Remote Sensing of Turbulence:
Lidar Activities

FY00 Year-End Report

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Introduction

In FY00, the lidar algorithm research occurred along two major themes: the continued analysis of the Juneau lidar data and the use of lidar and aircraft simulations to evaluate the utility of lidar Doppler second moments to accurately detect turbulence.

Analysis of Juneau Data

Analysis of Juneau lidar data has produced a consistent comparison between the spatial turbulence statistics using structure function analysis and a global description using the signal spectrum. An analysis region of 750 m in range and 706 m across range from a series of scans with fixed elevation angle and variable azimuth angle was chosen as a test case. That is, the raw lidar data (spectra) were averaged over this domain. The reason for averaging is to produce a “cleaner” spectrum from which the moments can be computed. As the lidar pulse volume is fairly small, the raw spectra can be fairly noisy—especially in weak signal to noise regimes. The spectral averaging produces cleaner spectra. The average lidar signal spectrum is shown in Figure 1 for light turbulence and in Figure 2 for moderate turbulence.

The average structure function from high-resolution velocity estimates of six consecutive scans of the same region is shown in Figure 3 along with the best-fit von Karman model which produces an eddy dissipation rate ($\varepsilon$) of 0.00062 m$^2$/s$^3$ (light turbulence). The results for eddy dissipation rate were in agreement with the results of aircraft measurements performed over nearby regions. The average of 1,000 structure functions from simulated lidar data with an isotropic von Karman wind field ($\varepsilon = 0.0006$ m$^2$/s$^3$, $L_0 = 475$ m) are shown in Figure 4 along with the best-fit model. There is a small bias in the measurements of $\varepsilon$ and outer scale, which are probably produced by a small amount of spatial averaging transverse to the lidar beam as the lidar scans the region. The performance of the estimation of $\varepsilon$ and $L_0$ from the best-fit structure functions from simulated lidar data for a single scan through the test region is shown in Figures 5-7. There is a large variability in the estimates due to the large sampling errors in the structure function estimates. The histogram of the 1,000 estimates of $\varepsilon$ is shown in Figure 8. There is a bias and a noticeable tail in the histogram at large values. The scatter in the estimates of $\varepsilon$ and $L_0$ is shown in Figure 9. There is
a small negative correlation between the two estimates ($L_0$ was not allowed to be smaller than 40 m for convergence of the fitting routine).

The average Doppler lidar signal spectrum was derived for a general statistical description of atmospheric turbulence including a von Karman spectrum. The results have been published in *Applied Optics* (Rod Frehlich and Larry Cornman, “Coherent Doppler Lidar Signal Spectrum with Wind Turbulence”, Vol. 38, pp. 7456-7466). A comparison of the average spectrum from this theory and the von Karman parameters extracted from the best-fit structure function of Figure 3 are compared with the Juneau data in Figure 10. There is good agreement with the data and the predictions of a Gaussian spectrum with the estimated second moment. This is an excellent verification of the consistency between the effects of turbulence on Doppler lidar data using structure functions and average signal spectra. This is a key aspect for understanding the measurements of wind turbulence because the simulations provide a test case where the underlying statistical description is known *a priori*. The statistical accuracy of turbulence metrics (eddy dissipation rate, outer scale of turbulence, spectral width) can be determined using end-to-end computer simulations of Doppler lidar data. Various estimation algorithms can be investigated to determine the merits of each.

**Detection of Turbulence using Lidar Doppler Second Moments as a Detection Metric**

Simulations of lidar data and aircraft response were performed for various parameters of a von Karman isotropic wind field. The lidar signal spectral width (square root of the second moment, $M_2$) was compared with various metrics of aircraft normal loading such as the rms and maximum normal loading over a given range-gate. A large number of realizations (1,000) were generated to produce useful detection and false-alarm probabilities as a function of different thresholds and atmospheric parameters such as the integral length scale and the velocity variance $\sigma_w^2$. An example scatter plot of spectral width versus maximum g-loading, g-max, for a 1920 m range-gate interval and $L_0 = 500$ m is shown in Figures 11 and 12 for $\sigma_w = 4.0$ and 6.0 m/s, respectively. The centroids of the scatter plot increase with increasing turbulence intensity, $\sigma_w$. There is a large scatter because the radial velocity (which determines the lidar signal) is
uncorrelated with the vertical velocity (which determines the aircraft g-loading). These scatter plots permit calculation of detection probabilities, false alarm probabilities, and missed detections by the appropriate ratio of events, e.g., the detection probability is the ratio of \(A/B\) where \(A\) is the number of spectral widths that are above a given threshold and also have a \(g_{\text{max}}\) above a detection threshold and \(B\) is the total number of spectral widths above the given threshold. These probabilities can be defined for a given state of the random atmosphere such as defined by a von Karman spatial spectrum. The performance of the detection algorithm can then be defined in terms of the detection probabilities as a function of the lidar parameters and the parameters of the von Karman spectrum \((\sigma_w)\), i.e., the statistical description of the atmosphere (truth) is known a priori.

