IMPROVING WIND PROFILER MEASUREMENTS EXHIBITING CLUTTER CONTAMINATION USING WAVELET TRANSFORMS

Raisa Lehtinen[1] and Jim Jordan[2]

[1]Vaisala Inc, Boulder Operations, P.O. Box 3659, Boulder, CO 80307-3659, USA
Tel. +1-303-262-4030, Fax +1-303-499-1767, E-mail raisa.lehtinen@vaisala.com
[2]NOAA Earth System Research Laboratory, Boulder, Colorado, USA

Abstract
Radar wind profiler data is subject to contamination from various non-atmospheric signals, including stationary and moving ground clutter, intermittent clutter, and radio frequency interference (RFI). The interfering signals have characteristics that differentiate them from atmospheric turbulence return signals at the time-series level. This allows the contamination to be separated from the atmospheric signal before conventional Doppler spectra and spectral moments processing.

This document describes a set of wavelet transform methods, developed by the NOAA Earth System Research Laboratory, that have been implemented within the Vaisala LAP-XM® wind profiler control and signal-processing application software. Statistical tests have been used to identify and reduce the effect of the contaminating signals. We also discuss a new method that uses the wavelet filtering method together with downstream processing algorithms to provide better quality wind measurements.

1. Introduction
The Vaisala digital receiver implementation has a number of advantages for LAP® wind profilers, including a larger dynamic range. The reflected power from various clutter sources can be more than 60 dB larger than clear-air turbulence[1]. If the largest and smallest signals are contained within the linear range of the receiver, the total signal is a sum of the contributions. This enables separating the components with time-series signal processing techniques. Such filtering methods have been developed in recent years[2,3]. When combined with other algorithms, they offer new possibilities for addressing contamination problems in operational wind profilers.

The LAP-XM® software uses a combination of Daubechies, Harmonic and Haar wavelets to localize interference components with different waveform characteristics. The basic technique was suggested by Jordan et al.[2], and for all three methods consists of computing a discrete wavelet decomposition, clipping large coefficients that match the addressed contaminating waveform, and computing an inverse transform to obtain filtered time-series. The purpose of the wavelet filtering is to reduce the amplitude of the interfering signal to help the standard algorithms, such as statistical averaging[4] or consensus[5], to remove any remaining contamination. An important aspect of the wavelet clutter reduction algorithms is defining thresholds for signal clipping. All methods use adaptive statistical tests, separating the highly localized clutter signal from the Gaussian random distribution of the atmospheric signal. The user is not expected to need to adjust parameters for different environments or wind profilers.

2. Ground clutter
Ground clutter signals are caused by radar reflections from stationary targets, such as power lines, vegetation, or buildings. Reflections from ground clutter are characterized by very long coherence times compared to atmospheric signals. This coherence time difference allows the clutter component to be separated from the atmospheric part of the signal in the wavelet domain. A higher order Daubechies wavelet, such as the DAUB20 (shown in the insert of Figure 1), is used in this application because it provides a good match to the smooth clutter signals.

Figures 1 to 4 illustrate the use of the method at a wind profiler site that receives a lot of ground clutter contamination. Figure 1 shows a time-series sequence before and after applying the Daubechies filtering algorithm. Figure 2 shows the corresponding power spectra. The weak atmospheric signal is just to the right from the ground clutter peak. The radial velocity estimated from the original spectrum is biased by the ground clutter. The wavelet filtered spectrum has greatly reduced ground clutter contamination, and less spectral leakage. Spectral moments calculated from this spectrum will have less ground clutter bias.

While the filtering algorithm can reduce the ground clutter and spectral leakage, the benefits over conventional methods are not yet obvious. The method will not remove all ground clutter, and it may prevent spectral domain clutter reduction methods[6] from recognizing the remaining near zero velocity peaks as clutter. However, this algorithm becomes especially effective when the filtering information is used with a multiple-peak picking algorithm for calculating the moments, such as the ETH MPP method[7]. If the wavelet method has removed a significant portion of the spectral energy near DC point, a measure of the reduction level can be used by the multiple peak algorithm to reject any residual signal as ground clutter. Initial tests with this method have indicated that it is possible to recover the correct wind profile in cases where spectral methods fail to identify the ground clutter signal. Figures 3a-d show a time-height spectral image from a profile where the atmospheric signal crosses the DC area. Conventional signal processing fails to detect the clutter peak, and considers the partly overlapping peaks as one. Wavelet filtering significantly reduces the ground clutter peak, but the radial velocity estimate from the standard single peak algorithm (Figure 3b) is biased at some range gates, and selects an interference peak at the lowest altitude. Multiple-peak picking algorithm (Figure 3c) is able to resolve the two peaks, but without proper clutter identification will select the highly continuous residual clutter profile. When wavelet filtering information is used to identify the residual peak (Figure 3d), multiple-peak picking selects the atmospheric signal. Figures 4a-b compare wind profiles from the two processing methods. The wind velocities at the lowest altitudes in 4a are biased by the ground clutter, and there are also several missing wind results. The new method is able to recover more measurement results, and the obtained winds are more consistent.

