Ground-Based Velocity-Measurement Performance of the NCAR Airborne Infrared Lidar System (NAILS)

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Velocity-Measurement Performance of the NCAR Airborne Infrared Lidar System
Determined by Ground-Based Testing

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PREFACE

The NCAR Airborne Infrared Lidar System (NAILS) has been under development for a number of years as a remote-sensing tool to assist in atmospheric science research. Although it has been used to measure backscatter profiles at infrared wavelengths in major field programs, only recently has the lidar been able to make Doppler velocity measurements in the cloud-free atmosphere. For this reason it is timely to document the performance of the system as an instrument for measuring appropriate components of the atmospheric velocity field.

This technical note provides more detail and extensive figures than would be appropriate for a journal article. We intend for the information to be useful to researchers intending to use data from the lidar in their experiments. Because the system is still being improved, we hope that readers will make suggestions on modifications to the instrument that would make it better suited to their needs, and on critical tests that would document its performance for particular applications. Some of the improvements that we have in mind are discussed in the last section of this note.

Ronald L. Schwiesow

October 1994
ABSTRACT

This report presents data that characterize the performance of the NCAR Airborne Infrared Lidar System for velocity measurement in its present state of development. Refinement of the instrument to increase its utility for atmospheric research is continuing.

After considering briefly the Doppler lidar system itself, the report describes data comparisons between the Doppler estimate of one component of the velocity at a single 100-m range cell and a nearby anemometer. We conclude that the two techniques compare within an average standard deviation of 0.4 m s\(^{-1}\) for 1-min averages taken with substantially different spatial samples. Comparisons of vertical velocity between the lidar and a radar profiler show a correlation coefficient as large as 0.76 at an optimum altitude with appropriate averaging.

We then make comparisons between predicted and observed turbulence statistics in the convective atmospheric boundary layer using data from multiple range gates and with faster sampling than used for the anemometer comparisons. These data give some idea of possible applications of the lidar and include results such as horizontal and vertical range-time displays, velocity spectra and autocovariances in both time and range, and a profile of the variance of vertical velocity.

Internal consistency of the data is illustrated by the agreement between the mean spatial cospectrum and the corrected mean temporal power spectrum converted to space as the independent variable using the mean velocity.

To increase the utility of the instrument for research, further developments could include vibration hardening for airborne applications and a scanner for ground-based applications. A more modern signal-processing system is needed to provide increased reliability and a measurement of the 0-velocity beat frequency for each pulse that is free from variable gain settings. Higher-speed digitization is necessary to simplify the processing electronics, and to allow increased flexibility for investigation of alternative algorithms for estimating the Doppler shift. This includes more-closely spaced lags, more samples in the autocorrelation calculation, and a digital intermediate frequency processing scheme.
ACKNOWLEDGEMENTS

We are especially grateful to Don Lenschow for his detailed guidance on the testing, analysis, and reporting procedures. Additional scientific advice on testing was provided by Al Cooper and Peter Hildebrand, and additional advice on analysis has come from Ken Davis. We acknowledge encouragement from lidar colleagues in various parts of the world to continue refinement and testing of the lidar.

Many individuals in ATD contributed supporting data for this performance evaluation. John Militzer provided extensive anemometer records from the PAM 2 system. Terry Hock provided data from the ISS radar wind profiler, and Steve Oncley contributed data from the ASTER facility operating at Marshall. Paul Spyers-Duran and Krista Laursen provided wind data from the Electra. Technical support from Herminio Avila helped keep the lidar operating.
1. Introduction

1.1 Purpose and background

This report on performance testing is designed to establish the credibility of velocity data from the Doppler lidar system under development at ATD and to give examples of some possible applications. In addition, it attempts to show a reasonable way to improve system performance, increase the range of possible applications, and move toward operational status. The lidar makes range-resolved air velocity measurements in a cloud-free atmosphere, especially in the boundary layer and near convective systems. It complements other remote sensors, such as ELDORA, the Doppler radars, and the ISS profilers.

The Doppler lidar is intended to add an important new measurement capability to the set of facilities available to university atmospheric scientists through ATD. The ability to sense remotely aspects of atmospheric dynamics in the clear air has a number of applications. Examples are entrainment velocities at the top of a stratus layer or into the side of a convective cell, convergence beneath a convective cell, updrafts in the echo-free vault of a thunderstorm, helical rolls in the boundary layer, vertical profiles of turbulence and momentum flux, and so on. In conjunction with lidars measuring constituent concentrations, a Doppler lidar allows measurement of large-eddy flux contributions and advection profiles, for example. Of course, a Doppler lidar measures backscatter in addition to velocity, so an infrared lidar operating at a wavelength of 10.6 μm provides information on aerosol scattering and attenuation that complements data available from shorter-wavelength instruments, such as the popular Nd:YAG backscatter lidars operating at wavelengths of 1.06 and 0.53 μm.

Doppler lidars require more optical and electronic sophistication than lidars that are able to measure only backscatter profiles; only a few have been built. Menzies and Hardesty (1989) review Doppler techniques. Post and Cupp (1990) report on a large, ground-based Doppler lidar system that uses three lasers and a single telescope to make atmospheric wind measurements. Alejandro et al. (1992) are developing a system similar to NAILS that is intended for a balloon platform. Pearson and Rye (1992) and Pearson (1992) have built a relatively compact Doppler lidar based on a laser master oscillator and power amplifier. A similar laser configuration was used by Bilbro et al. (1984, 1986) for a large airborne Doppler lidar. Targ et al. (1991, 1993) reported on the design and evaluation of another airborne system based on a master oscillator and power amplifier used to detect wind shear. At NCAR we are cooperating with a European consortium (Werner et al. 1991, Flamant et al. 1992 and Köpp et al. 1993) designing an airborne Doppler lidar that features a downward-pointing conical scan to measure vertical profiles...
of the horizontal wind and momentum flux. In addition to these development efforts that
are based on heterodyne detection of the Doppler shift and operate near 10.6 μm, other
developments are based on lasers in the wavelength region 0.4 to 2.1 μm and use either
heterodyne or direct high-resolution spectroscopy to measure the optical Doppler shift.
See Schwiesow and Spowart (1994), for example, for a brief listing of some of these other
Doppler lidars.

In general, these Doppler lidars have been used for feasibility and application
demonstrations rather than for detailed performance evaluations of the type reported in this
technical note. Post et al. (1978) showed some comparisons between velocity data from a
continuous-wave Doppler lidar and a tower-mounted anemometer, and Hall et al. (1984)
discussed the relation between horizontal winds measured with a conically scanning pulsed
Doppler lidar and an instrumented tower, a rawinsonde, a jimsphere, and an RF profiler.
Wind differences varied from an rms value of 0.34 m s\(^{-1}\) for sonic anemometers on a
tower to 2.5 m s\(^{-1}\) for an RF profiler. Post and Cupp (1990) analyzed the statistics of
Doppler lidar returns from a stationary hard target.

To understand the nature of the data from the lidar, it is helpful to understand how
the system makes remotely sensed velocity measurements.

