The Novel Nonlinear Adaptive Doppler Shift Estimation Technique and the Coherent Doppler Lidar System Validation Lidar

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Abstract

The signal processing aspect of a 2-μm wavelength coherent Doppler lidar system under development at NASA Langley Research Center in Virginia is investigated in this paper. The lidar system is named VALIDAR (validation lidar) and its signal processing program estimates and displays various wind parameters in real-time as data acquisition occurs. The goal is to improve the quality of the current estimates such as power, Doppler shift, wind speed, and wind direction, especially in low signal-to-noise-ratio (SNR) regime. A novel Nonlinear Adaptive Doppler Shift Estimation Technique (NADSET) is developed on such behalf and its performance is analyzed using the wind data acquired over a long period of time by VALIDAR. The quality of Doppler shift and power estimations by conventional Fourier-transform-based spectrum estimation methods deteriorates rapidly as SNR decreases. NADSET compensates such deterioration in the quality of wind parameter estimates by adaptively utilizing the statistics of Doppler shift estimate in a strong SNR range and identifying sporadic range bins where good Doppler shift estimates are found. The authenticity of NADSET is established by comparing the trend of wind parameters with and without NADSET applied to the long-period lidar return data.

Keywords: coherent lidar, Doppler shift, maximum likelihood, Nonlinear Adaptive Doppler Shift Estimation Technique, periodogram, subspace, Validation Lidar, wind profiling

I. Introduction

The area of wind parameter estimation using lidar returns and its theoretical analysis have been explored in various aspects by many researchers. The principles of such research lie in the processing of the time series data of lidar returns that are the superposition of the backscattered field of small atmospheric aerosol particles. Such returns are modeled by a zero-mean Gaussian stochastic process with additive and statistically independent white noise processes. The independence of the two processes originates from the assumption of uncorrelated aerosol particle movement being greater than the wavelength of the lidar between each data acquisition time instant [1]. When the signal-to-noise-ratio (SNR) is strong, the mean-frequency estimators are unbiased and the quality of wind parameter estimates remains high even with small number of stochastic lidar returns [2]. In the regime of weak signal environment, however, the estimates are biased and often accumulation of multiple lidar returns is performed in order to improve the quality of such estimates. Utilizing the stochastic moments of various orders of Gaussian stochastic processes, the lowest possible variance of the parameter estimates, Cramer-Rao (CR) bound, was investigated in order to achieve more quantitative measures of estimates [3–5]. The unfavorable influence of the Gaussian noise on the estimation of the second order centralized moment of Doppler spectra can be reduced in weak signal regime by identifying an optimal Gaussian noise threshold while assuming the Doppler spectra as the probability density function and the frequency as random variables [6]. The performance of such a method, however, experiences dramatic deterioration if the system noise does not remain at a constant level. The effect of spectral correlation of the return signals caused by backscatter variability on lidar returns and weather radar returns was investigated in [7]. The effort in minimizing the interference of Gaussian noise is also shown in [8] by whitening the noise assuming that the tail of lidar time series data represents negligible aerosol signals. The impact of noise whitening on wind parameter estimation using a lidar system at NASA Langley Research Center is presented in [9].

The lidar system VALIDAR (validation lidar) at NASA Langley Research Center in Hampton, Virginia is a 2-μm wavelength coherent system, which is a high-energy Doppler lidar to measure wind profiles and CO_2 concentration, serving as a calibration source for future airborne and spaceborne lidar missions. The uniqueness of VALIDAR is its transmitted pulse energy in the 100 mJ range, as opposed to the 1–5 mJ lidars also in use at this wavelength. The optical design of VALIDAR is introduced in [10–12] and a variety of research outcomes with such a system are reported in [9–18]. The efforts in improving the quality of wind parameter estimates in low SNR regime in particular are the main goal in [9, 13–15]. The current VALIDAR has the capability of processing lidar returns simultaneously as the data acquisition process occurs in real time. The hardware configuration of VALIDAR consists of (1) Compact PCI chassis by PEP Modular with eight slots, (2) PEP Modular CP603 64-bit cPCI Pentium III at 850 MHz with 768 MB SDRAM, (3) Acqiris DC240 with two-channel simultaneous sampling capability at up to 2 GHz with 8 bit resolution, and (4) BittWare ADSP-21160M HammerHead DSP module with eight DSP processors. The data processing program is developed in VisualC++ with the GUI drivers from LabWindows CVI developed by National Instruments in Windows 2000 operating system. The data transfer rate of direct upload and download sustains the overheads of the maximum of 2–2.5 MB/sec transfer rate from DSP to host (upload) and 13–15 MB/sec transfer rate from host to DSP (download). The data transfer, however, is implemented via bus mastering, which provides the maximum transfer rate of 90 MB/sec for upload and 30 MB/sec for download.