For any real world situation, the statistical description of the atmosphere is unknown. In some cases, a von Karman spectral model may approximate it. However, the parameters of the von Karman model are difficult to determine from data (see Figures 5-9) because many independent samples of a homogeneous random process are required to produce accurate estimates of \(\sigma_w\) and \(L_0\) or equivalently, \(\epsilon\) and \(L_0\). Therefore, for realistic performance analysis, a random turbulence intensity should be used in the simulations. An example scatter plot of spectral width versus maximum g-loading for the same parameters as Figures 11 and 12 but with a random \(\sigma_w\) between 1 and 10 m/s is shown in Figure 13. The scatter plot now displays the correlation between the measurable metric \((\sqrt{M_2})\) and the aircraft response metric \(g_{\text{max}}\) as well as the increase in scatter with the increase in turbulence intensity. New metrics are required to describe the detection performance for this more realistic case. The same analysis can be produced from real data and any other realistic random wind field such as meso-scale model output, large-eddy simulations, or direct numerical simulations provided the spatial statistics and grid spacing of these fields are satisfactory in the sense that they produce accurate reproductions of the scatter plots that are the basis for the evaluation of the detection algorithms. Ideally, real-world data would be used to generate the scatter plots that would identify the most robust detection metric and detection algorithm. This may be prohibitive because of the rare nature of accident causing events, especially clear air turbulence at cruising altitudes. However, it may be that the von Karman model for a random wind field is the worst-case scenario since there is no correlation between the radial and vertical velocity and the aircraft flight path. If performance is acceptable for this worst-case
scenario, then this case can be the benchmark for validation and certification of a turbulence detection algorithm.

Figure 14 illustrates the performance statistics for the aircraft/lidar simulations. These calculations were made using similar data to that show in Figures 11-13. A threshold is chosen for the g-max and the lidar-measured spectrum width values, then points in the upper right quadrant are correct detections, points in the lower left quadrant and correct misses, points in the upper left quadrant are false alarms and points in the lower right quadrant are missed detections. This process was then repeated for various values of the turbulence intensity (σ_w). The upper portion of Figure 14 compares a number of different turbulence and aircraft response metrics as a function of varying the turbulence intensity. The parameters used are: eddy dissipation rate (calculated from the rms intensity and the length scale), the 90\textsuperscript{th} percentile of the vertical acceleration root mean square (given a rms value above the threshold, 90\% of the values are above the indicated point), the 90\textsuperscript{th} percentile of the vertical acceleration maximum (given a maximum acceleration value above the threshold, 90\% of the values are above the indicated point), the rms value of the vertical accelerations (g_{rms}), the rms of the angle of attack from the aircraft simulation (α) and finally, the ratio of the lidar-measured spectrum width to the mean value of the spectrum width (i.e., a normalized spectrum width value). The results of this analysis, shown in Figure 14, indicate that the aircraft and turbulence parameters monotonically increase and asymptote to a (relatively) steady-state value (upper portion of Figure 14). In the bottom portion of Figure 14, the classical performance of a correlated process is seen. Figure 13 shows that the Doppler spectrum width increases proportionally with g_{max}. This maximum g-loading value is proportional to increasing turbulence intensity, hence the spectrum width is proportional to increasing turbulence intensity. Therefore, the bottom portion of Figure 14 shows that increasing the turbulence intensity, while keeping the spectrum width threshold fixed, increases the probability of detection (POD) while simultaneously reducing the false alarm ratio (FAR). This, of course, is good news. The detection statistics for stronger levels of turbulence intensity are quite acceptable. For example, at a turbulence intensity of σ_w = 5.0 m/s, the POD is 0.8 and the FAR is 0.2.
Figure 1. Average lidar signal spectrum for light turbulence from Juneau data (circles) with prediction for no turbulence (dashed line) and Gaussian prediction from measured second moment (solid line).
Figure 2. Average lidar signal spectrum for moderate turbulence from Juneau data (circles) with prediction for no turbulence (dashed line) and Gaussian prediction from measured second moment (solid line).
Figure 3. Average structure function from the Juneau data of Figure 1 (circles) with best-fit model including pulse spatial averaging (lower line) and corresponding point sensor result (upper line).
Input $\varepsilon=0.600000\text{E-03}\text{ m}^2/\text{s}^3 \quad L_0=475.0\text{ m}$