3. Bird interference

Migrating birds produce a well-known quality control problem for wind profilers. The persistent, nearly constant velocity radar return signal can cause a significant bias to the measured wind speed and direction. Bird signal contamination has a discernible structure that can be identified in the profiler time-series signal. The wing and body motion of a flying bird produces a sinusoidal signal characteristic with a 90-degree phase difference between I and Q components. Movement of a bird through the radar beam causes a frequency sweep, and a localized appearance during the dwell period. This type of vibrating signal can be analyzed with the complex Harmonic wavelets. The frequency presentation of a Harmonic wavelet has a box-shape that covers a band of frequencies. In the time-domain, the wavelet consists of real and imaginary sinusoidal wavelets that closely match the bird signal (Figure 5). The discrete Harmonic wavelet transform can be calculated using a Fast Fourier Transform. To avoid frequency leakage, a strong radar return signal should first be filtered with the Daubechies wavelet method.

Figures 6 and 7 show time-series and power spectra from a site that experienced significant bird data contamination. The interfering signal amplitudes are overwhelming compared to other signal components, as shown in Figure 6a, where the contamination occurs near the end of the dwell time. The statistical averaging method failed at several range gates due to the long duration of the interference, and this resulted in corrupted spectra as shown in Figure 7. The Daubechies method is able to remove most of the signal energy, and the Harmonic wavelet method reduces the remaining oscillations. The contamination is almost completely removed from the power spectra, and the atmospheric profile can be recovered.

4. Radio frequency interference

RFI from cell phones or spread spectrum transmitters generates sharp localized peaks in the time-series signal. This type of contamination raises the noise floor in the Doppler spectra that can sometimes mask the atmospheric signal. While the interference can be easily identified, it is important to remove it in a way that does not cause additional distortions to the spectra. The algorithm utilizes the jagged shape of the Haar wavelet (shown in the insert of Figure 8), which provides a good match to narrow interference peaks. A single level Haar wavelet decomposition is used to separate the smallest scale components from the time-series. Interference signals will appear as pronounced peaks in the fine resolution wavelet coefficients. A statistical test is used to determine the maximum atmospheric coefficient value. This value determines a threshold for removing interfering coefficients. Figure 8 shows a time-series array before and after applying the Haar filtering algorithm. Figure 9 shows the corresponding power spectra. Haar wavelet filtering has slightly reduced the noise floor fluctuations. This helps identifying the very weak atmospheric signal around 1.5 m s^{-1} radial velocity in the example.

5. Conclusions

This document describes three wavelet filtering algorithms that have been implemented in an operational wind profiler signal processing application. The studied methods combine a set of discrete wavelet transforms with statistical methods to remove unwanted contamination. A new method is also introduced where the amount of filtered spectral power is used to detect and remove residual ground clutter. The algorithms have been shown to improve wind measurement reliability at sites that experience severe clutter contamination. Along with other improvements in wind profiler signal processing, they are expected to increase the range of possible sites and applications where wind profilers can be used.

The U.S. Dept. of Commerce is the holder of U.S. patents 5,592,171 and 5,686,919, which are applied in the clutter reduction methods described here.

References

1. Jordan, J.R., J.L. Leach, and D.E. Wolfe, 2003: Operation of a Mobile Wind Profiler In Severe Clutter Environments. *12th Symposium on Meteorological Observations and Instrumentation*, Louisville, CO, USA.
2. Jordan J.R., R.J. Lataitis, and D.A. Carter, 1997: Removing ground and intermittent clutter contamination from wind profiler signals using wavelet transforms. *J. Atmos. Oceanic Technol.*, **14**, 1280-1297.
3. Lehmann V., and G. Teschke, 2006: A new intermittent clutter filtering algorithm for Radar Wind Profiler, 7th International Symposium on Tropospheric Profiling.
4. Merritt, D.A., 1995: A statistical averaging method for wind profiler Doppler spectra. *J. Atmos. Oceanic Technol.*, **12**, 985-995.
5. Fischler, M.A., and R.C. Boller, 1981: Random sample consensus: A paradigm for model fitting with applications to image analysis and automated cartography. *Commun. Assoc. Comput. Mach.*, **24**, 381-395.
6. Riddle, A.C., and W.M. Angevine, 1992: Ground clutter removal from profiler spectra. Proc. *Fifth Workshop of Technical and Scientific Aspects of MST Radar*, Aberystwyth, Wales, United Kingdom, URSI/SCOSTEP 418-420.
7. Griesser, T., and H. Richner, 1998: Multiple peak processing algorithm for identification of atmospheric signals in Doppler radar wind profiler spectra. *Meteorol. Zeitschrift*, **7**, 292-302.