A series of the most recent research studies in light of wind parameter estimation improvement with VALIDAR can be found in [9, 13–15]. The impact of power spectrum estimation on the quality of wind parameter estimation by maximum likelihood method, the Bartlett, the Welch, and the Blackman and Tukey method was shown insignificant in [13]. The Doppler shift estimates, however, were improved in terms of frequency resolution by means of zero padding. The application of noise whitening [8] to data processing of VALIDAR was investigated in [9]. Assuming the tail of each lidar return time series represents the noise, the power spectrum of noise was estimated by a nominal number of samples in the tail of lidar return and was used to normalize the noise in the spectrum of signal. Modeling the noise by a small order of linear predictor was also investigated in the same paper. In addition, different types of windowing functions were applied to the time series data and their contribution to the quality of wind parameter estimates was observed, too. Implemented were both time and frequency independent and dependent windows such as the Rectangular, the Hanning, the Kaiser-Bessel, and the Apodized windows. It was concluded in [9] that the improvement in the wind parameter estimates was not recognizable. Then, a signal subspace approach was studied in the realm of lidar signal processing in [14]. The principle of orthogonality between the signal and the noise subspaces, which are the spans of the signal and the noise eigenvectors, was explored and the identification of maximum power frequency in the power spectrum of lidar time series data in each range bin was improved by removing erroneous power spikes present in the original power spectrum. Despite the removal of such spurious peaks in the power spectrum, however, the overall improvement in the wind parameter estimates was not manifest. Such a series of mathematically tractable methods in an attempt to improve wind parameter estimates in low SNR in particular with exiguous evidence of amelioration gave a rise to a nonlinear method to deal with a low signal level in the stochastic lidar returns, and this paper introduces a new Doppler shift and power estimation method NADSET (Nonlinear Adaptive Doppler Shift Estimation Technique) developed for VALIDAR. The details of NADSET is presented in this paper and another performance analysis of NADSET with a different set of long-period lidar return data can also be found in [15]. The meteorological perspective of the NADSET algorithm is presented in [19]. The brief overview of the signal processing algorithm of VALIDAR is presented in the following section, followed by the detailed description of NADSET and its principle in section III. Section IV demonstrates the influence of NADSET on long-period lidar return time series data acquired by VALIDAR. The conclusion and the future direction of research are in Section V. The look direction of the lidar system is indicated by <*a*, *b*> where *a* is the azimuth angle and *b* is the elevation angle in degrees. Lowercase bold letters represent column vectors such as **x**, and uppercase bold letters indicate matrices and fast Fourier transform (FFT) of a data array such as **X**.

II. Lidar Signal Processing of VALIDAR

The latest version of the wind parameter estimation algorithm of VALIDAR is briefly summarized. The detailed description can be found in [17].

Step 1 A nominal number of lidar returns $\mathbf{s}_n^p(t)$ are acquired repeatedly (accumulated) at a selected look direction and such a procedure is repeated for three different directions. The subscript *n* is the accumulation index and the superscript *p* indicates the index of time elapse.

Step 2 Divide $\mathbf{s}_n^p(t)$ into *M* vectors, $\mathbf{x}_{0,\,n}^p$, $\mathbf{x}_{1,\,n}^p$, …, $\mathbf{x}_{M-1,\,n}^p$, with a certain percentage of overlap.

