Filtering Algorithm of Airborne Doppler Lidar Measurements for Improved Wind Estimation*

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In this paper, we describe a filtering algorithm for removing the error of wind velocity arises in airborne Doppler lidar measurements. The algorithm is based on the Kalman filter with a simplified Kalman gain, which assumes zero variance for correct wind velocity and infinite variance for incorrect wind velocity. The algorithm is applied to 17,487 seconds of airborne Doppler lidar measurements, where a sequence of measurements along the lidar's measurement range is obtained every one second. The reduction of incorrect wind velocity is evaluated at the distance where correct wind velocity exists at least 20–30% of the time out of all measurements. The average standard deviation of filtered wind velocity at the above mentioned distance results in 17.2% of the original value, which is similar magnitude to correct measurements.

Key Words: Filtering Algorithm, Airborne Doppler Lidar, Atmospheric Turbulence

Nomenclature

d : flight distance between measurement sequences, m
 f_{IF} : central frequency, Hz
 f_s : sampling frequency, Hz
 FS_i : Doppler shift for range-bin i
 GW : gate width
 k : FFT point
 k_{ave} : average of spectrum peaks in short ranges
 k_{dif} : difference of spectrum peaks between neighboring range-bins
 k_e : end FFT point of moment calculation
 $K_{i,j}$: Kalman gain
 k_s : start FFT point of moment calculation
 k_{1st} : FFT point for the first spectrum peak
 k_{2nd} : FFT point for the second spectrum peak
 L : range-bin interval, m
 N_{fft} : number of FFT points
 PK_i : FFT point for the location of a spectrum peak
 R_1, R_2 : reliable distances, m
 $s_{i,j}$: signal-to-noise ratio (SNR), dB
 $SP_{i,k}$: spectrum for range-bin i
 T_j : time, s
 T_s : time interval of measurement sequence, s
 $v_{i,j}$: wind velocity, m/s
 V_{ref} : reference velocity, m/s
 Δf_d : frequency resolution, Hz
 λ : wave length, m
 $\sigma_{i,j}$: standard deviation of wind velocity, m/s

Subscripts
 i : index for range-bin

j : index for time

k : index for FFT point

Superscripts

(+): filtered state

(–): predicted state

(m): measured state

1. Introduction

The detection of weather conditions along a flight path is very important for a safe flight. In this sense, most airliners today are equipped with airborne radar systems that enable advanced warning of hazardous weather conditions. However, these pieces of equipment rely on the reflected radio waves from water particles (i.e., rain drops), and thus they are not able to detect hazardous wind shear occurring under clear air conditions, namely, clear air turbulence (CAT). Reported incidents caused by wind shear suggest that the currently available sensors are not always sufficient or appropriate to advise pilots on the weather conditions ahead.

In recent years, airborne equipment based on lidar (light detection and ranging) technology has been investigated as a more effective forward-looking sensor to equip airliners.^{1–4)} A lidar does not require the presence of rain drop as it measures wind speed using aerosol particles in the atmosphere, making it able to detect CAT. Such a forward-looking device could realize predictive gust load alleviation control.^{5,6)} Japan Aerospace Exploration Agency (JAXA) has been developing a turbulence detection system using an airborne lidar.^{7,8)} Following the successful demonstration of lidars with measurement ranges of one and three nautical miles, the current development is directed to a lidar with a five-nautical-mile range.

In fact, the measurement range should be made as large as possible, since it is directly reflected in the lead time for crew

and passengers to take appropriate actions about the turbulence. A typical jet airliner, for example, cruises at an air-speed of about 250 m/s, taking approximately 37 s to fly the distance of five nautical miles. A larger measurement range could be achieved by using a higher powered laser; however, it usually requires larger and heavier peripheral devices, which are not favorable for airborne applications. Therefore, even though increasing the measurement range is surely necessary, it is also important that the whole nominal range of the lidar equipment be used effectively. Regarding this point, we will see that there is considerable decay in the quality of wind velocity estimates as the distance from an aircraft increases, such that the lidar fails to provide correct measurements of wind velocity throughout its nominal range. Accordingly, if this decay can somehow be alleviated, it would result in practical extension of the measurement range.