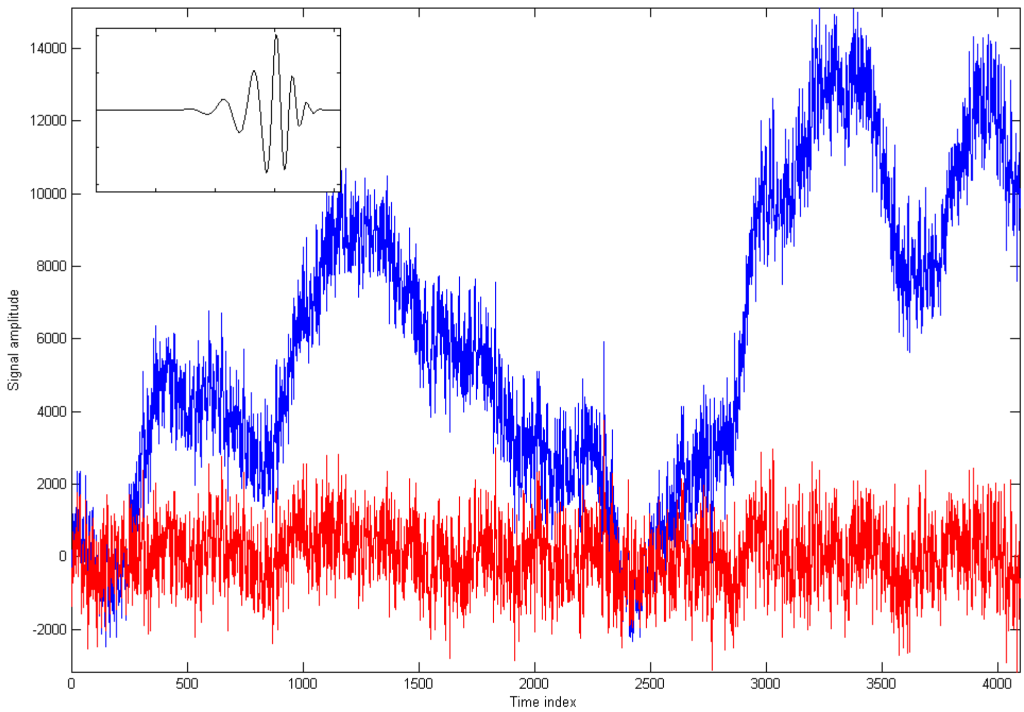

Figure 1. Time-series data from a 915MHz wind profiler at Storrs, Connecticut, Oct. 4, 2004, 22:03:43 UTC, range gate 5. The original in-phase component is shown in blue, the wavelet filtered component in red. Daubechies 20 wavelet (insert) was used in the discrete wavelet transform.