Step 3 Compute the power spectrum $\mathbf{X}_{m,\,n}^p(f)$ of each vector $\mathbf{x}_{m,\,n}^p$. Check if $f_{\min} \leq f_{0,\,n}^p \leq f_{\max}$, where $f_{0,\,n}^p = \max_{f \geq F}\left[\mathbf{X}_{0,\,n}^p(f)\right]$, and $f_{\min}$ and $f_{\max}$ are the minimum and the maximum limits of Doppler frequency and *F* is the lower threshold of frequency estimation. The first $f_{0,\,n}^p$ that satisfies this constraint is used as a reference frequency in estimating the Doppler shift.

Step 4 Estimate $\mathbf{Y}^p = \{\mathbf{Y}_1^p, \ldots, \mathbf{Y}_{M-1}^p\}$, where each element is the average of the frequency adjusted power spectra, i.e., $\mathbf{Y}_m^p(f) = \frac{1}{Q}\sum_{n=0}^{Q-1}\hat{\mathbf{X}}_{m,\,n}^p(f)$, where $m = 1, \ldots, M-1$, *Q* is the number of pulse returns that satisfy the frequency constraint, and $\hat{\mathbf{X}}_{m,\,n}^p(f)$ is the frequency aligned version of $\mathbf{X}_{m,\,n}^p(f)$. (This frequency alignment is called zero Doppler normalization.) The final products $\mathbf{Y}^p$ are used to estimate wind parameters such as Doppler shift, power, wind speed, and wind direction. This paper presents the data processing results with twenty lidar returns ($n = 1, \ldots, 20$) at each look direction and 512-point FFT is used to compute the periodogram of the *M* vectors. *p* is 1 indicating that a data set of single repetition is used to illustrate the NADSET algorithm.

Figures 1 and 2 show an example of VALIDAR software output screen where Doppler shift (DS), power spectral density (PSD), wind speed (WS), and wind direction (WD) are displayed in real time. The stochastic lidar return time series data were 50,000 samples long, and twenty repeated lidar returns were used to perform averaging of the periodogram of each bin data. Such 50,000 samples were divided into the segments of 512 samples with 50% overlap with adjacent segments. The sampling frequency was 500 MHz and the Rectangular window was used before computing the periodogram. The details of the impact of different windowing functions can be found in [9]. The Doppler shift frequency window ranges from 95 MHz to 115 MHz in those figures. The data were acquired on June 16, 2005 at NASA Langley Research Center in Hampton, Virginia. In particular, Figure 1(a) shows the software band-passed averaged periodogram in the seventeenth range bin over twenty pulses. The passband of the hardware filter is set by an analog filter in place prior to digitization in order to prevent aliasing. A slope exists in the 65 MHz to 145 MHz passband that results from the spectral characteristics of the heterodyne photodetector in use.

III. NONLINEAR ADAPTIVE DOPPLER SHIFT ESTIMATION TECHNIQUE (NADSET)

NADSET takes a different approach to wind profiling based on the nature of continuous wind characteristics and significantly improves the quality of Doppler shift estimate in low SNR ranges. The authenticity of NADSET is established by comparing the trend of wind parameters with and without NADSET applied to the lidar returns acquired over a long period of time by VALIDAR. The algorithm has two parts: Range Bin Interval Identification and Wind Parameter Estimation.

A. Range Bin Interval Identification (Part I)

Step 1 Estimate the Doppler shift estimates DS[m] using the periodogram of lidar returns in each bin, where m is the bin index.

Step 2 Find $\frac{d}{ds}\mathrm{DS}(s)$, where DS($s$) indicates that the Doppler shift estimate is a function of continuous range s. The following discrete version is used for NADSET:

$$\Delta\mathrm{DS}[m] = \frac{\mathrm{DS}[m+\Delta m] - \mathrm{DS}[m]}{\Delta m} \text{ [MHz/bin]}, \tag{3}$$

where ΔDS[m] is the slope of DS at the mth bin, and a unity increment is chosen without loss of generality (Δm = 1 bin).

Step 3 Identify the bin indices m where the absolute value of ΔDS[m] exceeds a user-set Absolute DS Slope Threshold A [MHz/bin].