1.2 System characteristics

The performance parameters of the lidar, based on the design, are given in Table 1.
The minimum range is determined by the tail of the laser pulse obscuring the return from
closer ranges and the time for the detector and electronics to recover from the overload
that comes from the transmitted pulse being scattered in the common transmit-receive
optical train. Under strong scattering conditions in the boundary layer, the system exhibits
an adequate signal-to-noise ratio (SNR) to beyond 10 km, but the memory in the present
signal-processing system provides the upper limit on the observable range. By range
resolution we mean the ability to detect regions in the atmosphere at different locations
having different velocities. This is determined by the laser pulse length, discussed later,
and the number of data samples of the backscatter time series used to make a velocity
estimate for each range gate, as discussed in detail later in this section. By range
accuracy we mean the uncertainty in determining the distance to a scattering feature, such
as a cloud edge. This is taken to be plus or minus one sample interval of the time series.
The velocity range is determined by the bandwidth of the detector and signal-processing
electronics; this is presently ± 5 MHz about a center frequency of 10 MHz, but this is not
a fundamental limitation of the technique. The velocity accuracy is calculated
(Schwiesow and Spowart 1994) for high SNR and an average of returns from 20 pulses.
It degrades with SNR in a fashion discussed by Lee and Lee (1980) and Keeler and
Richter (1980). This velocity accuracy is a statistical uncertainty on the velocity estimate
from the averaged data rather than a result of low signal-to-noise ratio. The statistical
uncertainty becomes smaller with more averaging.
TABLE 1. NAILS Performance Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>operating range*</td>
<td>0.6 to 10 km</td>
</tr>
<tr>
<td>range resolution</td>
<td>± 50 m</td>
</tr>
<tr>
<td>range accuracy</td>
<td>± 15 m</td>
</tr>
<tr>
<td>velocity range</td>
<td>± 26 m s⁻¹</td>
</tr>
<tr>
<td>velocity accuracy</td>
<td>± 0.4 m s⁻¹</td>
</tr>
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</table>

*at design backscatter coefficient of $5 \times 10^{-9} \text{m}^{-1} \text{sr}^{-1}$

The NCAR Airborne Infrared Lidar System (NAILS) operates at a wavelength of 10.6 μm in the middle infrared. It is well within the ANSI standards for eye safety. Atmospheric scattering targets are particles, usually in the range of 1 to 3 μm particle radius (Post 1978). Smaller particles have insufficient backscatter cross section (backscatter proportional to radius to the 6th power in the Rayleigh region), and the number density of larger particles is usually too small (except in the case of clouds).

The transmitter is a pulsed CO₂ laser at a carrier frequency of approximately 30 THz (wavelength 10.6 μm) that operates in a transverse-excitation, atmospheric pressure (TEA) configuration. It is constrained to be offset approximately 10 MHz from a stabilized, continuous-wave (cw) CO₂ laser that serves as the local oscillator (LO). The LO is mixed with the received, backscattered optical signal to produce a heterodyne beat signal on the cooled detector. The heterodyne output is a radio-frequency (rf) signal at approximately 10 MHz. If the scatterers are moving with respect to the lidar, the backscattered optical signal is Doppler shifted with respect to the transmitter frequency by 189 kHz per 1 m s⁻¹ of velocity component along the lidar line of sight. In the existing system it is practical to work with an rf signal bandwidth of 5 to 15 MHz, centered at 10 MHz, which gives a measurement range for velocity of ± 26 m s⁻¹.

Further details of the lidar hardware are summarized in table 2.

TABLE 2. NAILS Hardware Characteristics

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
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<tbody>
<tr>
<td>laser pulse energy</td>
<td>100-200 mJ</td>
</tr>
<tr>
<td>laser pulse width</td>
<td>approx. 667 ns</td>
</tr>
<tr>
<td>pulse repetition frequency</td>
<td>to 64 Hz</td>
</tr>
<tr>
<td>telescope aperture</td>
<td>300 mm</td>
</tr>
<tr>
<td>telescope configuration</td>
<td>f/3 Dall Kirkham</td>
</tr>
<tr>
<td>detector</td>
<td>HgCdTe photovoltaic</td>
</tr>
<tr>
<td>preamplifier</td>
<td>current mode, DC coupled</td>
</tr>
</tbody>
</table>
These hardware parameters lead to additional performance characteristics. The sample volume of the lidar is a thin cylinder approximately 100 m long (equal to half the laser pulse length), aligned along the line of sight, and 30 cm in diameter near the lidar, with a beam divergence of approximately 80 μrad full angle. For example, at a range of 5 km the beam has diverged to just over twice its initial diameter. Electric fields scattered from each particle in the sample volume add coherently, so the received optical signal power is subject to builds and fades as the particles are rearranged on the scale of an optical wavelength. In a turbulent atmosphere, the time during which the scatterers can be considered fixed is the order of 1 μs, so the lidar return from each pulse is not coherent with that from any other. As a consequence, and in contrast to radar, a Doppler velocity estimate must be made separately for the heterodyne time series resulting from each lidar pulse.

To make the velocity estimate, the heterodyne time series is mixed with an rf oscillator called a coherent oscillator (CohO) because its frequency is tuned to match the frequency difference between the transmitter and the LO for each transmit pulse in less than a microsecond following the start of each pulse. The frequency difference between the transmitter and LO (corresponding to a heterodyne signal from an atmosphere with no velocity component along the lidar line of sight) is measured with an analog discriminator and used to tune the CohO. When the 5- to 15-MHz heterodyne signal is mixed with the CohO of approximately 10 MHz in a phase-sensitive mixer, the result is two signals of 0 MHz to 5 MHz, termed the in-phase (I) and quadrature (Q) components, with frequency 0 Hz corresponding to a velocity of 0 m s\(^{-1}\). The I and Q signals are digitized at 10 megasamples per second (MS s\(^{-1}\)) with 12-bit resolution and are both written to tape and used for calculating velocities for a real-time display. 667 digital samples correspond to a maximum range of 10 km. Real-time velocity estimates for all ranges are displayed on the system monitor and those from three range gates centered about a chosen gate are written to the system disk to produce three time series of velocity that can be readily accessed for comparison with other instruments.

The algorithm for estimating velocity at each range gate is based on a complex covariance of the processed heterodyne signal. The first step is to remove any bias (residual direct-current (dc) offset) from the I and Q values by evaluating the mean at long ranges. Seven consecutive samples of I and Q are then processed to give values of the autocovariance function at lags of zero and one sample interval for each range gate. The real-time processor can compute autocovariances for multiple lags and various numbers of samples. Lagged values are simply the original time series shifted by a time step of the digitizer, which is a lag increment of 100 ns. The lagged autocovariance values from a number of pulses (usually chosen to provide a 2-s data average for real-time display and a 1-s average for post-processing) are averaged for each range gate to improve the velocity estimate. The velocity estimate is derived from the phase of the complex covariance. The advantage of averaging autocorrelation functions rather than velocity estimates is that data with a poor signal-to-noise ratio (a necessary consequence of Rayleigh phasor statistics on the heterodyne return) are automatically weighted to have less influence on the averaged
estimate in autocorrelation averaging than in velocity averaging.

Backscattered total power is estimated from \( I^2 + Q^2 \), which is available from each digitized sample and is the same as the autocovariance function at zero lag \(|R_0|\). Backscattered coherent power is estimated from the magnitude of the autocovariance vector at the single lag \(|R_1|\). Normalized coherent power is coherent power divided by total power and is an indicator of the signal to noise ratio. We estimate the relative aerosol backscatter coefficient from coherent power corrected for range squared. Additional details on the lidar and signal processing can be found in Schwiesow and Spowart (1994) and Schwiesow and Spowart (1992).

We have chosen a sign convention with velocity positive away from the lidar, corresponding to positive upward for a ground-based system measuring vertical velocity. Because the time series of I and Q are recorded from each pulse, there is considerable flexibility in processing the data using various techniques for averaging in space and time. For example, it is possible to emphasize accuracy in mean values at a cost of less spatial resolution or to consider spatial correlations averaged over a substantial time. Although the velocity estimates are made over a sample of data 100 m long, data on range to a strong gradient in backscatter (e.g., a cloud) are available with a resolution of 15 m, as determined by the digitizing rate, because of the sharp leading edge of the laser pulse as shown in fig. 1.2.1.