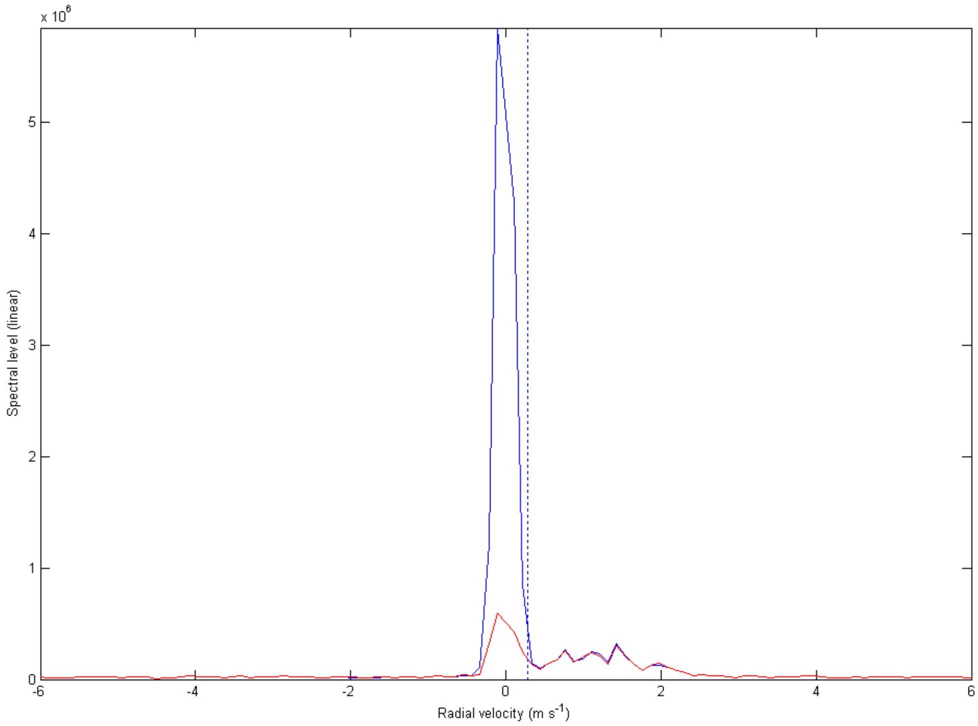

Figure 2. A detail of the power spectra calculated from the time-series in Figure 1. The original power spectrum (blue) is compared to the filtered power spectrum (red). The DC point has been interpolated. The dashed line shows the estimated radial velocity from the original power spectrum.