Step 4 Find the smallest bin index m_A such that $|\Delta\mathrm{DS}[m_A]| \geq A$.

Step 5 In the region where the SNR is high and the Doppler shift estimate is stable, compute the first order moment and the second order centralized moment as follows:

$$\mu = E\{\mathrm{DS}[m]\} \text{ [MHz]},$$

$$\sigma^2 = E\{(\mathrm{DS}\,[m] - \mu)^2\} \text{ [MHz}^2\text{]},$$

where E is the expectation or the ensemble average operator. The following discrete versions are used for NADSET:

$$\mu_A = \frac{1}{m_A - L + 1}\sum_{m=L}^{m_A} \mathrm{DS}[m], \tag{1}$$

$$\sigma_A^2 = \frac{1}{m_A - L + 1}\sum_{m=L}^{m_A} \left(\mathrm{DS}[m] - \mu_A\right)^2, \tag{2}$$

where L is the user-selectable beginning bin index for the moment calculation. The current value of L is 4. Note that m_A, μ_A, and $\sigma_A{}^2$ indicate that they are all a function of the parameter A.

Step 6 Among the chosen bin indices m in Step 3, find m_1 and m_2 where $m_1 < m_2$, and $\Delta\mathrm{DS}[m_1]$ is the first negative $\Delta\mathrm{DS}[m]$ and $\Delta\mathrm{DS}[m_2]$ is the first positive $\Delta\mathrm{DS}[m]$, meeting the following requirements:

$$\mu_A - \sigma_A D \leq \mathrm{DS}[m_1] \leq \mu_A + \sigma_A D, \tag{4}$$

$$\mathrm{DS}[m_1] - B \leq \mathrm{DS}[m_2] \leq \mathrm{DS}[m_1] + B, \tag{5}$$

where B is the Secondary DS Continuity Margin in MHz and D is the unitless Stationary DS Deviation Margin. Each is a user-set positive constant.

Step 7 If the new m_1 is m_2 from the previous search, the new m_2 replaces the previous m_2. (Range merging) This can occur if the DS estimate shows positive and negative slopes about a bin index.

Step 8 If $m_2 - m_1 > C$, where C is the Maximum DS Continuity Range Margin in the unit of bin index, discard m_1 and m_2. Otherwise, mark those bin indices. C is also a user-specified positive parameter.

Step 9 Repeat Steps 6-8 until the algorithm exhausts the entire bins.

B. Wind Parameter Estimation (Part II)

Step 1 Find the frequencies f_1 and f_2 where the zero-Doppler normalized periodogram in the range bins m_1 and m_2 is maximal, respectively. Assume $f_1 < f_2$ without loss of generality.

Step 2 For range bin indices from $m_1 + 1$ to $m_2 - 1$, find a new maximal power in $[f_1, f_2]$

and its frequency. The new Doppler shift frequency is estimated by using the frequency at the new maximum power.

Step 3 Wind speed and wind direction are estimated using the new Doppler shift estimate.

C. Parameters of NADSET

The algorithm is based on the seven parameters such as μ, σ^2, Δm, A, B, C, and D. The two moments μ and σ^2 provide a reference point of Doppler shift frequency in strong SNR regime. The increment Δm in the numerical slope calculation reflects the degree of correlation of Doppler shift estimates between range bins. A unity increment is implemented assuming the independence of DS estimates across the range bin. The Absolute DS Slope Threshold A reflects the severity of deterioration in the quality of DS estimate due to the loss of signal strength. A larger value of A implies more robust quality of the original DS estimates since NADSET will attempt to preserve the original DS estimates until the DS estimate experiences a severe fluctuation. The Stationary DS Deviation Margin D in (4) is to confirm if an identified DS[m_1] could have been a more reasonable estimate than the original DS estimate at $m = m_1$ if it had not been for the low SNR. The Secondary DS Continuity Margin B in (5) shows the degree of assumption in the continuity of wind profiling. Since wind speed and wind velocity are closely related to Doppler shift and the behavior of wind in any nearby range bins should be of similar nature, so should be the Doppler shift estimates in nearby range bins, for example, within the range of B MHz. The Maximum DS Continuity Range Margin C imposes restriction on the range of continuous wind profile, especially the merged bin ranges that NADSET has identified. When the values of the parameters based on the bin range such as Δm, B, and C are selected, the length of each range bin should be taken into account in determining the values of the other parameters.