Development of the heterodyne version of NAILS has focused primarily on velocity measurement. The present data system does not measure the transmitted laser pulse energy and the LO power level on the cooled optical heterodyne detector. Both levels have a primary influence on the heterodyne signal level. As a result, it is not possible currently to provide reliable calibration on received power levels. Relative aerosol backscatter estimates are subject to change with systematic variations in detected power from either laser. Improvements to compensate for these variations are discussed in the appendix to this report.
Figure 1.2.1. Transmitted TEA pulse (top trace) and heterodyned pulse shape (bottom trace) showing sharp leading edge and rf beats between the LO and TEA lasers. The horizontal scale is 200 ns div$^{-1}$, and the vertical scale is power in arbitrary units.
2. **Comparison with an anemometer and a profiler**

To establish the credibility of the velocity estimates from the Doppler lidar, it is essential to compare those estimates with other methods of wind measurement. One classical measurement method is a tower-mounted anemometer. For the comparison we have taken data using both techniques for over 8 hours under a variety of weather conditions. More extensive comparison data are being collected.

Direct comparison of the time series of velocity measurements from the two techniques gives a qualitative sense of the measurement performance and quantitative values for comparison of mean values and correlation. Plotting the velocity estimate from the lidar against the estimate from the anemometer (scatter diagram) allows a least-squares fit of a line to the plotted data to determine any offset between the estimates (zero intercept) and any velocity-dependent difference (departure of the slope from 1). These comparisons show encouraging correlation and need for further study of details of the lidar signal-processing techniques used so far.

### 2.1 Experimental setup and data reduction

NAILS was installed in a laboratory on the upper floor of the north side of building FL1 at the NCAR Foothills Laboratory complex. A PAM-2 station with a 2-axis anemometer at a height of 10 m was installed south west of the intersection of 47th street and Jay Road. Figure 2.1.1 shows that the range to the PAM station was approximately 1.5 km at an azimuth of 344°. The PAM anemometers were aligned N-S and E-W. The lidar elevation was approximately 0.6° to clear a line of trees 200 m beyond the PAM site so that data could be taken out to a range of 10 km. This placed the lidar sample volume approximately 10 m above the PAM anemometer.

Lidar velocity data were taken from the real-time velocity estimates for three range gates centered about 1.5 km, which were written to the disk on the lidar data system. An estimate was written every second. For these tests the lidar was usually operated at a pulse-repetition frequency (PRF) of 10 Hz with 20 pulses averaged for a velocity estimate. This means that a new velocity estimate is available every 2 s. For comparison with PAM data, the time series of lidar velocity estimates were averaged over 60 s. Archived PAM data were read with a special version of the program "robot" that determined the wind component along the lidar line of sight from the two measured orthogonal components and wrote the result to an ASCII file.

Data files from NAILS and PAM were manipulated, plotted, and analyzed initially with MATLAB and later with PV Wave.

Figures 2.2.1 to 2.2.4 illustrate steps involved in post-processing the velocity time series from NAILS. The first two figures (2.2.1-2.2.2) are plots of the post-processed data at intervals of 1 s before filtering. These data were then filtered (figs. 2.2.3-2.2.4) to
Figure 2.1.1. Map showing location of lidar (large X just west of Hayden Lake) and PAM2 (small x southwest of Jay Road and 47th Street). Tall trees are on the north side of Jay Road behind PAM2.
objectively remove outliers. These spikes resulted from short periods where the servo between the two lasers lost lock or where the LO level on the cooled detector drifted too high and drove the signal to the velocity processing circuit to a level that caused inaccurate operation. The filter uses a running estimate of standard deviation over the preceding 120 s to flag those data points that fall more than 3 standard deviations from the mean for the period. Flagged values are then removed and replaced via linear interpolation between neighboring values. After removing outliers, the time series are processed by 60-s block averaging to produce the velocity time series used for PAM comparison.

2.2 Time series

Figures 2.2.5 and 2.2.6 show examples of the data from NAILS and PAM. Time averages over periods of approximately an hour differ by less than 0.3 m s⁻¹. One expects differences in the velocity data between the two sensors because of the different sample volumes (spatial averaging) inherent in the two techniques and because of the different heights of the sample volumes.

While all comparisons made show a correlation between the two instruments similar to that in these two figures, data taken early in the intercomparison experiment sometimes showed differences in hourly means. This difference was found to be associated with drifts in the delay time between the data-system trigger and optical output from the TEA laser. The discriminator currently used to measure the frequency difference between the LO and TEA lasers for each pulse is sensitive to the differences in delay. The problem was solved in later data by triggering the discriminator from a new optical pulse monitor.

Additional comparisons between NAILS and PAM are shown in figs. 2.2.7 through 2.2.11. These data were taken after the improved discriminator triggering scheme was installed. While the correlation is generally good, the mean velocity measured by the two techniques is sometimes offset. We are still working on this problem as discussed in more detail later.

As noted in section 2.1, for most measurements the lidar sample volume was approximately 10 m above the top of the PAM tower, which was at 10 m. The difference in mean wind with height can be approximated by

\[ \frac{v(z_2)}{v(z_1)} = \left(\frac{z_2}{z_1}\right)^\alpha \]  \hspace{1cm} (2.1)

(Panofsky and Dutton 1984). For neutral stability, \( \alpha = 1/7 \), and the velocity ratio is approximately 1.1. For clear daytime conditions with light winds, \( \alpha \) is smaller, and for clear night time conditions it is larger. Our comparison data are consistent with this model.
Figure 2.2.1. Raw time series of velocity estimates from NAILS for 29 June 94, 1217-1340 LT. The three traces are from ranges of 1.4, 1.5, and 1.6 km reading from bottom to top.

Figure 2.2.2. Raw time series of velocity estimates from NAILS for 29 June 94, 1340-1500 LT. The three traces are from ranges of 1.4, 1.5, and 1.6 km reading from bottom to top.
Figure 2.2.3. Time series of velocity estimates from NAILS with objective spike removal for 29 June 94, 1217-1340 LT. The three traces are from ranges of 1.4, 1.5, and 1.6 km reading from bottom to top.

Figure 2.2.4. Time series of velocity estimates from NAILS with objective spike removal for 29 June 94, 1340-1500 LT. The three traces are from ranges of 1.4, 1.5, and 1.6 km reading from bottom to top.
Figure 2.2.5. Comparison of NAILS and PAM velocity estimates 14 April 94, 1730-1900 local time (LT). The mean of the NAILS velocity is 0.77 m s\(^{-1}\) and of the PAM velocity is 0.80 m s\(^{-1}\). The correlation is 0.97.

Figure 2.2.6. Comparison of NAILS and PAM velocity estimates 18 April 94, 1625-1745 LT. The mean of the NAILS velocity is 2.62 m s\(^{-1}\) and of the PAM velocity is 2.87 m s\(^{-1}\). The correlation is 0.94.
Figure 2.2.7. Comparison of NAILS and PAM velocity estimates 29 June 94, 1230-1330 LT. The mean of the NAILS velocity is -0.18 m s$^{-1}$ and of the PAM velocity is -0.02 m s$^{-1}$. The correlation is 0.76.

Figure 2.2.8. Comparison of NAILS and PAM velocity estimates 29 June 94, 1330-1450 LT. The mean of the NAILS velocity is -1.95 m s$^{-1}$ and of the PAM velocity is -1.87 m s$^{-1}$. The correlation is 0.74.
Figure 2.2.9. Comparison of NAILS and PAM velocity estimates 16 June 94, 1400-1500 LT. The mean of the NAILS velocity is $1.39 \text{ m s}^{-1}$ and of the PAM velocity is $0.56 \text{ m s}^{-1}$. The correlation is 0.96.