$\varepsilon=0.616536\text{E-03}\text{ m}^2/\text{s}^3 \quad L_0=425.6\text{ m}$

Figure 4. Average structure function from 1,000 simulated data scans (circles) with best-fit model including pulse spatial averaging (lower line) and corresponding point sensor result (upper line). The dashed lines indicate the input von Karman model for the simulations.
Input \( \varepsilon=0.600000\text{E-03} \text{ m}^2/\text{s}^3 \) \( L_0=475.0 \text{ m} \)

\( \varepsilon=0.119555\text{E-02} \text{ m}^2/\text{s}^3 \) \( L_0=1206400.0 \text{ m} \)

Figure 5. Average structure function from a single simulated data scan (circles) with best-fit model including pulse spatial averaging (lower line) and corresponding point sensor result (upper line). The dashed lines indicate the input von Karman model for the simulations (\( \varepsilon = 0.0006 \text{ m}^2/\text{s}^3 \), \( L_0 = 475 \text{ m} \)).
Input $\varepsilon=0.600000E-03 \text{ m}^2/\text{s}^3$ $L_0=475.0 \text{ m}$

$\varepsilon=0.273527E-02 \text{ m}^2/\text{s}^3$ $L_0=71.0 \text{ m}$

Figure 6. Average structure function from a single simulated data scan (circles) with best-fit model including pulse spatial averaging (lower line) and corresponding point sensor result (upper line). The dashed lines indicate the input von Karman model for the simulations ($\varepsilon = 0.0006 \text{ m}^2/\text{s}^3$, $L_0 = 475 \text{ m}$).
Input $\varepsilon=0.600000\times10^{-3}$ m$^2$/s$^3$  $L_0=475.0$ m
$\varepsilon=0.109743\times10^{-2}$ m$^2$/s$^3$  $L_0=436.8$ m

Figure 7. Average structure function from a single simulated data scan (circles) with best-fit model including pulse spatial averaging (lower line) and corresponding point sensor result (upper line). The dashed lines indicate the input von Karman model for the simulations ($\varepsilon = 0.0006$ m$^2$/s$^3$, $L_0 = 475$ m).
Figure 8. Histogram of the $\epsilon$ (energy dissipation rate) from the best-fit structure function models.
Figure 9. Scatter plot of the $\varepsilon$ (eddy dissipation rate) and outer scale from the best-fit structure function models.
Figure 10. Average lidar signal spectrum for light turbulence from Juneau data (circles) (see Figure 1) with the prediction of the theoretical prediction (solid line) based on the best-fit von Karman model to the average structure function (see Figure 3) and the Gaussian spectral model based on the measured second moment.
BOEING 757-200 40,000 feet altitude

\[ M_2^{1/2} = 3.0439 \text{ m/s} \quad \text{SD}[M_2^{1/2}] = 0.69369 \text{ m/s} \quad w_t = 3.184 \text{ m/s} \]

\[ g_{\text{rms}} = 0.19188 \quad \text{SD}[g_{\text{rms}}] = 0.38310E-01 \quad \Delta v = 0.6250 \text{ m/s} \]

\[ g_{\text{max}} = 0.52518 \quad \text{SD}[g_{\text{max}}] = 0.99724E-01 \quad \rho = -0.00493 \]

\[ \alpha_{\text{rms}} = 0.93681^\circ \quad \text{SD}[\alpha_{\text{rms}}] = 0.31459^\circ \quad \rho_{\text{wt}} = 0.96248 \]

\[ \alpha_{\text{max}} = 1.8623^\circ \quad \text{SD}[\alpha_{\text{max}}] = 0.61351^\circ \]

\[ \sigma_w = 4.00 \text{ m/s} \quad L_i = 500.0 \text{ m} \quad \epsilon^{1/3} = 0.446899 \text{ m}^{2/3}/\text{s} \quad \tau = 0.500 \mu \text{s} \]

\[ M = 512 \quad m_r = 2 \quad N_{\text{pulses}} = 100 \quad N_{\text{est}} = 1000 \quad \Delta R = 1920.00 \text{ m} \quad \sigma_{\text{thr}} = 2.0 \]