IV. Application of NADSET to Lidar Returns

In this section, the results with and without NADSET are first compared using one set of lidar returns at the direction <0, 90>. Then, the performance of NADSET is analyzed by applying it to lidar returns acquired over a long period of time. Such analysis will serve as a stepping stone to establish the authenticity of the algorithm.

A. Performance of NADSET

The performance of NADSET is shown using the lidar return time series data at <0, 90>. The length of each lidar return was 50,000 and each lidar return was segmented into bins of 512 samples with 50% of overlap with adjacent bins, resulting 190 bins (M = 190). The first 512 time series in 50,000 represented the lidar return before the 10-Hz TTL trigger in order to estimate the zero Doppler frequency accurately, and the first 1024 samples including the 512 pre-trigger time series were used for zero-Doppler frequency estimation. The sampling frequency was 500 MHz and twenty lidar returns were averaged at the look direction. The interval of zero Doppler frequency was set to [95MHz, 115MHz] and each bin was 153.49 meters long. The power spectrum in each bin was estimated by the periodogram with the Rectangular window. The lidar return time series data in this comparison analysis were acquired at 1:21 P.M. E.S.T. on June 16th, 2005 at NASA Langley in Hampton, Virginia. The empirical values of the

NADSET parameters were: Δm = 1 bin, A = 5 MHz/bin, B = 5 MHz, C = 15 bins, and D = 4.5.

Figures 3 through 8 show the comparison of DS estimates with and without NADSET applied. In order to display the difference clearly, the entire bins were divided into three intervals, and the DS estimates are displayed against the bin index instead of range in km. The bin index begins at zero instead of one due to the nature of the programming language, and there are a total of 190 bins. In each figure, the upward and the downward vertical lines indicate the beginning and the end of an interval that NADSET has identified to enhance the quality of DS estimates. The two of the seven parameters, μ_A and σ_A^2, were estimated using the DS estimates in the bin index range [2, 43], where the SNR was strong resulting in stable DS estimates. Figure 3 shows the first interval candidate [44, 48] and Figure 4 shows the improved DS estimates. Figure 5 shows the next candidates [62, 64], [65, 67], [68, 70], and [71, 96], and Figure 6 shows the result of the application of NADSET. Similarly, Figure 7 shows that the two intervals [97, 102] and [131, 145] are the next ones where NADSET will re-estimate the DS, and the result is shown in Figure 8. Note that NADSET did not recognize the peaks in [103, 130] or [146, 189] as candidates for improvement since they did not meet the conditions that were presented in the previous algorithm section. Figures 9 and 10 show the comparison of both DS and PSD for the entire bin range. The new PSD estimates in Figure 10 show lower power than the original estimates because the latter were the maximum power values in each range bin.

B. Validation of the performance of NADSET

In order to test the accuracy of the wind measurements produced by NADSET, we applied the algorithm to a long continuous data set to see if the measurements made sense from a meteorological interpretation. Atmospheric profiles were recorded over a span of approximately 9 1/2 hours on June 28, 2005 and were processed both with and without NADSET applied. The goal of this study was to assess where wind measurements were improved with NADSET and under what conditions spurious false data might be created. Setting wide parameters on the NADSET algorithm can allow more false readings, but restricting the parameters can limit the benefits of the algorithm. The best setting of the NADSET parameters for this set of data was empirically found to be A = 5 MHz/bin , B = 9 MHz, C = 15 bins, and D = 4.5.

The recorded wind profiles, shown in Figures 11–13, were made with the lidar beam pointed in three different directions to form measurements of the horizontal wind and vertical wind profiles. The first two directions were made at 45 degree elevation angle and orthogonal azimuths to find the two components of the horizontal wind vector. The vector sum of these two components is shown in the first two panels of Figure 11 and Figure 12 as the horizontal wind speed and horizontal wind direction. The third look direction was directed upward to measure the vertical wind motion and the presence of clouds. Vertical wind speed and the backscatter power form the lower two panels of Figure 11 and Figure 12.

