance than the simple vector conversion method; however, it is still difficult to estimate the wind field values for atmospheric condition (e) with both methods. Atmospheric condition (e) has larger noise than other conditions, and when the noise exceeds a certain level, it is difficult to estimate the airflow regardless of the method applied.

The findings of this study are subject to certain limitations. The target size of the atmospheric turbulence by the proposed algorithm is assumed to be comparable or larger than the observation area between the Lidars. Therefore, it is difficult to estimate a wind field with turbulence smaller than that of the observation area between the Lidars. However, the effect on the aircraft vibration due to such minor turbulence is minimal, and it is considered to be excluded from the proposed algorithm. The second limitation is that the current results are obtained from numerical experiments and not from evaluations of actual observations. Currently, the LIDAR system is being modified to be smaller and lighter in order to suit small experimental aircraft. Flight demonstrations are to be performed in 2021. The results of this research will be applied to this flight demonstration.

The proposed algorithm can satisfy the performance demands for preview control in both estimation performance and computational cost. The proposed method can estimate a two-dimensional distribution that cannot be estimated by existing methods. This is valuable information for improving the accuracy of the preview control: for example, it is now possible to cope with a critical case where the flight direction of the aircraft is at a steep angle with the aircraft either ascending or descending. This point is also an advantage of the proposed method.

Author Contributions

Ryota Kikuchi, Takashi Misaka, and Shigeru Obayashi designed the experiments and Ryota Kikuchi performed the experiments, developed the model code, performed the simulations, and prepared the manuscript with contributions from all co-authors. Hamaki Inokuchi contributed to the analysis and interpretation of data related to Lidar, and assisted in the preparation of the manuscript. All authors approve the final version of the manuscript, and agree to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

Competing Interests

The authors declare that they have no conflict of interest.

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Preprint. Discussion started: 29 June 2020

References

Airbus, Flight Operations Briefing Notes Adverse Weather Operations Optimum Use of the Weather Radar, available at: https://safetyfirst.airbus.com/optimum-use-of-weather-radar/, 2020.

Barny, H.: DELICAT - Demonstration of LIdar based Clear Air Turbulence detection, Innovation for Sustainable Aviation in a Global Environment, in: Proceedings of the Sixth European Aeronautics Days, 253, 2012.

Boeing: Statistical Summary of Commercial Jet Airplane Accidents, 2015.

Federal Aviation Administration, Preventing injuries caused by turbulence 2006, available at: https://www.faa.gov/regulations_policies/advisory_circulars/index.cfm/go/document.information/documentid/99831, 2020.

Fezans, N., Joos, H.D., and Deiler, C.: Gust load alleviation for a long-range aircraft with and without anticipation, CEAS Aeronautical Journal, 2019, 1-25.

Hamada,Y.: New LMI-based conditions for preview feedforward synthesis, Control Engineering Practice, 90, 19-26, 2019

Hinton, D. A., and Tatnall, C. R.: A candidate wake vortex strength definition for application to the NASA aircraft vortex spacing system (AVOSS), NASA Technical Reports, 1997.

Huber, P. J.: Robust Statistics, Springer, Berlin, Heidelberg, 2008.

Inokuchi, H., Tanaka, H., and Ando, T.: Development of an onboard doppler lidar for flight safety, Journal of aircraft, 46.4, 1411-1415, 2009

Inokuchi, H., and Akiyama, T.: Flight Demonstration of an Airborne Coherent Doppler Lidar, Asia Pacific International Symposium on Aerospace Technology, 2019.

International Air Transportation Association, Safety Report 2015, 2016.

Japan Transport Safety Board, "2003-2012: Aircraft accident reports", available at: http://www.mlit.go.jp/jtsb/, 2020.

Kikuchi, R., Misaka, T., and Obayashi, S.: Real-Time Flow Prediction of Low-Level Atmospheric Turbulence, 33rd Wind Energy Symposium, 2015.

Kameyama, S., Ando, T., Asaka, K., Hirano, Y., and Wadaka, S.: Compact all-fiber pulsed coherent Doppler lidar system for wind sensing, Applied Optics, 46.11, 1953-1962, 2007

Machida, S.: Project Overview of R&D for Onboard Turbulence Detection System, Proceedings of Asia-Pacific International Symposium on Aerospace Technology 2017, Plenary Lecture 4 (Seoul, Korea, 2017).

Misaka, T., Nakabayashi, F. K., Obayashi, S., and Inokuchi, H.: Filtering Algorithm of Airborne Doppler Lidar Measurements for Improved Wind Estimation, Transactions of the Japan Society for Aeronautical and Space Sciences, 58.3, 149-155, 2015

Newsom, R. K., et al.: Validating precision estimates in horizontal wind measurements from a Doppler lidar, Atmospheric Measurement Techniques (Online) 10. NREL/JA-5000-68401 (2017).

Regan, C.D., and Jutte, C.V. (2012), Survey of applications of active control technology for gust alleviation and new challenges for lighter-weight aircraft. NASA Technical Memorandum, NASA-TM-2012-216008.

Saito, K., Ishida, J. I., Aranami, K., Hara, T., Segawa, T., Narita, M., and Honda, Y, Nonhydrostatic atmospheric models and operational development at JMA, Journal of the Meteorological Society of Japan 85B, 271-304, 2007.

https://doi.org/10.5194/amt-2020-106
Preprint. Discussion started: 29 June 2020

Schmitt, N. P., Rehm, W., Pistner, T., Zeller, P., Diehl, H., and Navé, P.: The AWIATOR airborne LIDAR turbulence sensor, Aerospace Science and Technology, 11.7, 546-552, 2007

Sermi, F., Cuccoli, F., Mugnai, C., and Facheris, L.: Aircraft hazard evaluation for critical weather avoidance, Metrology for Aerospace (MetroAeroSpace), IEEE, 2015.

Soreide, D. C., Bogue, R. K., Ehernberger, L. J., Hannon, S. M., and Bowdle, D. A.: Airborne coherent LIDAR for advanced in-flight measurements (ACLAIM) flight testing of the LIDAR sensor, NASA Technical Reports, 2000.

Woltring, H. J." A Fortran package for generalized, cross-validatory spline smoothing and differentiation." Advances in Engineering Software, 8.2, 104-113, 1986