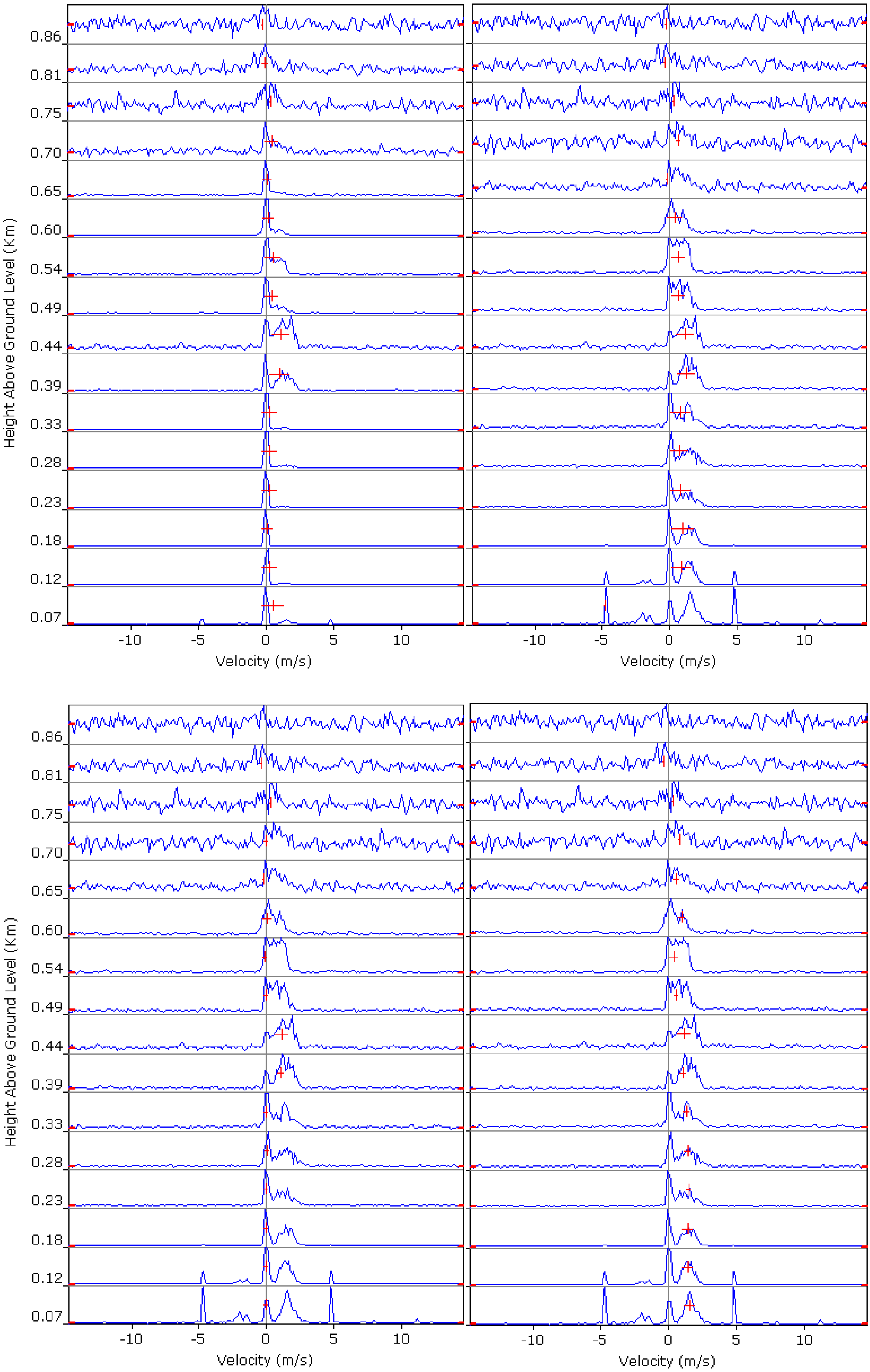

Figure 3. From top left to bottom right: Power spectra and moments using (a) standard processing, (b) wavelet filtering and standard moments estimation, (c) wavelet filtering and multiple-peak picking, (d) wavelet filtering, multiple-peak picking and ground clutter detection based on the amount of wavelet filtered spectral power. Data source as in Figure 1, showing range gates 1-16.

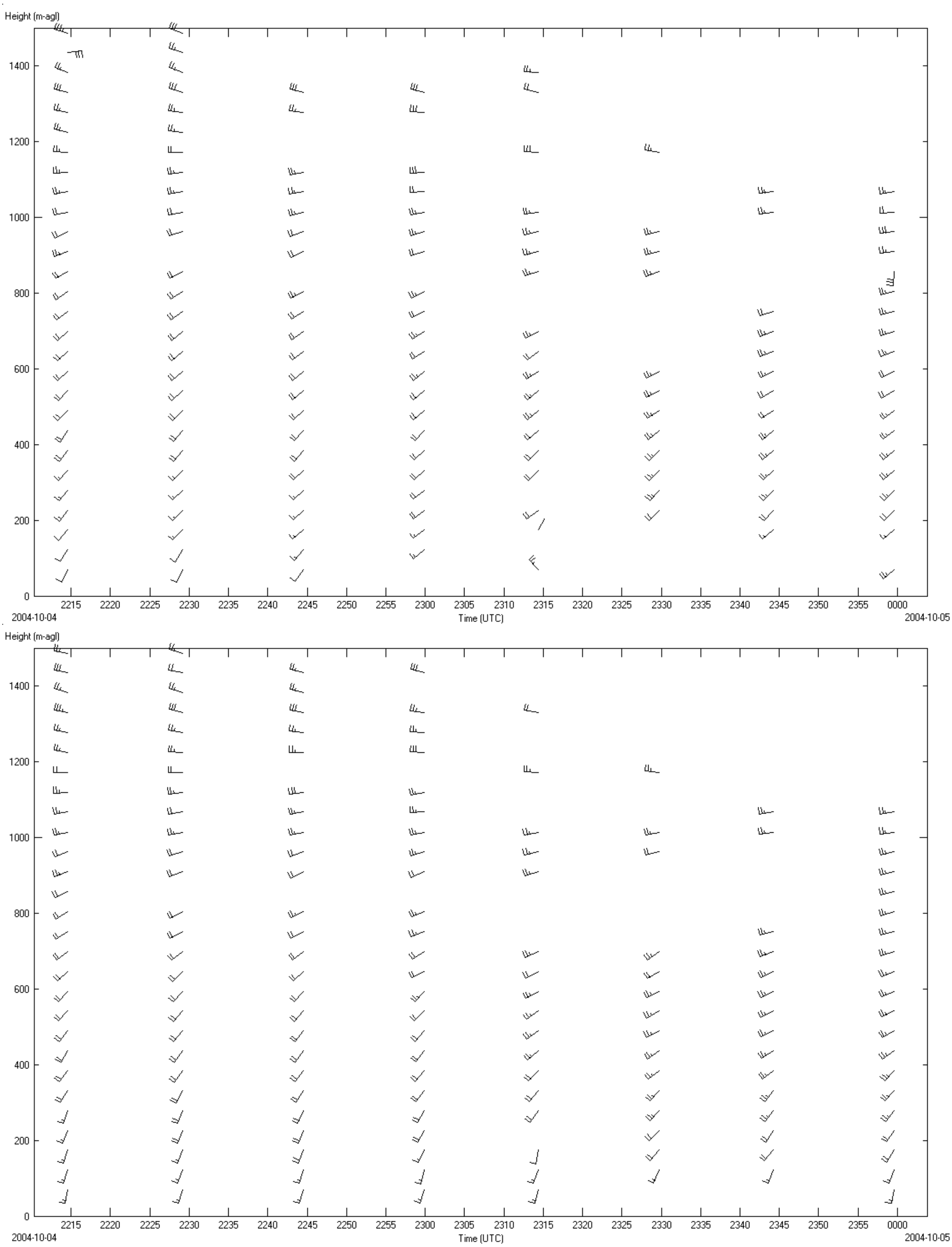

Figure 4. Wind profiles from the 915 MHz Storrs wind profiler, showing the lowest 1500 m of altitudes from the low mode. (a) Using standard processing, and (b) using wavelet filtering and the multiple-peak picking algorithm with wavelet filtering information.