This data set contains a good variety of atmospheric conditions for testing

NADSET with clouds at multiple altitudes, layering of aerosols, a variety of wind speeds, and precipitation. The benefit of NADSET is best seen in the gaps of Figure 11 where the aerosol backscatter drops at altitudes near 3500 m and 5000 m throughout the first half of the data set. The horizontal wind speed, reproduced in Figure 13 for a convenient side-by-side comparison with and without NADSET, has the gap filled in with the application of NADSET. The speed in the filled in gap is consistent over time, a trend to be expected and showing that NADSET is making accurate wind measurements. The larger gap seen beginning near 5000 m altitude in the first half of the data set occurs as the aerosol density drops, but the signal reappears as clouds are encountered at higher altitudes. NADSET works very well in this situation, filling in data in some cases to achieve an extra 2 km of altitude. The data filled in by NADSET is also consistent with time, and more definitively identifies a wind shear that occurs at 5 km altitude.

The second half of the data set provides a good opportunity for testing NADSET in its potential for providing false estimates, in that thick clouds occurred. These clouds are thick enough to extinguish the transmitted pulse energy, hence there should be no measurements close to the good values measured beneath the clouds. When making an estimate on a spectrum of noise, the algorithm’s peak detection will find a random peak in the noise. However, the noise spectrum in the photodetector used here is tilted (see Figure 1a), so the peak detector tends to select a value on an extreme end of the spectrum. The false extremes of the wind speed measurement occur outside the range of values displayed in the scale of Figures 11–13, and are displayed as grey. If the full range of wind speeds were set to cover the entire passband of +/– 40 MHz Doppler shift, then multicolored points would appear where the data are noisy (this effect can be seen in the wind direction displays). With the application of NADSET, the wind speed measurements above the clouds in the 2nd half of the data showed grayed out results that are not misleading to interpret as true. The few false data points within the range of wind speed displayed could possibly be eliminated or flagged by adding a feature to the algorithm that, for example, measures the continuity of wind measurements with altitude.

V. CONCLUSION

The new nonlinear wind parameter estimation algorithm NADSET is presented in detail in this paper. The motivation of such development of a nonlinear algorithm is ascribed to the ambiguous improvement in wind parameters estimated by mathematically driven methods, especially in low SNR regime [9, 13–14]. NADSET takes advantage of the continuous nature of wind and adaptively re-estimates DS and PSD (and WS and WD consequently) by feeding back the information of Doppler shift from the range bins where signal strength is identified as strong. The authenticity of NADSET is established and its benefits are demonstrated by means of the meteorological interpretation of long-period lidar return data. The application of NADSET to such a set of lidar return shows that the new wind parameters are meaningful while compensating the weakness of signal strength in the quality of wind parameter estimates.

NADSET currently relies on the two good DS estimates to identify a range to be compensated and its performance is closely related to the properly chosen values of the seven parameters among which five of them are user-dependent. The most latest version of NADSET allows users to experiment on different values of parameters using a user-selectable single set of three-direction lidar return time series in order to find the best parameters empirically. Such a step can be automated by integrating into the algorithm various aspects of criteria such as the statistics of current and past weather condition and the time of the year. A single-sided version of NADSET is also under investigation where one good DS estimate is used to identify a range to be enhanced instead of two. NADSET will continue to evolve while incorporating such features in the future work.

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Bibliography

[1] R. G. Frehlich, "Coherent Doppler Lidar Signal Covariance Including Wind Shear and Wind Turbulance," *Applied Optics*, Vol. 33, No. 27, pp. 6472–6481, September 1994.

[2] R. G. Frehlich and M. J. Yadlowsky, "Performance of Mean-Frequency Estimators for Doppler Radar and Lidar," *J. of Atmospheric and Oceanic Technology*, Vol. 11, pp. 1217–1230, October 1994.