Figure 2.2.10. Comparison of NAILS and PAM velocity estimates 16 June 94, 1500-1600 LT. The mean of the NAILS velocity is $1.82 \text{ m s}^{-1}$ and of the PAM velocity is $1.51 \text{ m s}^{-1}$. The correlation is 0.69.
Figure 2.2.11. Comparison of NAILS and PAM velocity estimates 28 June 94, 1630-1730 LT. The mean of the NAILS velocity is 2.06 m s$^{-1}$ and of the PAM velocity is 2.27 m s$^{-1}$. The correlation is 0.82.
2.3 **Scatter diagrams**

Another way to compare the velocity estimates from the lidar and from the PAM is to consider scatter diagrams as shown in figs. 2.3.1 to 2.3.8. The least-squares fit of a line to the comparison data shows good agreement. The rms departure of the points from the line is a quantitative measure of the agreement between the two measurement techniques and includes both the measurement uncertainty of the anemometer and that of the lidar velocity estimates. The fitting parameter sigma from PV-Wave is the rms vertical distance from the fitted line to the points, which assumes no measurement uncertainty in the anemometer. A more realistic estimate of the measurement uncertainty is the rms perpendicular distance to the line, which is approximately sigma times 0.707. The resulting values are consistent with the standard deviation in velocity estimate of 0.4 m s\(^{-1}\) for an average of 20 pulses calculated by Schwiesow and Spowart (1994) when one considers the difference in the volumes sampled by the two measurement techniques.

Note particularly the small perpendicular fitting uncertainty in fig. 2.3.3 of 0.33 m s\(^{-1}\) for a case with low wind. This is more representative of the instrumental differences than cases with larger variations in the wind. Large wind variations such as in figs. 2.3.1 and 2.3.2 give a better measure of the slope of the fit between the two techniques. The average slope is 1.08 for these cases. There is a small intercept of the fitted line or measurement offset of approximately 0.2 m s\(^{-1}\) in most cases. This can be eliminated by adjusting the gain of the circuit controlling the CohO, but we have not obtained enough data on the consistency of the offset to be sure of the value of the adjustment. Figures 2.3.5 through 2.3.8 show data where an offset in the mean exists; they are representative of the poorest comparisons. Note however the generally small fitting uncertainty in these offset cases.

The variable offset is not a problem for eddy flux measurements, where removal of the mean is the first step, nor for applications such as flux profiles, but it should be fixed. We have improved the stability of the mean value estimate from the lidar by decoupling the lasers, by stabilizing the gas pressure in the TEA head (which affects the delay between triggering the laser and optical output and the laser frequency chirp), and by triggering the zero-frequency heterodyne frequency discriminator from the TEA optical output. Data collected so far has not been enough to assure that these measures have eliminated the variable offset. Future plans include reducing the variable level of radio-frequency interference (rfi) on the reference detector, which can influence the discriminator output, and studying the possibility of a dependence of the velocity estimate on the LO level. Changing the signal-processing system to use a rapidly sampled digital representation of the reference wave form and digital extraction of frequency rather than a discriminator may eliminate the offset problem. (See the appendix.)
Figure 2.3.1. NAILS velocity estimates vs. PAM velocity estimates for data of 14 April 94, 1730-1900 LT. The standard deviation of the points from the fitted line is 0.51 m s\(^{-1}\).

Figure 2.3.2. NAILS velocity estimates vs. PAM velocity estimates for data of 18 April 94, 1625-1745 LT. The standard deviation of the points from the fitted line is 0.58 m s\(^{-1}\).
Figure 2.3.3. NAILS velocity estimates vs. PAM velocity estimates for data of 29 June 1994, 1230-1330 LT. The standard deviation of the points from the fitted line is 0.33 m $s^{-1}$.

Figure 2.3.4. NAILS velocity estimates vs. PAM velocity estimates for data of 29 June 1994, 1330-1450 LT. The standard deviation of the points from the fitted line is 0.49 m $s^{-1}$.
Figure 2.3.5. NAILS velocity estimates vs. PAM velocity estimates for data of 16 June 94, 1400-1500 LT. The standard deviation of the points from the fitted line is 0.19 m s\(^{-1}\).

Figure 2.3.6. NAILS velocity estimates vs. PAM velocity estimates for data of 16 June 94, 1500-1600 LT. The standard deviation of the points from the fitted line is 0.38 m s\(^{-1}\).
Figure 2.3.7. NAILS velocity estimates vs. PAM velocity estimates for data of 28 June 94, 1630-1730 LT. The standard deviation of the points from the fitted line is 0.29 m s\(^{-1}\).
2.4  Profiler comparison

Although the lidar measures velocity using different tracers than the ISS radar profiler, and has a much smaller sample volume, comparisons help to establish that results from both NAILS and the profiler are reasonable. Neither instrument is yet a reference standard. Only limited comparisons have been made so far.

Data on vertical velocity were collected at Jeffco airport for four days in early May using both the Doppler lidar and the ISS radar profiler (e.g., Ecklund et al. 1988 and Angevine et al. 1994). The lidar was located in the Jeffco optics laboratory, and the ISS trailer was parked at the east edge of the NCAR ramp, about 100 m from the lidar. The ISS measured with the beam pointed vertically for 30 s every 200 s to produce an estimate of the vertical velocity. For comparison, lidar data were averaged for the same 30-s period. Velocity data from both instruments were evaluated every 105 m in altitude.

An example of the comparison between vertical velocity values estimated by the two instruments is shown in figs. 2.4.1 and 2.4.2. Both time series and scatter diagrams are shown. Note that the correlation coefficient, r, increases with increasing altitude from 630 m above ground level (AGL) to a maximum of r=0.88 at 1050 m AGL and decreases above that altitude, with the exception of data at 735 m and 840 m, where the large negative spike on the ISS data gives a spurious value for correlation. Low correlation at lower altitudes may be caused by the lateral separation of the two instruments. Low correlation at higher altitudes is likely caused by the great difference in sample volumes between the two instruments (ISS beamwidth of 8° and lidar beamwidth of 0.005°).

Thus, although the comparison is not ideal because of the lateral separation of the instruments and the difference in sample volumes, the correlations indicate that both instruments are measuring vertical motion.
Figure 2.4.1. Comparison of vertical velocity measured by the ISS radar profiler and the lidar on 09May94. The altitude for each pair of displays is indicated on the display. \( r \) is correlation coefficient. Each data point is an average for 30 s every 200 s.
Figure 2.4.2. Comparison of vertical velocity measured by the ISS radar profiler and the lidar on 09May94. The altitude for each pair of displays is indicated on the display. r is correlation coefficient. Each data point is an average for 30 s every 200 s.
3. Tests for internal consistency

Another way to establish the credibility of the velocity estimates from NAILS data is to examine the internal consistency of the results. In doing so, we take advantage of aspects of the measurements, such as multiple range gates and shorter sampling time, that did not enter in the comparison with the anemometer in the previous chapter. Qualitative tests of internal consistency include range-time displays and time-height displays to see if there is reasonable consistency in time and space; i.e., whether or not the displays make meteorological sense.

Quantitative measures of internal consistency include such aspects as spectral densities of the time series of velocity values and autocorrelation functions in space and time. Symmetrical distribution in histograms of averaged radial velocity values show freedom from signal processor and algorithm bias errors. Comparison of measured variance profiles with those expected for a typical boundary layer also give confidence that NAILS velocity measurements are reasonable. Spatial autocorrelation functions show a consistent pattern as well.