In this paper, we describe a filtering algorithm to remove the error in wind velocity arising in Doppler lidar measurements. The algorithm is based on a simple representation of the Kalman filter. The selective feature of the algorithm is introduced by considering only two values of the Kalman gain, zero or one, which corresponds to assume zero variance for correct wind velocity and infinite variance for incorrect wind velocity. Since the algorithm is closely coupled with the processing of spectrum data obtained by Doppler lidar measurements, the procedure of wind velocity estimation from the spectrum data is briefly described. In addition, the mechanism responsible for the error in the wind velocity estimates at distant range-bins is also reported, which explains a supportive background to employ the simplified Kalman gain in this filtering algorithm. The algorithm is applied to 17,487 seconds of airborne Doppler lidar measurements acquired during a measurement campaign from July 23 to 25, 2007. The quantitative evaluation of filtered wind velocity was conducted by the post-processed standard deviation of wind velocity at each range-bin because the error appears as large and random wind velocity compared to its true value. Hence, the standard deviation obtained by post-processing can be one of the measures to distinguish correct or incorrect wind velocity from actual lidar measurements. The rest of this paper is structured as follows. Section 2 describes the processing of spectrum data obtained by Doppler lidar measurements. Section 3 presents a filter algorithm developed in this study. Since the mechanism responsible for the incorrect wind velocity considered in this study is hard to reproduce for validation, the filtering algorithm is evaluated using actual lidar measurements in Section 4. Finally, we conclude this study in Section 5.

2. Processing of Lidar Measurements

The procedure to obtain wind velocity estimates from lidar spectrum data is briefly described to make this paper as consistent as possible. Note that the parameters in this section are based on the values used in an actual Doppler lidar and are fixed during the course of algorithm development.

The optimization of the parameters is beyond the scope of this paper.

JAXA's airborne Doppler lidar provides sequences of wind velocities and their standard deviations, which are offset by a distance d due to the distance traveled by an aircraft during the time interval of $T_s = T_j - T_{j-1} = 1$ s. Each sequence has its measurements spaced at $L = 150$ m intervals as shown in Fig. 1. The distance d is defined by $d = V_{ref} \times T_s$, where a reference speed V_{ref} is set to the fixed value of 61.7 m/s. Therefore, a true air speed (TAS) becomes the sum of V_{ref} and wind velocity measured by the lidar. A typical member of this sequence $v_{i,j}$ represents the value of wind velocity along the line-of-sight (LOS) direction for a range-bin i at time T_j . Additional information for each measurement sequence includes the standard deviation of the wind velocity $\sigma_{i,j}$ and signal-to-noise ratio (SNR) $s_{i,j}$.

For wind measurement, the current equipment employs a pulsed laser beam with a wavelength of $1.5 \mu\text{m}$, which is emitted and scattered by moving aerosol particles in the atmosphere. The backscattered pulse data is processed by fast Fourier transform (FFT), resulting in spectrum data at each range-bin. Since the backscattered signal of a single pulse has a very low magnitude, multiple pulses are emitted so that the backscattered signal can be detected after the incoherent integration. In the resulting power spectrum, the noise level varies with the signal frequency, becoming an obstacle for wind estimation. Therefore, pre-processing of this spectrum data at each range-bin is necessary, and this involves the following steps: first, an inverse fast Fourier transform (IFFT) is performed and then the auto-correlation function is calculated. The results near zero correspond to noise components that are removed from the data. Next, the FFT brings the values back to the original frequency domain. Finally, the peak value in the obtained spectrum data is chosen as the representative value of the lidar signal, from which the wind velocity can be calculated. Following the above procedure of peak detection in the spectrum data, the Doppler shift in terms of number of FFT points can be calculated as follows:

$$FS_i = \frac{\sum_{k=k_s}^{k_e} k SP_{i,k}}{\sum_{k=k_s}^{k_e} SP_{i,k}}, \quad (i = 1, 2, \dots, N_{fft} - 1), \quad (1)$$

where FS_i is the Doppler shift for range-bin i , $SP_{i,k}$ is the normalized value of spectrum data for range-bin i and FFT is point k . The lower and upper limits k_s and k_e are given by $k_s = PK_i - GW$ and $k_e = PK_i + GW$, where PK_i is the index that gives the location of the peak value in the spec-