[3] B. J. Rye and R. M. Hardesty, "Detection Techniques for Validating Doppler Estimates in Heterodyne Lidar," *Applied Optics*, Vol. 36, No. 9, pp.

1940–1951, March 1997.

[4] B. J. Rye and R. M. Hardesty, "Discrete Spectral Peak Estimation in Incoherent Backscatter Heterodyne Lidar. I: Spectral Accumulation and the Cramer-Rao Lower Bound," *Proc. IEEE Trans. on Geoscience and Remote Sensing*, Vol. 31, No. 1, pp. 16–27, January 1993.

[5] B. J. Rye and R. M. Hardesty, "Discrete Spectral Peak Estimation in Incoherent Backscatter Heterodyne Lidar. II: Correlogram Accumulation," *Proc. IEEE Trans. on Geoscience and Remote Sensing*, Vol. 31, No. 1, pp. 28–35, January 1993.

[6] P. H. Hildebrand and R. S. Sekhon, "Objective Determination of the Noise Level in Doppler Spectra," *J. of Applied Meteorology*, Vol. 13, pp. 808–811, October 1974.

[7] B. J. Rye, "Spectral correlation of atmospheric lidar returns with range-dependent backscatter," *J. Opt. Soc. Am.*, Vol. 7, No. 12, pp. 2199–2207, December 1990.

[8] R. G. Frehlich, S. M. Hannon, and S. W. Henderson, "Coherent Doppler Lidar Measurements of Winds in the Weak Signal Regime," *Applied Optics*, Vol. 36, No. 15, pp. 3491–3499, May 1997.

[9] J. Y. Beyon, G. J. Koch, and Z. Li "Noise Normalization and Windowing Functions for VALIDAR in Wind Parameter Estimation," submitted to *Defense and Security Symposium 2006, Orlando, FL*, April, 2006.

[10] G. J. Koch, M. Petros, B. W. Barnes, F. Amzajerdian, M. J. Kavaya, U. N.

Singh, J. Yu, and J. Y. Beyon, "Wind Measurements with a High Energy 2-μm Coherent Doppler Lidar," the 22nd International Laser Radar Conference, Matera, Italy, June, 2004.

[11] G. J. Koch, M. Petros, B. W. Barnes, J. Y. Beyon, et. al., "Validar: A Testbed for Advanced 2-μm Coherent Doppler Wind Lidar," in *Proc. of the 12th Coherent Laser Radar Conference*, pp. 29–32, June, 2003.

[12] G. J. Koch, M. Petros, J. Yu, J. Y. Beyon, et. al., "2-μm Coherent DIAL Measurements of CO_2," in *Proc. of the 12th Coherent Laser Radar Conference*, pp. 195–198, June, 2003.

[13] J. Y. Beyon and G. J. Koch, "Resolution Study of Wind Parameter Estimates by a Coherent Doppler Lidar System," submitted to *Defense and Security Symposium 2006, Orlando, FL*, April, 2006.

[14] J. Y. Beyon and G. J. Koch, "Wind Profiling by a Coherent Doppler Lidar System VALIDAR with a Subspace Decomposition Approach," submitted to *Defense and Security Symposium 2006, Orlando, FL*, April, 2006.

[15] J. Y. Beyon and G. J. Koch, "Novel Nonlinear Adaptive Doppler Shift Estimation Technique (NADSET) for the Coherent Doppler Lidar System VALIDAR," submitted to *Defense and Security Symposium 2006, Orlando, FL*, April, 2006.

[16] G. J. Koch, J. Y. Beyon, B. W. Barnes, M. Petros, , et. al., "High-Energy Doppler Lidar for Wind Measurements," submitted to the *Journal of Atmospheric and Oceanic Technology*, December 2005.

[17] G. J. Koch, B. W. Barnes, M. Petros, J. Y. Beyon, et. al., "Coherent differential absorption lidar measurements of CO_2," *Applied Optics*, Vol. 43, No. 26, pp. 5092–5099, September 2004.

[18] G. J. Koch, M. Petros, B. W. Barnes, J. Y. Beyon, et. al., "VALIDAR: A Testbed for Advanced 2-micron Doppler Lidar," in *Proc. of SPIE*, vol. 5412, pp. 87–98, April, 2004.