3.1 Range-time display

Typical range-time display of velocity data are shown in figs. 3.1.1 and 3.1.2. (See color plates at end of report.) Figure 3.1.1 is data taken looking approximately 0.6° above horizontal at an azimuth of 344° from FL1 on 18 April 94, and fig. 3.1.2 is data taken looking vertically upward at Jeffco on 8 May 94. Figure 3.1.3 gives auxiliary data on the processed signal. These displays give a qualitative indication of the internal consistency of the data in both range and time, and they show an example of the type of visualization of the dynamics of the cloud-free portions of the boundary layer available from a Doppler lidar. The first case (18 April) involved an afternoon frontal passage with a strong northerly wind component beginning near the end of the period shown, and the second case (8 May) was a convective boundary layer with rain a little over an hour after the period shown.

The range-time displays are calculated from raw I (in-phase) and Q (quadrature) data and contain a velocity value calculated every 15 m in range (smoothed by the pulse laser length of approximately 100 m) and every 1 s in time. No smoothing is applied in time to maintain the temporal resolution in the image; smoothing would increase the signal-to-noise ratio (SNR) with a cost of loss of detail in time-dependent structures.

3.2 Variance in time

At any range where adequate SNR exists, we can generate a time series of velocity from the I and Q data. An example of time series with a 2-s integration time for three adjacent range gates is shown in figs. 3.2.1 and 3.2.2. These velocity data were taken along the test path used for the comparisons with PAM on 16 June 94 and are from the
Figure 3.2.1. Time series of the radial (horizontal) velocity component at ranges of 1.4, 1.5, and 1.6 km (reading from bottom to top) for 16 June 94, 1400-1500 LT.
Figure 3.2.2. Time series of the radial (horizontal) velocity component at ranges of 1.4, 1.5, and 1.6 km (reading from bottom to top) for 16 June 94, 1500-1600 LT.
real-time calculation of velocity without the filtering algorithm discussed in section 2.2. Conditions for the first hour included cloud cover and neutral stability. The range-time plot showed flow organized on a scale of a few km. The second hour was sunny with a more well-mixed boundary layer. Note the difference in the time series for the two periods, with more large-scale variation in the first period.

Spectral densities multiplied by frequency, corresponding to the time series on 16 June, are shown in figs. 3.2.3 and 3.2.4 along with a -2/3 comparison slope. The slopes of the spectra are roughly +1 at higher frequencies, which indicates that random uncorrelated noise is significant. Note that the spectra for the first hour show more power in the region of 0.001-0.01 Hz than do spectra for the second hour, as is expected from the character of the time series.

Autocorrelation functions for the time series of 16 June 1994 are shown in figs. 3.2.5 and 3.2.6. The data show correlation out to at least 20 s for the well-mixed boundary layer (3.3.6). Autocorrelations for the first hour, which had correlated structures, show larger values at all lags than the values for the second hour. By extrapolating from the single (2-s) lag value of the autocorrelation back to zero lag, it appears that the noise on the derived velocity time series is approximately equal to the signal. In other cases, particularly for filtered data, the SNR is greater.

Histograms provide another view of the statistics of the time series of velocity. Distributions in figs. 3.2.7 and 3.2.8 show a symmetric structure. These data correspond to the time series of figs. 2.2.7 and 2.2.8 of 29 June 1994. There are a few outliers on the positive velocity side not eliminated by the filter (despike) routine. Note that the standard deviation of the histogram includes both instrument noise and atmospheric variability. The scatter diagrams of section 2.3 give a better measure of measurement uncertainty.

Another example of velocity time series data available from the lidar is shown in fig. 3.2.9. This is vertical velocity taken at altitudes of 0.9, 1.0, and 1.1 km. To calculate velocity variance from such time series at each altitude, we calculate the autocovariance as a function of lag for 1-s lag intervals. An example of three autocovariance functions corresponding to the time series in fig. 3.2.9 is shown in fig. 3.2.10. Note that figs. 3.2.5-6 for horizontal velocity are (normalized) autocorrelation functions, whereas figs. 3.2.10-11 for vertical are unnormalized autocovariance functions with values greater than 1. By linearly extrapolating the autocovariance from 1 and 2-s lags back to zero, we estimate the autocovariance at zero lag in the absence of noise. This value is an estimate of the variance at that altitude. Examples of the procedure are shown in fig. 3.2.11, which shows an expanded lag scale for two adjacent altitudes. Note that a linear extrapolation appears to be a valid representation of the data between lags 1 s and 9 s, and that the SNR in the filtered data is approximately 3.
Figure 3.2.12 shows a plot of the variance of the vertical velocity as a function of altitude. Variances were calculated at 15-m altitude intervals. The dotted lines are the variance according to the empirical relation

\[
\frac{\overline{w^2}}{w_*^2} = 1.8(z/z_i)^{2/3}[1-0.8(z/z_i)]^2
\] (3.1) (Lenschow et al. 1980) with \(z_i\) set as 1600 m from the middle of the layer of broken clouds. Velocity \(w_*^2\) is taken as 3, 3.5, and 4 m\(^2\) s\(^{-2}\) for the three curves. The next steps in the analysis are to estimate \(z_i\) from the lidar data and use \(w_*\) from ASTER data at the Marshall site to scale the variance data. With the variable cloud cover during the day, and the difference in locations, it is possible that \(w_*\) at the Marshall site is substantially different from that at Jeffco, where the lidar was located.
Figure 3.2.3. Spectrum of the radial (horizontal) velocity component at a range of 1.5 km for 16 June 94, 1400-1500 LT. A 5-point running average has been applied to the raw spectral estimates.
Figure 3.2.4. Spectrum of the radial (horizontal) velocity component at a range of 1.5 km for 16 June 94, 1500-1600 LT. A 5-point running average has been applied to the raw spectral estimates.
Figure 3.2.5. Temporal autocorrelation of the radial (horizontal) velocity component at ranges of 1.4, 1.5, and 1.6 km for 16 June 94, 1400-1500 LT.
Figure 3.2.6. Temporal autocorrelation of the radial (horizontal) velocity component at ranges of 1.4, 1.5, and 1.6 km for 16 June 94, 1500-1600 LT.
Figure 3.2.7. Histogram of velocity component at ranges of 1.4, 1.5, and 1.6 km for 29 June 94, 1217-1340 LT.
Figure 3.2.8. Histogram of velocity component at ranges of 1.4, 1.5, and 1.6 km for 29 June 94, 1340-1500 LT.
Figure 3.2.9. Time series of vertical velocity at altitudes of 0.9, 1.0, and 1.1 km above ground level (AGL) for 1353-1516 LT, 09 May 94.
Figure 3.2.10. Vertical velocity autocovariance functions at altitudes of 0.9, 1.0, and 1.1 km AGL for 1353-1516 LT, 09 May 1994.
Figure 3.2.11. Vertical velocity autocovariance function at 915 and 930 m AGL, 1229-1329 LT, 09 May 1994.
Figure 3.2.12. Profile of the variance of vertical velocity for 09 May 94, 1229-1353. Dotted lines are empirical approximations (see text).
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3.3 Space and time statistics

To examine the statistics of velocity data from the Doppler NAILS, we have chosen a segment of data taken along a horizontal path from the Foothills Laboratory (see fig. 2.1.1) where the turbulent velocity field appeared to be homogenous and stationary. These data were collected on 28 June 1994 from 16:55:30 to 17:17:29 LT. During this time, the u component of the wind at the PAM site (range 1.5 km) was approximately 2 m s\(^{-1}\) (±1 m s\(^{-1}\) standard deviation) from the east at the beginning of the period, changing to 1 m s\(^{-1}\) from the east near the end. The v component was approximately 3 m s\(^{-1}\) (±2 m s\(^{-1}\) standard deviation) from the north for the entire period.