Fig. 1. Schematic of airborne lidar measurement where L denotes range-bin interval, while d is a flight distance between measurement times T_{j-1} and T_j .

trum data, and GW is gate width, which is fixed to 5. Frequency resolution is then calculated by $\Delta f_d = f_s / N_{fft}$, where f_s is the sampling frequency (216 MHz) and N_{fft} is the number of FFT points (256 points). The Doppler shift in terms of wind velocity can be calculated from:

$$v_{i,j} = \frac{\lambda}{2} (FS_i \Delta f_d - f_{IF}) \Big|_j, \quad (2)$$

where f_{IF} is the central frequency (128 MHz) and λ is the wavelength (1.5 μm). Finally, the standard deviation of the wind velocity and SNR are calculated from:

$$\sigma_{i,j} = \frac{\lambda}{2T_j} \sqrt{\sum_{k=k_s}^{k_e} (PK_i - k)^2 SP_{i,k} \Big/ \sum_{k=k_s}^{k_e} SP_{i,k}} \Big|_j, \quad (3)$$

$$s_{i,j} = 10 \log_{10}(SP_{i,PK_i}) \Big|_j. \quad (4)$$

Concerning the processes to obtain wind velocity, standard deviation and SNR described above, as well as the appearance of the spectrum at each range-bin, please also refer to Asahara et al.^{9,10)}

The detection of a spectrum peak is critically important to obtain correct wind velocity. The peak detection from spectrum data fails in distant measurement ranges because the backscattered signal level becomes smaller than the measured noise level. This false detection of the spectrum peak leads to incorrect wind velocity, i.e., random and intermittent wind velocity. Figure 2 shows examples of SNR and wind velocity along a measurement range. The wind velocity starts to exhibit a powerful magnitude at around 5,400 m, which corresponds to a SNR lower than 4.5 dB. The measured spectrum data at this range has multiple peaks due to a noise component, and the resulting false detection of a spectrum peak causes random and intermittent wind velocity. In addition, it is confirmed that a certain SNR value such as 4.5 dB is not robust enough to detect incorrect wind velocity because the background noise level varies depending on measurement conditions. From the above observations, a filtering algorithm is designed so that it can reject incorrect wind velocity based on a threshold obtained during the peak detection process.

Fig. 2. Examples of wind velocity and signal-to-noise ratio (SNR) along a measurement range.

3. Construction of Filtering Algorithm

We introduce a filtering algorithm based on the Kalman filter in the following equations:

(Prediction)

$$v_{i,j+1}^{(-)} = \frac{L-d}{L} v_{i,j}^{(+)} + \frac{d}{L} v_{i+1,j}^{(+)}, \quad (5)$$

$$\left(\sigma_{i,j+1}^{(-)}\right)^2 = \frac{L-d}{L} \left(\sigma_{i,j}^{(+)}\right)^2 + \frac{d}{L} \left(\sigma_{i+1,j}^{(+)}\right)^2, \quad (6)$$

(Kalman gain)

$$K_{i,j+1} = \frac{\left(\sigma_{i,j+1}^{(-)}\right)^2}{\left(\sigma_{i,j+1}^{(-)}\right)^2 + \left(\sigma_{i,j+1}^{(m)}\right)^2}, \quad (7)$$

(Update)

$$v_{i,j+1}^{(+)} = v_{i,j+1}^{(-)} + K_{i,j+1} \left(v_{i,j+1}^{(m)} - v_{i,j+1}^{(-)}\right), \quad (8)$$

$$\begin{aligned} \left(\sigma_{i,j+1}^{(+)}\right)^2 &= \left(\sigma_{i,j+1}^{(-)}\right)^2 - K_{i,j+1} \left(\sigma_{i,j+1}^{(-)}\right)^2 \\ &= K_{i,j+1} \left(\sigma_{i,j+1}^{(m)}\right)^2. \end{aligned} \quad (9)$$

Here, Eqs. (5) and (6) predict wind velocity $v_{i,j}^{(-)}$ and its standard deviation $\sigma_{i,j}^{(-)}$ in the next time step by linear interpolation between range-bins. Equation (7) gives Kalman gain $K_{i,j}$ which corresponds to a weighting factor between predicted and measured states. Then, predicted states are updated to incorporate new measurements $v_{i,j}^{(m)}$, $\sigma_{i,j}^{(m)}$ into the predicted states, which are done by Eqs. (8) and (9) for $v_{i,j}^{(+)}$, $\sigma_{i,j}^{(+)}$. These equations realize a simple representation of a Kalman filter algorithm. The construction of the algorithm is similar to the algorithm developed by Stratton et al., however, the present algorithm is further simplified due to the absence of equations for F -factor.¹¹⁻¹⁵⁾ In addition, the present algorithm employs the standard deviation of wind velocity directly from lidar measurements to update the variance of system states, which further simplifies the algorithm and make it more reliable compared to providing it using the prescribed noise structure, e.g., white noise.