Figure 11. Scatter plot of the lidar signal spectral width (square root of the second moment, \( M_2 \)) versus the maximum aircraft g-loading, \( g_{\text{max}} \), for a Boeing 757-200 aircraft at 40,000 feet and a von Karman velocity field with a 1920 m observation range-gate, 100 lidar pulses, integral length scale of 500 m, and velocity standard deviation of 4 m/s.
BOEING 757-200 40,000 feet altitude

\[ M_2^{1/2} = 4.3336 \text{ m/s} \quad \text{SD}[M_2^{1/2}] = 0.98941 \text{ m/s} \quad w_t = 4.775 \text{ m/s} \]

\[ g_{\text{rms}} = 0.28783 \quad \text{SD}[g_{\text{rms}}] = 0.57466 \times 10^{-1} \quad \Delta v = 0.6250 \text{ m/s} \]

\[ g_{\text{max}} = 0.78771 \quad \text{SD}[g_{\text{max}}] = 0.14954 \quad \rho = -0.02478 \]

\[ \alpha_{\text{rms}} = 1.4052^\circ \quad \text{SD}[\alpha_{\text{rms}}] = 0.47189^\circ \quad \rho_{\text{wt}} = 0.91332 \]

\[ \alpha_{\text{max}} = 2.7934^\circ \quad \text{SD}[\alpha_{\text{max}}] = 0.92029^\circ \]

\[ \sigma_w = 6.00 \text{ m/s} \quad L_i = 500.0 \text{ m} \quad \varepsilon^{1/3} = 0.670348 \text{ m}^{2/3}/\text{s} \quad \tau = 0.500 \mu\text{s} \]

\[ M = 512 \quad m_r = 2 \quad N_{\text{pulses}} = 100 \quad N_{\text{est}} = 1000 \quad \Delta R = 1920.00 \text{ m} \quad \sigma_{\text{thr}} = 2.0 \]

Figure 12. Scatter plot of the lidar signal spectral width (square root of the second moment, \( M_2 \)) versus the maximum aircraft g-loading, \( g_{\text{max}} \), for a Boeing 757-200 aircraft at 40,000 feet and a von Karman velocity field with a 1920 m observation range-gate, 100 lidar pulses, integral length scale of 500 m, and velocity standard deviation of 6 m/s.
BOEING 757-200 40,000 feet altitude

\[ M_2^{1/2} = 3.9219 \text{ m/s} \quad \text{SD}[M_2^{1/2}] = 1.9180 \text{ m/s} \quad w_t = 0.796 \text{ m/s} \]

\[ g_{\text{rms}} = 0.25810 \quad \text{SD}[g_{\text{rms}}] = 0.13476 \quad \Delta v = 0.6250 \text{ m/s} \]

\[ g_{\text{max}} = 0.70663 \quad \text{SD}[g_{\text{max}}] = 0.36314 \quad \rho = 0.75737 \]

\[ \alpha_{\text{rms}} = -17.568^\circ \quad \text{SD}[\alpha_{\text{rms}}] = 22.746^\circ \quad \rho_{\text{wt}} = 0.96947 \]

\[ \alpha_{\text{max}} = 2.5171^\circ \quad \text{SD}[\alpha_{\text{max}}] = 1.4956^\circ \]

\[ \sigma_w = 1.00 \text{ m/s} \quad L_i = 500.0 \text{ m} \quad \varepsilon^{1/3} = 0.111736 \text{ m}^{2/3}/\text{s} \quad \tau = 0.500 \mu\text{s} \]

\[ M = 512 \quad Mr = 2 \quad N_{\text{pulses}} = 100 \quad N_{\text{est}} = 1000 \quad \Delta R = 1920.00 \text{ m} \quad \sigma_{\text{thr}} = 2.0 \]

Figure 13. Scatter plot of the lidar signal spectral width (square root of the second moment, \( M_2 \)) versus the maximum aircraft g-loading, \( g_{\text{max}} \), for a Boeing 757-200 aircraft at 40,000 feet and a von Karman velocity field with a 1920 m observation range-gate, 100 lidar pulses, integral length scale of 500 m, and a random velocity standard deviation from 1 to 10 m/s.
Boeing 757-200 40,000 ft.
\( w_{\text{thr}} = 2.0 \text{ m/s} \), \( L_i = 500.0 \text{ m} \), range-gate=1920.0 m
bin size=0.6250 m/s bins averaged= 8 \( N_{\text{pulses}} = 100 \)

Figure 14. Performance statistics for lidar turbulence detection based on simulation data. Values are given as a function of the standard deviation of the vertical wind field. In the upper plot, a variety of parameters related to the turbulence (wind field and aircraft response) are shown. In the lower plot, the contingency table result for lidar spectrum width vs. standard deviation of the wind field is given.