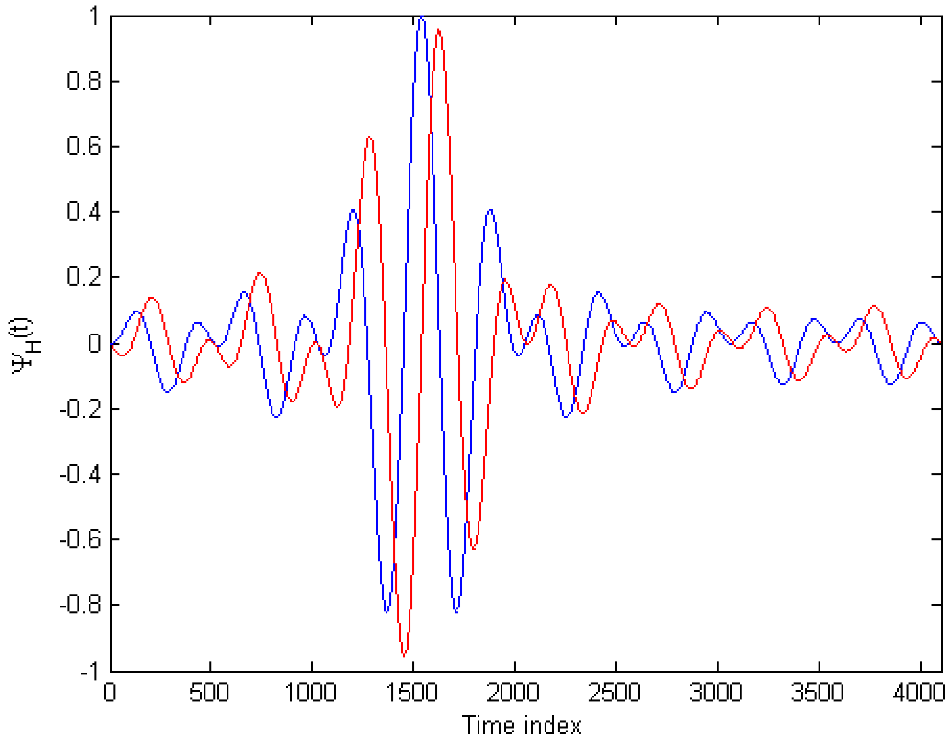

Figure 5. The real (blue) and imaginary (red) parts of the Harmonic wavelet shown at one scale and displacement.