A selective feature of the algorithm is introduced by considering only two values of the Kalman gain, one or zero, which corresponds to assume zero variance for correct wind velocity and infinite variance for incorrect wind velocity. In contrast to the standard Kalman filter, which optimally blends measurement and model prediction based on those reliability represented by the variance, the present algorithm rejects incorrect wind velocity completely because the incorrect wind velocity has a very large value and blending based on variances degrades the model prediction. A similar procedure can be found in the handling of censored data.¹⁶⁾ Based on the observations of spectrum data at each range-bin, it is possible to define the validity of measurements during the peak detection process described in the previous section. We consider two thresholds for defining the correct wind velocity from spectrum data; (1) the largest and second largest spectrum values ($k_{1st} = PK_i$ and k_{2nd}) adjoin with each other, i.e., the distance in FFT point between the largest and sec-

and largest spectrum values is equal to one and (2) the distance in FFT point from the averaged spectrum peak k_{ave} is less than a certain allowance k_{dif} , where k_{ave} is the index that gives the location of the spectrum peak averaged in short ranges, e.g., 2–30 range-bins from the lidar origin. Based on these thresholds, a simplified Kalman gain is defined as follows:

$$K_{i,j} = \begin{cases} 1 & |k_{1st} - k_{2nd}| = 1 \\ & \text{and } |k_{1st} - k_{ave}| < k_{dif} \\ 0 & \text{Others,} \end{cases} \quad (10)$$

where k_{dif} is the only parameter in the present algorithm. The filtering results with different k_{dif} are discussed in a later section. Basically, the smaller value of k_{dif} does not allow a large variation in wind velocity along the measurement range.

In the present lidar measurements, the validity of wind velocity cannot always be related to either the magnitude of standard deviation $\sigma_{i,j}$ or the SNR $s_{i,j}$ in distant range-bins. Therefore, the incorrect wind velocity in the distant range-bins is not removed if the standard deviation of lidar measurements is directly employed in the filtering algorithm. However, the selective filtering algorithm itself would be applicable to lidar measurements without the simplified Kalman gain if the magnitude of the standard deviation correlates well with the validity of wind velocity. From Fig. 2, it seems to be possible to determine the simplified Kalman gain based on SNR; however, a fixed threshold value of SNR lacks flexibility for defining the validity of wind velocity.

4. Evaluation of Error Reduction Capability

4.1. Flight case at 10:23 a.m. on July 24, 2007

The filtering algorithm is evaluated qualitatively by visualizing filtered wind velocity and quantitatively by reducing the post-processed standard deviation of wind velocity.

Figure 3 shows the wind velocity distribution measured by the JAXA's airborne Doppler lidar. Wind shear was clearly measured, where the fluctuations of wind velocity propagate from the left-top to the right-bottom of Fig. 3. The horizontal axis shows time in seconds and the vertical

axis shows the measurement range in meters. In this case, random errors of wind velocity are observed from approximately 4,000 m in the measurement range, where the magnitude of the wind velocity appears very large compared to the correct wind velocity near the lidar origin. Figures 4 to 6 show filtered wind velocity distributions with different threshold values $k_{dif} = 5, 10$ and 15, where these values correspond to 3.2, 6.5 and 9.7 m/s wind velocities, respectively. From the figures, it is confirmed that the random errors in wind velocity are removed in distant range-bins. Especially, there is a marked recovery in wind velocity distribution in the measurement range between 4,000 and 5,000 m; that is, the wind velocity shows smooth distribution while keeping the structure of the measured wind shear. The influence of different k_{dif} is seen in distant range-bins. With a larger threshold value, $k_{dif} = 15$, some part of incorrect wind velocity remains. Smoother wind velocity distribution is obtained, as witnessed by the smaller value of $k_{dif} = 5$; however, the wind shear structure in distant range-bins tends to be overly smoothed out. Figure 7 shows the distribution of the simplified Kalman gain defined by Eq. (10) for the case shown in Fig. 5 ($k_{dif} = 10$). Figure 8 shows the distribution of SNR again for the case in Fig. 5. It is difficult to determine the validity of wind velocity only from the value of SNR because the definition of a certain threshold value of SNR is not a triv-