[19] G. J. Koch, M. J. Kavaya, B. W. Barnes, J. Y. Beyon, et. al. "Wind Measurements with High-Energy Doppler Lidar," submitted to the 86th American Meteorological Society Annual Meeting, Atlanta, GA, Jan., 2006.

[20] J. G. Proakis, C. M. Rader, F. Ling, and C. L. Nikias, *Advanced Digital Signal Processing*, Macmillan, 1992.

[21] L. R. Rabiner and B.-H. Juang, *Fundamentals of Speech Recognition*, Prentice Hall, 1993.

[22] P. Stoica and R. Moses, *Spectral Analysis of Signals*, Prentice Hall, 2005.

[23] C. W. Therrien, *Discrete Random Signals and Statistical Signal Processing*, Prentice Hall, 1992.

Biographies

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Grady J. Koch received a BS in electrical engineering in 1991 from Virginia Tech, an MS in electrical engineering in 1995 from the University of Illinois at Urbana-Champaign, and a Ph.D. in electrical engineering in 2001 from Old Dominion University. In 1987 he began work at NASA Langley Research Center as a cooperative education student, taking regular employment there in 1991. His research interests include coherent lidar, differential absorption lidar, solid-state lasers, and diode lasers.

FIGURE CAPTIONS

Figure 1 The averaged periodogram in the 17th range bin and the estimates of Doppler shift and power spectral density from the coherent lidar system VALIDAR. The look direction was <0, 90> and the parameters were estimated from 50,000 lidar return time series, sampled at 500 MHz and repeated twenty times for averaging. 512-point FFT was used to compute the periodogram of the data with the Rectangular window in each range bin. The lower and the upper limits of the Doppler shift frequency range were 95 MHz and 115 MHz.

Figure 2 The estimates of wind speed and wind direction from the coherent lidar system VALIDAR using the lidar returns from three look directions. The look directions were <0, 30>, <90, 30>, and <0, 90> and the system setup was identical with that in Figure 1.

Figure 3 Bin range identification by NADSET. The upward vertical line indicates the beginning and the downward, the end of range identified by NADSET. Only the first 50 bins have been shown in this figure and the direction was <0, 90>. The thick solid line is the Doppler shift estimates without NADSET.

Figure 4 The Doppler shift estimates by NADSET. The upward vertical line indicates the beginning and the downward, the end of range identification by NADSET. Only the first 50 bins have been shown in this figure and the direction was <0, 90>.

Figure 5 Bin range identification by NADSET. Only the 45th–100th bins have been shown in this figure and the direction was <0, 90>. The thick solid line is the Doppler shift estimates without NADSET.

Figure 6 The Doppler shift estimates by NADSET. Only the 45th–100th bins have been shown in this figure and the direction was <0, 90>.

Figure 7 Bin range identification by NADSET. The last 90th–190th bins have been shown in this figure and the direction was <0, 90>. The thick solid line is the Doppler shift estimates without NADSET.

Figure 8 The Doppler shift estimates by NADSET. The last 90th–190th bins have been shown in this figure and the direction was <0, 90>.

Figure 9 The Doppler shift estimate comparison. The dotted line is the estimates without NADSET and the thick solid line shows the estimates with NADSET.

Figure 10 The power estimate comparison. The dotted line is the estimates without NADSET and the thick solid line shows the estimates with NADSET.

Figure 11 Wind profile taken on June 28, 2005 processed without NADSET. The panels of data show, from top to bottom, 1) horizontal wind speed, 2) horizontal wind direction, 3) vertical wind speed (red upward, purple downward), and 4) backscatter signal power from zenith viewing. Vertical gaps appear in the data as one set of data ends and other begins or as problems occurred with the control computer. A speed or direction display in gray indicates that the measured value is out of range of the color scale.

Figure 12 The same set of data as Figure 11 with NADSET applied. Areas are circled in which NADSET created a benefit.

Figure 13 Horizontal wind measurements without (upper plot) and with (lower plot) NADSET applied reproduced from Figures 11 and 12 for convenient comparison.