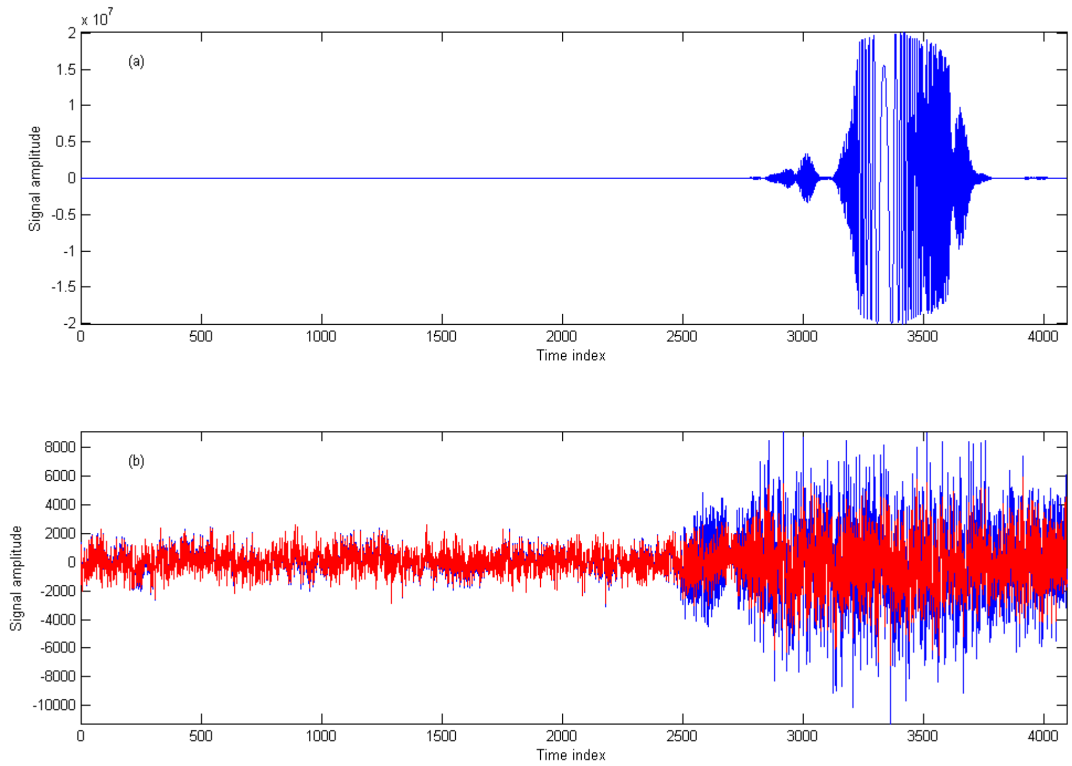

Figure 6. Time-series data from the Boulder Atmospheric Observatory 449 MHz wind profiler, Oct. 10, 2003 at 23:06:40 UTC, range gate 21, (a) original data and (b) after Daubechies20 (blue), and Harmonic (red) wavelet filtering.

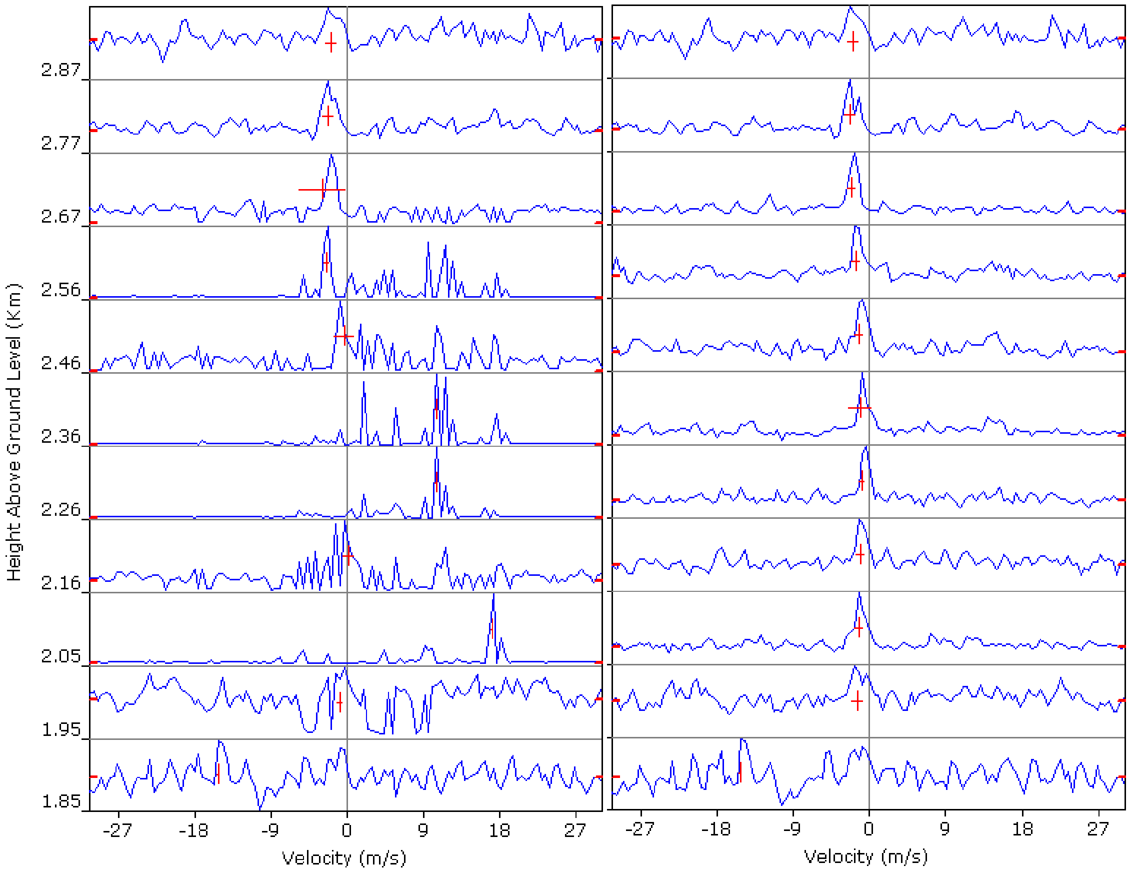

Figure 7. Power spectra and moments using standard processing (left) and Daubechies20 and Harmonic wavelet filtering (right). The data are from the same measurement as in Figure 6, showing range gates 17 to 27.