Fig. 4. Time history of the wind velocity filtered with $k_{dif} = 5$ for the flight at 10:23 a.m. on July 24, 2007.

Fig. 3. Time history of the original wind velocity for the flight at 10:23 a.m. on July 24, 2007.

Fig. 5. Time history of the wind velocity filtered with $k_{dif} = 10$ for the flight at 10:23 a.m. on July 24, 2007.

Fig. 6. Time history of the wind velocity filtered with $k_{dif} = 15$ for the flight at 10:23 a.m. on July 24, 2007.

Fig. 8. Time history of signal-to-noise ratio (SNR) for the flight at 10:23 a.m. on July 24, 2007.

Fig. 7. Time history of correct (white) and incorrect (black) wind velocity defined by K_{ij} in Eq. (10) for the flight at 10:23 a.m. on July 24, 2007.

Fig. 9. Number of correct wind velocity measurements along the measurement range and the reliable distances R_1 and R_2 defined by the plot.

ial problem, and the magnitude of SNR and the validity of wind velocity are not well correlated in distant range-bins.

The evaluation is focused on the range between 3,000 and 4,500 m in Fig. 7, where the number of correct wind velocity measurements starts to decrease and reaches its lowest value. With the help of correct wind velocity existing in this range, the selective filter can recover missing (incorrect) wind velocity. Basically, the selective filter provides smooth wind velocity distribution compared to the original distribution; however, the reliability of the filtered wind velocity is limited due to the decreased number of correct wind velocity measurements in distant range-bins. A linear decrease in correct wind velocity measurements starts at a certain range-bin and the number of correct wind velocity measurements becomes nearly 20–30% of total measurements over time. Figure 9 shows the number of correct wind velocity measurements in each range-bin evaluated over time using the case described above; the solid line shows the number of correct wind velocity measurements that satisfy the conditions in Eq. (10) with $k_{dif} = 10$, the broken line is the number with a SNR larger than 4.5 dB, and the dotted line is that larger than 9.0 dB. From these plots, it is confirmed that the number of correct wind velocity measurements starts to drop at 2,800 m and reaches the lowest value at around 4,500 m. The plots from the conditions in Eq. (10) and from a SNR

of 4.5 dB show a similar distribution; hence, the SNR of 4.5 dB might be used to determine the validity of wind velocity measurements in this case. However, the discrepancy, which starts to appear from 4,500 m, results in a relatively large difference in filtered wind velocity.

For the quantitative evaluation of error removal capability, we define certain distances in the measurement range from where correct wind velocity starts to drop and the correct wind velocity reaches its lowest value, denoted by R_1 and R_2 , respectively. In the case shown in Fig. 9, the distances are defined as $R_1 = 2,850$ m and $R_2 = 4,800$ m using a line based on a linear drop in correct wind velocity, i.e., a line fitted to the plot between 3,000 and 4,500 m. The distances R_1 and R_2 are also shown in Figs. 3 to 10. For the evaluation, we focus on the standard deviation of filtered wind velocity evaluated over time. The existence of incorrect wind velocity measurement is not visible in the averaged wind velocity value because the positive and negative values of incorrect wind velocity cancel out; however, it is observed in the standard deviation calculated from wind velocity. Figure 10 shows the plots of standard deviation obtained from the filtered wind velocity with several threshold values k_{dif} . The standard deviation from the original wind velocity is also shown in the figure. In the original data, the standard deviation increases significantly from R_1 and R_2 . By applying the selec-

Fig. 10. Standard deviation of wind velocity measurements along the measurement range with various threshold values k_{dif} .