The space-time velocity field was developed from velocity profiles (velocity as a function of range) obtained from raw data taken at a 10-Hz rate and averaged for 1 s. This amounts to 1320 profiles spaced by 1 s in time, each profile containing 600 samples of velocity data (sampled at approximately 15-m intervals) from 510 m to 9495 m in range (for a total of 791,400 velocity values in the domain). The first step in calculating the following statistics is to subtract the mean of this 2-dimensional data field, which is 1.7 m s\(^{-1}\).

We discuss first individual space and time autocovariance functions to see the statistics in each dimension. Then we generalize to the two-dimensional autocovariance function, which is computed by a different technique. Identity of the peak and first-lag autocovariance values gives confidence that the calculations are internally consistent.

The mean spatial autocovariance function is shown in fig. 3.3.1. The bottom plot is merely an expanded view of the first 500 m of lag in the top plot. The first 8 data points (corresponding to 105 m of lag) show enhanced correlation caused by noise. The noise is correlated because of the signal-processing scheme and the length of the laser pulse. Notice the distinct change in slope of the function at 105 m. Beyond a lag of 105 m, spatial correlations in the velocity field are caused by the tail of the laser pulse and microscale atmospheric motions. The spatial autocovariance function was obtained by computing the spatial autocovariance function for each of the 1320 profiles and averaging the autocovariance functions (ACFs) together. The result is a mean ACF in the spatial (i.e., range) dimension.

In the same fashion, one can calculate a temporal ACF at each of the 600 ranges and average the ACFs from each range together to produce a mean ACF in time. The resulting mean temporal autocovariance function is shown in fig. 3.3.2. The elevated point at zero lag is caused by uncorrelated instrument noise. Profiles separated by 1 s are independent, i.e., they share no common data, so correlation at lags other than zero can be attributed to atmospheric motions since non-random instrument errors with time constants longer than 1 s are thought not to be a problem in this data set.
Figure 3.3.1. Mean spatial autocovariance function for the period 16:55:30 to 17:17:29 on 28 June 94. The first vertical dashed line is at zero lag and the second is at a lag of 7 samples.
Figure 3.3.2. Mean temporal autocovariance function for ranges from 510 m to 9495 m for 28 June 94. The vertical dashed line is at a lag of 0 s.
Figure 3.3.3. 2-dimensional autocovariance function of the velocity field from 28 June 94.
Comparing the spatial and temporal ACFs, the peak values of both functions that are computed in the manner outlined above is 1.63. The value of the first lag on the mean temporal autocovariance function is 0.71.

A complete 2-dimensional autocovariance function of the 2-dimensional velocity field can be obtained by calculating the Fourier transform of the velocity field. We take the absolute square of this result and again perform a Fourier transform to arrive at the 2-dimensional autocovariance function. This 2-dimensional result is shown in fig. 3.3.3. As a check on the procedure, the peak of the surface at the center, which represents zero lag in both the spatial and temporal dimensions, and the shoulder value in the temporal direction are consistent with those of figs. 3.3.1 and 3.3.2.

A striking feature of this 2-dimensional ACF surface (fig. 3.3.3) is the large, elevated ridge that runs along zero temporal lag in the spatial direction. The sharp triangular fin in the center is seen in the mean spatial autocovariance function (fig. 3.3.1). As in all autocovariance functions, this ACF is point symmetric about the zero spatial and temporal lag. However, it is not readily apparent from figs. 3.3.1 and 3.3.2 that this ridge is elevated from its neighboring values in time. This is caused by uncorrelated noise in the velocity data from one second to the next. The smooth upward trend of the surface as lags approach the center of the ACF from all directions (with the exception of the fin) is caused by correlation of microscale turbulence.

To reduce the influence of variability of the wind field on a scale of 1 s and reveal the effect of the tail of the laser pulse on the velocity measurements, we subtracted the mean (over space) of each 1-s record before computing the ACF. The resulting ACF is shown in fig. 3.3.4. The sharp symmetric fin extends from -105 m to +105 m spatial lag. This is consistent with our signal-processing scheme, which uses seven in-phase and quadrature points to calculate the velocity at a range point. The low portion of the fin extending beyond ±105 m in range must be caused by the tail of the laser pulse. It appears to have a noticeable effect on the ACF out to ±195 m. This is consistent with the pulse shape shown in fig. 1.2.1.

A mean spatial power spectrum can be calculated by averaging together the spatial power spectra calculated for each 1-s profile. This spectrum is shown as the upper solid curve in fig. 3.3.5. Each individual spatial power spectrum was windowed to minimize leakage across the spectrum, which is likely when sharp gradients exist in the spectrum, such as the gradient between 0.004 and 0.01 m\(^{-1}\) in fig. 3.3.5. The shape of the spectrum above 0.004 m\(^{-1}\) is a result of the signal-processing scheme and the pulse length. Note that we plot the spectrum as a function of reciprocal wavelength (\(\lambda^{-1}\)), which is wavenumber/\(2\pi\), consistent with plotting the temporal power spectrum in terms of reciprocal time rather than angular frequency. Reciprocal wavelength also allows easy interpretation of results in terms of lidar range. The calculation of a mean spatial cospectrum between adjacent pairs of velocity profiles removes uncorrelated noise. The mean spatial cospectrum is the lower solid curve in fig. 3.3.5.
Figure 3.3.4. Reduced 2-dimensional autocovariance function of the velocity field from 28 June 94 with the individual mean subtracted from each 1-s profile.
Figure 3.3.5. Mean spatial power spectrum (upper solid curve) and mean spatial cospectrum between adjacent pairs of velocity profiles (lower solid curve). Dashed reference curves are explained in the text. Velocity data are from 28 June 94.
Figure 3.3.5 uses a log-linear presentation for the spectra. The upper dotted curve in the figure follows the \(-5/3\) power law, i.e.,

\[ S(\lambda^{-1}) \propto \lambda^{5/3}. \quad (3.2) \]

The lower dotted curve is a \(-5/3\) power law multiplied by a transfer function \(f(\lambda^{-1})\) given by the expression

\[ f(\lambda^{-1}) = \text{sinc}^2(\pi\lambda_0/\lambda) \quad (3.3) \]

where \(\text{sinc}(x) = \sin(x)/x\) and \(\lambda_0 = 105\) m. The filtering is roughly equivalent to a 105-m running mean. The spatial cospectrum in fig. 3.3.5 is similar to the filtered \(-5/3\) power law in the region \(0.002-0.01\) m\(^{-1}\). This point is emphasized in fig. 3.3.6, where the solid curve is the mean spatial cospectrum divided by the transfer function and the dotted curve is the \(-5/3\) power law (3.2). Here the similarity between the corrected mean spatial cospectrum and the power law extends to near the highest frequency. Note that all spectra shown in this section have had log-smoothing applied to eliminate densely spaced data points at the high-frequency end of the spectrum.

The mean temporal power spectrum (averaged over all ranges) in the form of spectral density multiplied by frequency is shown as the upper curve in fig. 3.3.7. If we assume white noise is added to the signal, we can subtract a level of white noise determined from the high-frequency end of the spectrum from the entire spectrum to obtain the lower solid curve in fig. 3.3.7. This produces a corrected mean temporal power spectrum.