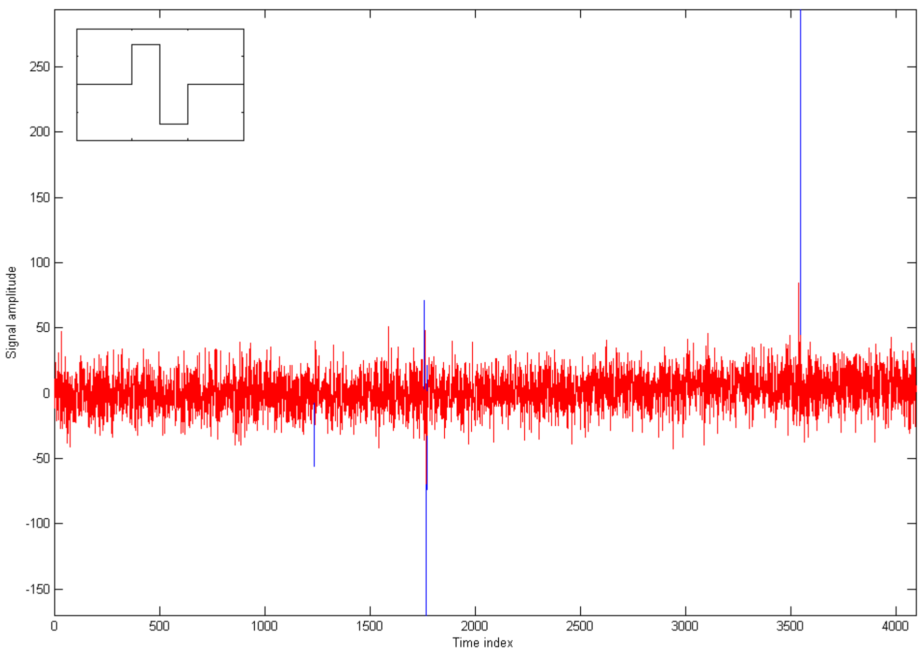

Figure 8. Time-series data from a boundary layer wind profiler at the Hong Kong airport, March 12, 2001, 13:21:55 UTC, range gate 3. The wavelet filtered in-phase component (red) is shown on top of the original component (blue). The Haar wavelet (insert) was used in the discrete wavelet transform.

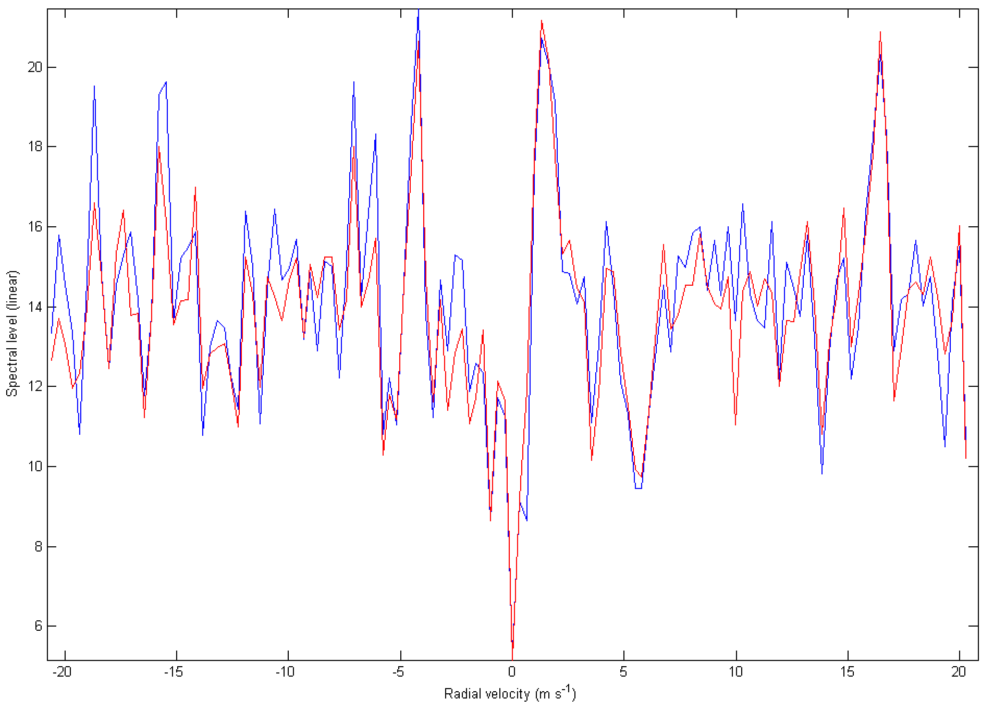

Figure 9. Power spectra computed from the time-series in Figure 8, before (blue) and after (red) Haar wavelet filtering.