Fig. 11. Time history of the original wind velocity from the measurements in the morning of July 25, 2007.

tive filter, the standard deviation at R_2 was a similar order as the value at R_1 . In addition, the lower threshold value realizes a smaller standard deviation at R_2 . The magnitude of standard deviation obtained from filtered wind velocity ($k_{dif} = 10$) at R_2 is 16.6% of that from the original wind velocity (see also Table 2).

4.2. Statistical evaluation of flight cases

A selective filter is applied to the larger number of measurements. The behavior of the selective filter is similar to the previous case. In that sense, the selective filter shows robustness in error removal capability. Figure 11 shows the wind velocity measured on the morning of July 25, 2007 and Fig. 12 is the corresponding filtered wind velocity with $k_{dif} = 10$. In the original data, incorrect wind velocity measurements appear from 3,000 m in the measurement range. The incorrect wind velocity is removed in the filtered wind velocity while keeping the time variation of wind velocity. A quantitative evaluation is performed as in the previous section. Table 1 shows the specifications of lidar measurements acquired during a measurement campaign from July 23 to 25, 2007. Table 2 shows the standard deviation in wind velocity at the distances R_1 and R_2 . There are variations in the standard deviation at R_1 and R_2 ; however, the ratio of the standard deviations between filtered and original data at R_2 is in the range between 13.4 and 20.0%, and is 17.2% on average.

Fig. 12. Time history of filtered wind velocity from the measurements in the morning of July 25, 2007.

Table 1. Reliable distances R_1 and R_2 obtained from lidar measurements acquired during a measurement campaign from July 23 to 25, 2007.

Date	Measurement time [s]	R_1 [m]	R_2 [m]	Altitude [m]
July 23 a.m.	2,132	3,150	5,400	500–934
July 23 p.m.	3,495	2,550	3,900	1,463–1,651
July 24 a.m.	4,026	1,950	3,600	168–968
July 25 a.m.	4,057	2,250	3,600	232–989
July 25 p.m.	3,777	1,350	2,550	566–1,601
July 24 11:23 a.m. the case shown in Figs. 3–10	220	2,850	4,800	620–677

Table 2. Standard deviations of the original and filtered wind velocities at reliable distances R_1 and R_2 .

Date	$\sigma_o _{R_1}$ [m/s]	$\sigma_f _{R_1}$ [m/s]	$\sigma_o _{R_2}$ [m/s]	$\sigma_f _{R_2}$ [m/s]	$\sigma_f/\sigma_o _{R_1}$
July 23 a.m.	1.015	0.374	15.063	2.516	16.7%
July 23 p.m.	0.608	0.580	12.444	2.035	16.3%
July 24 a.m.	1.548	0.993	12.913	2.527	19.6%
July 25 a.m.	2.367	0.815	12.828	1.715	13.4%
July 25 p.m.	1.994	1.016	14.119	2.823	20.0%
July 24 11:23 a.m. the case shown in Figs. 3–10	2.107	1.550	12.519	2.084	16.6%

Note that the bottom case in Tables 1 and 2 corresponds to the case shown in Figs. 3 to 10.

5. Conclusion

A filtering algorithm for measurements taken by JAXA's airborne Doppler lidar is described in this paper. Because of the selective property of the filtering algorithm, the wind velocity error is removed and the resulting velocity distribution becomes smooth while keeping the structure of the measured wind shear. The reliability of filtered wind velocity measurement is limited to the range where correct wind velocity is at least 20–30% of total measurements over time, because the quality of the filtered wind velocity relies on the number of correct wind velocity measurements at range-bins nearby. A quantitative evaluation of the filtering algorithm is performed by evaluating the standard deviation of wind velocity over time. The reduction of incorrect wind velocity

measurements is quantified in the range where the correct wind velocity reaches its lowest value after a linear drop, which is denoted as R_2 in this paper. The average standard deviation of the filtered wind velocity from 17,487 s of measurements is 17.2% of the original value, which is a similar magnitude to the value of correct wind velocity measurements in range-bins near the lidar's origin. Although the filtered wind velocity had a smooth distribution for the whole measurement range, we emphasize that the algorithm tends to provide reliable wind velocity measurement until the distance shown by R_2 . A smoothed wind velocity is favorable for the evaluation of hazard indices because the indices are often calculated by the derivative of wind velocity, as in the case of F -factor. These overall procedures can easily be applied to measurement devices with similar data processing.

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