To close the loop and show internal consistency of the Doppler lidar data, we can convert the corrected mean temporal power spectrum to a spatial spectrum by using the mean horizontal wind vector at the PAM site \((3.2\) m s\(^{-1}\) from azimuth \(18^\circ\)) to convert the independent variable from frequency to reciprocal wavelength. The resulting converted corrected mean temporal power spectrum is shown as the dotted curve in fig. 3.3.8. The solid curve is the mean spatial cospectrum also shown as the lower curve in fig. 3.3.5. The two spectra agree with each other very well. We conclude that the space-time lidar data exhibit excellent internal consistency.
Figure 3.3.6. Mean spatial cospectrum between adjacent pairs of velocity profiles divided by the transfer function. The dashed reference curve is a -5/3 power law. Velocity data are from 28 June 94.
Figure 3.3.7. Mean temporal power spectrum (upper curve) and corrected mean temporal power spectrum with white noise subtracted (lower curve). Velocity data are from 28 June 94.
Figure 3.3.8. Mean spatial cospectrum (solid curve) and converted corrected mean temporal power spectrum (dotted curve) showing good agreement between space and time analyses of the space-time velocity field measured by NAILS Doppler lidar.
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4. Conclusions

It is useful to compare the measurement capabilities of the lidar as illustrated in the data comparisons and analyses with the estimated performance parameters given in Table 1 (section 1.2). Minimum and maximum range values are met or exceeded for many values of ambient aerosol backscatter coefficient. We will begin efforts to measure the SNR as a function of aerosol backscatter in the future. Range resolution is as specified, determined primarily by the 7 samples used in calculating the autocovariance estimate of the velocity. Velocity range has not been tested in these measurements, but the signal processing hardware meets the bandwidth specifications to provide the range.

Velocity accuracy is tested primarily by comparisons between lidar and anemometer measurements. These show an average standard deviation of less than 0.4 m s\(^{-1}\) on 1-minute averages for approximately ten hours of typical data taken under various conditions. In evaluating the scientific significance of the standard deviation, recall that the lidar averages over a sample volume 100 m long along the line of sight, whereas the anemometer is essentially a point measurement. The lidar sample volume was approximately 10 m above the anemometer. Larger variances are associated with strong positive gradients in backscatter because of the chirp (change in frequency with time) on the transmitted laser pulse. Slopes of the fits to the scatter diagrams average 1.02 for those cases where the range of velocities is enough larger than the variances to establish a meaningful slope. Mean differences (intercepts of the fitted lines) vary from less than 0.1 m s\(^{-1}\) to as much as 0.9 m s\(^{-1}\) in the worst case. This means that a complete characterization of the system is still lacking. Changes in the mean difference may be reduced or practically eliminated with a new signal-processing system that eliminates the variable gain and offset existing between the analog discriminator and voltage-controlled oscillator.

Beyond the tabulated design specifications, the performance tests reveal more of the scientific applicability of the lidar. Autocorrelation functions calculated for the lidar time series show that the noise on the time series is approximately equal to the signal. By extrapolating the 1 and 2-lag autocovariance functions from the data back to zero lag, variance of the velocity values caused by the atmosphere can be determined and used to plot profiles of the variance of the vertical component of the wind, for example. A typical velocity variance profile is consistent with mixed-layer similarity predictions for the boundary layer. Spectral densities multiplied by frequency for the time series are limited by noise to frequencies lower than the inertial subrange, but do resolve the energy-containing region of the spectrum. The corrected mean temporal power spectrum and the mean spatial co-spectrum derived from the range-time velocity field agree with each other very well, which shows excellent internal consistency in the Doppler lidar measurements.
Appendix: Future work

Because NAILS is an ongoing development effort, it is appropriate to discuss system improvements. The highest priority is to modify the system to make it suitable for airborne applications. This involves mechanical and optical refinements discussed in section A.2 and an upgraded signal-processing system discussed in section A.3. With the requested resources, these improvements should take approximately 1 year.

Modifications for ground-based applications are discussed in section A.4. These modifications involve mostly purchased services and equipment, and they could be done in parallel with the modifications for airborne work. However, because of the cost of a properly prepared seatainer shelter and hemispherical scanner, we propose these modifications for a second calendar year.

More esoteric studies of new signal- and data-processing techniques and algorithms as mentioned in section A.5 will proceed at a relatively low level in parallel with the preparations for airborne and ground-based applications.

A.1 Additional comparisons

Further coordinated measurements of the type discussed in chapter 2 need to be made. Anemometer comparisons can be used to help identify the source of the variable offset in the mean velocity estimate between the two techniques. Profiler comparisons can help in interpreting the results from both instruments. Lateral separation needs to be reduced for future experiments. Alternate means of estimating vertical wind with the profiler, such as scanning both sides of vertical to estimate divergence and fixed vertical pointing, need to be tested.

In addition, velocity-component fields from NAILS can be compared with those from the ELDORA test-bed Doppler radar when the atmosphere contains sufficient scatterers for the radar without too much attenuation for the lidar.

One coordinated measurement on horizontal structure of the wind field was made using the Doppler lidar and the Electra. The lidar was pointed upward at a 3° elevation angle parallel to, but offset by approximately 800 m from, the glide slope to runway 29R. Although the wind field measured by the lidar and aircraft sensors are not expected to be directly comparable, the scale of structure in the wind field should be similar. Work on analyzing these data is underway. This type of experiment is analogous to the analysis of variance in space (section 3.3).

A.2 Airborne applications

For airborne applications, NAILS development issues include vibration hardening and provision of a suitable scanner. Vibration affects the system by causing the servo that
locks the TEA resonator at 10-MHz offset from the LO to lose lock and by distorting the reference beat signal to cause an error in the velocity estimate. We found in ASTEX that it is possible to operate in a high-vibration environment by manually tracking the offset; approximately 40% of the pulses had a frequency offset within the acceptance band, but the reference pulse was very ragged. Some scan patterns will need an aircraft view port other than the window presently available on the Electra.

Much is yet to be learned about the response of the system to vibration. Vibration hardening is largely an issue of study time and experimentation rather than the purchase of available subsystems, as in the case of packaging for ground-based applications. The issue can be addressed by hiring a good consultant or by a focused NCAR effort using skills of existing staff. A rough estimate of resources required is 9 to 12 person-months and $25 k in parts and shop, but not enough is known about the behavior of the system in a harsh environment to make an accurate estimate of money and time required to solve the problems. We are attacking vibration hardening on a number of different fronts, but a considerable increase in effort will be needed before reliable operations are assured.

Moving from kinematic to gimbal mirror mounts on the TEA laser resonator should help stabilize the frequency difference between the TEA and the LO. Another improvement to test is sealing the optical path in the TEA resonator. The LO resonator needs to be examined for possible modifications to reduce susceptibility to vibration; we do not know the relative sensitivity of the two lasers to vibration. Perhaps sensitive accelerometers can be mounted on the TEA resonator structure to monitor motions and provide input to an active stabilization system using the piezoelectric translator (PZT) on the laser output mirror to correct for changes in the optical path length. Another approach is to apply known vibrating forces at various locations on the optical subsystem and observe the optical response by heterodyning with the LO or an auxiliary, isolated cw laser. The present lidar system is connected to the aircraft by shock mounts that resonate near the propeller frequency of the Electra. Softer mounts are possible, but difficult to provide with adequate crash safety and allow for pressurization effects on the telescope mounting.

The optical mounting system can be redesigned from two separate optics modules and lasers individually mounted on the lowboy rack to a more monolithic optical bench. We have made a preliminary design as part of considering a cooperative effort with the DLR WIND project. DLR has a telescope, scanner, and aircraft (Falcon 50) with an excellent downward-looking view port, but they need a laser and optical processing system to complete a lidar. We could meet that need and gain access to a scanner, port, and low-vibration aircraft that we do not now have.

Improvements to our signal-processing system, particularly a more robust measurement of the reference frequency (section A.3.2) should help the servo operate in an aircraft vibration environment.
A.3 Signal processing

NAILS needs a new signal-processing system. In addition to the research flexibility provided by a new digital approach, we need the reliability of a new computer; the old Sun 3E is subject to crashes and is no longer supported by Sun. The 68020 auxiliary processor used to increase the overall speed of the system has bus conflicts with the Sun. The developmental digitizer card has been heavily modified and should be replaced with a more reliable unit. We estimate approximately $70 k in commercial boards, 8 person-months, and 5 months calendar time to assemble and test a new signal processor.

A.3.1 High-speed digitization

The use of digitizers with a maximum rate of 10 MS s$^{-1}$ (although with 12 bits of resolution) requires significant analog preprocessing in the present system to reduce the signal from the cooled, heterodyne detector of 5 to 15 MHz to I and Q channels with bandwidths of 0 to 5 MHz. Some of the components used include a quadrature mixer, CohO, various filters, and a tuning circuit for the CohO. High-speed digitization (e.g., 70 MS s$^{-1}$, 10 bits) would allow substantial simplification of the analog portion of the signal-processing system and allow increased flexibility in testing various recording and velocity-estimation algorithms.

A.3.2 Reference frequency measurement

As mentioned in section 1.2, the heterodyne frequency offset between the TEA and LO lasers (see fig. 1.2.1) is measured with an analog discriminator in the present signal-processing system. If the heterodyne reference pulse between the two lasers were digitized at an adequate speed (100 MS s$^{-1}$, 8 bits), it would be possible to apply various digital techniques to filter the reference signal and estimate its effective mean frequency, chirp, and other parameters. This expanded data on the characteristics of the heterodyne signal between the two lasers would increase the effectiveness of research on lidar performance and system improvements. In addition, digital processing of the reference frequency is consistent with improvements in backscatter signal processing discussed in section A.3.1.

A.3.3 Laser power recording

The present signal-processing system does not measure the LO level on the heterodyne detector or the TEA laser output energy. Making these measurements would allow for better estimates of the aerosol backscatter coefficient and greatly reduce the banding and striations now visible on the range-time plot of relative backscatter.

LO level determines the heterodyne conversion gain of the signal detector. This
level drifts over times of minutes because of changes in system alignment over interferometric distances. At present, this dc level is filtered from the signal channel, which operates at 5 to 15 MHz for velocity estimation, but it is available for monitoring on an oscilloscope. Recording the dc level would require another data channel and appropriate modifications to the recording software, but the digitizer for LO level needs to have only modest dynamic range (8 bits) and frequency response (10 kHz or so). Because the noise on the signal depends on the LO level, it should be possible to estimate LO level from the return at long ranges, but often there is substantial signal at the maximum range of the present signal-processing system (see section A.3.4).

The TEA output energy is a basic factor in the lidar equation used to estimate backscattered power. The system now has a detector to monitor the TEA output, but the information is displayed only on an oscilloscope. Recording the TEA pulse energy requires a high-speed digitizer (50 to 100 MS s\(^{-1}\)) and modest dynamic range (8 bits).

A.3.4 Range extension

The present signal-processing system is limited to 667 range gates (10 km) by hard-wired limitations on memory available. It turns out from our tests of the system that adequate SNR for good estimates of velocity and relative backscatter coefficient is available at greater ranges for some operating conditions with a ground-based system. To record these data from greater ranges we need expanded high-speed memory. Essentially, this means a new signal-processing system.

A.3.5 Increase laser pulse repetition frequency

We have recently reduced a problem with the TEA laser frequently misfiring on some pulses with an arc discharge (which provides no useful output) rather than a glow discharge. With the reduction in arcing, we can now run reliably at a PRF of 20 Hz. The laser is specified for operation at a PRF of up to 150 Hz. We will test that capability as part of the data-system upgrade. The new data system will be designed to operate at PRFs above 60 Hz to allow adequate spatial resolution along the aircraft flight track and adequate signal averaging for ground-based applications with low SNR.

A.4 Ground-based applications

Lidar measurement of clear-air velocity can contribute to research topics such as longitudinal rolls and thermals in the boundary layer, initial growth and subsequent decay of small cumulus clouds, and clear-air turbulence from lee-wave rotors. Such applications require the lidar to be able to scan in azimuth and elevation and to be installed in an independent, portable housing.

These requirements could be met by adding a two-mirror scanner and mounting the system in a seatainer. The scanner would allow complete hemispherical coverage and the
ability to do VAD and RHI scans, for example. A commercially available 12" lidar scanner with mirrors flat enough for a heterodyne optical system and computer control costs $65 k from DFM Engineering. Delivery is approximately 8 months after receipt of order. There is no known good, less-costly alternative. We would modify NAILS with an upward-pointing telescope beneath the scanner requiring no new optical components.

Mike Howard estimates approximately $25 k for a seatainer fixed up with doors, windows, insulated walls, power, air conditioning, floating floor (like ASTER), and scanner mount. Portability requires a trailer, like ISS, for about $5 k in addition. We need only about half the volume of a seatainer, but the need for frequent transport and a clear roof for the scanner would make it difficult to double up with another system. We could offer spare space to SABL or use something smaller than a seatainer, like a construction trailer or cargo van.

In addition to a scanner and housing, we should upgrade the signal-processing system, as outlined in section A.3, for serious scientific applications.

A.5 Signal-processing techniques

A.5.1 Pulse compression

The TEA laser pulse has a sharp rise and slowly decaying tail as well as a frequency chirp (fig. 1.2.1) caused by the plasma and acoustic physics of the laser action. This chirp adds to the velocity measurement uncertainty in the presence of strong reflectivity gradients. We have designed the TEA resonator to use a passive Q-switch to reduce the laser pulse width and thereby the chirp, but this technique has not yet been implemented. It may be possible to use the chirp as is, in a pulse-compression scheme. Preliminary studies of pulse compression as applied to NAILS are under way.

Figure A.5.1 shows a simulated heterodyne pulse that has amplitude and frequency characteristics that are somewhat similar to the NAILS transmitter output. An appropriate pulse-compression filter can modify the shape of the pulse in time. Figure A.5.2 shows that the ambiguity function for such a compressed pulse is sharpest at the designed center frequency of the pulse-compression filter, 10 MHz, but is usable for pulses off the design center. Clearly these are only preliminary results and much work needs to be done. The next steps are to extend the tests with a digitized representation of a heterodyned signal from an actual NAILS pulse and review the filter calculations. For this purpose, we need faster digitization of the reference pulse than can be done with our present signal-processing system (see section A.3.2).
A.5.2 Kalman filtering and the Gabor spectrogram

A number of new or rediscovered data analysis tools have recently become available. We should examine their applicability to the NAILS Doppler data. Among the tools is Kalman filtering (Rye and Hardesty 1988), which is a recursive technique for smoothing and filtering with an emphasis on outlier rejection.

Improvements in the signal-processing algorithms are also possible. We can study the effect on the velocity estimate from multiple-lag autocorrelation analysis. The Gabor spectrogram is a joint time-frequency analysis technique that is based on the Gabor transform rather than the Fourier transform. Its advantages include speed over an FFT, but performance with respect to a covariance frequency (velocity) estimator needs to be studied.

Figure A.5.1. Simulated pulse from NAILS showing amplitude decay and chirp to lower frequency.
Figure A.5.2. Ambiguity diagram for compression of pulses of various frequencies by a filter designed for a 10-MHz initial frequency.
REFERENCES


Pearson, G.N., 1992: A pulsed CO$_2$ Doppler lidar for boundary layer monitoring. 


