WAVELET BASED METHODS FOR IMPROVED WIND PROFILER SIGNAL PROCESSING

Volker Lehmann
Deutscher Wetterdienst
D-15864 Lindenberg

Gerd Teschke
Universität Bremen, ZeTeM
D-28334 Bremen

Radar Wind Profiler (RWP) technology has reached a stage, where Meteorological Services consider their operational use within the Global Observing System (GOS), see [9]. In this contribution we concentrate on systems which employ the widely used Doppler-Beam swinging (DBS) method for the determination of the vertical profile of the horizontal wind.

The operational experience with these systems has shown, that the "classical" signal processing for the DBS method (see, for instance [10]) is not optimal with respect to the effective filtering of non-atmospheric signals. Especially ground and intermittent clutter signals can lead to serious degradations of the computed winds. Improved signal processing using Wavelets was proposed by [6, 1], but the main problem with this technique so far has been the lack of fine-tuning procedures.

The currently used digital processing assumes that the signal consists of two parts: The signal that is produced by the atmospheric scattering process and noise. This is certainly *not true*. Additional signal contributions emerge from ground clutter echoes, intermittent clutter and occasionally spurious Radio Frequency (RF) signals of internal or external origin. In the following, we will concentrate on the clutter problem and demonstrate the potential of Wavelet filtering with one typical example, where the standard signal processing yielded erroneous wind data.

The used data were sampled using the 482 MHz profiler at the Observatory Lindenberg of the Deutscher Wetterdienst on the 1st of December 1999. A more detailed look into the I/Q-Timeseries of the East Beam's Gate 11 and 17 at 08:53:38 UTC (Figure 1) and the resulting power spectra makes immediately clear that advanced signal processing for RWP is necessary to increase the accuracy of wind vector reconstruction. The timeseries at Gate 11 shows the typical signature of a slowly fading, large amplitude ground clutter signal component, which corresponds to the narrow spike centered around point 1024 (zero Doppler shift) in the resulting power spectrum [8]. In contrast, the timeseries at Gate 17 shows a strong transient component in the last quarter. Such a signature is quite typical for a flier echo, as was shown by [1]. This transient almost completely covers up any atmospheric signal in the power spectrum.

Motivated by [3, 7] our purpose was to embed the filtering procedure into the known mathematical theory of wavelets. Wavelet techniques seem to be more than promising because very important is the fact that the contamination appears often instationary and with a priori unknown scale structure. In order to localize clutter components one may use a great variety of wavelet filters [2] i.e. to choose a certain wavelet one has to determine the properties of clutter.

The main emphasis of doing wavelet domain filtering is to create a suitable, i.e. problem matched, coefficients selecting procedure. We apply statistical estimation theory to separate the atmospheric component. A side effect of using statistics is to get a measure of reconstruction quality. This reveals a objective evaluation and a self-acting filter algorithm.

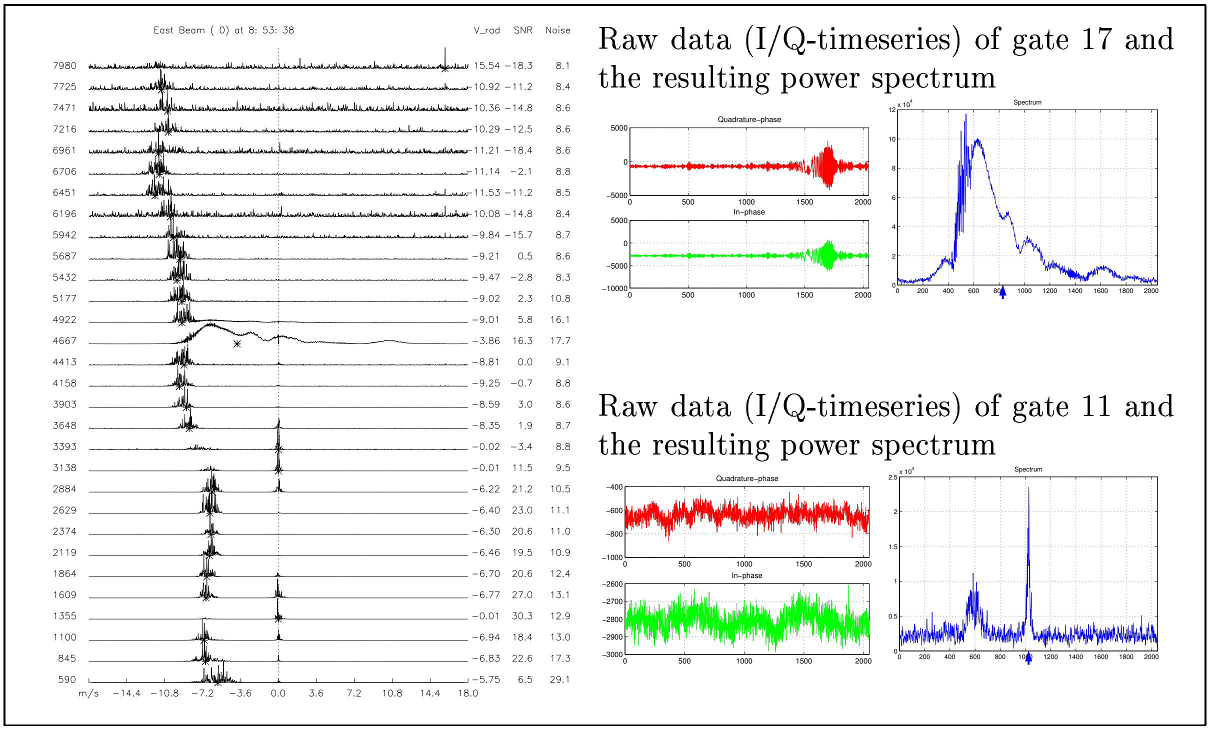

Figure 1: This figure shows the East beam and a detailed look into raw data.

We assume that our data f may be represented as a series

$$f(x) = \sum_k \alpha_k \phi_{0k}(x) + \sum_j \sum_k \beta_{jk} \psi_{jk}(x).$$

This expansion is a special kind of orthogonal series. In case of orthogonal series estimation the idea of reconstructing the desired atmospheric signal is not difficult.

From given measurements $(Y_1, \ldots, Y_n)$ we want to estimate the function f in the simple model

$$Y_i = f(X_i) + \varepsilon_i,$$

where ε is a stochastic process. The basic idea is to replace the wavelet coefficients in the series expansion by empirical estimates $\hat{\alpha}_{jk} = \frac{1}{n}\sum_{i=1}^{n} Y_i \cdot \varphi_{jk}(X_i)$ and $\hat{\beta}_{jk} = \frac{1}{n}\sum_{i=1}^{n} Y_i \cdot \psi_{jk}(X_i)$, where the X_i are timestamps and the Y_i are observations. A straightforward linear estimation is given by the projection

$$\hat{f}_{j_1}(x) = \sum_k \hat{\alpha}_{j_0 k} \varphi_{j_0 k}(x) + \sum_{j=j_0}^{j_1} \sum_k \hat{\beta}_{jk} \psi_{jk}(x).$$

To appraise this estimator it is known that one may solve the expected loss or the risk $E\|\hat{f}_{j_1} - f\|_2^2$ (mean integrated squared error).

Obviously this kind of linear estimation includes all clutter components, because we have taken the whole set of wavelet coefficients , i.e. we have not performed any filtering step so far.

In the following we want to apply so-called hard thresholding and soft thresholding respectively. These routines were introduced and adapted to several problems by Donoho

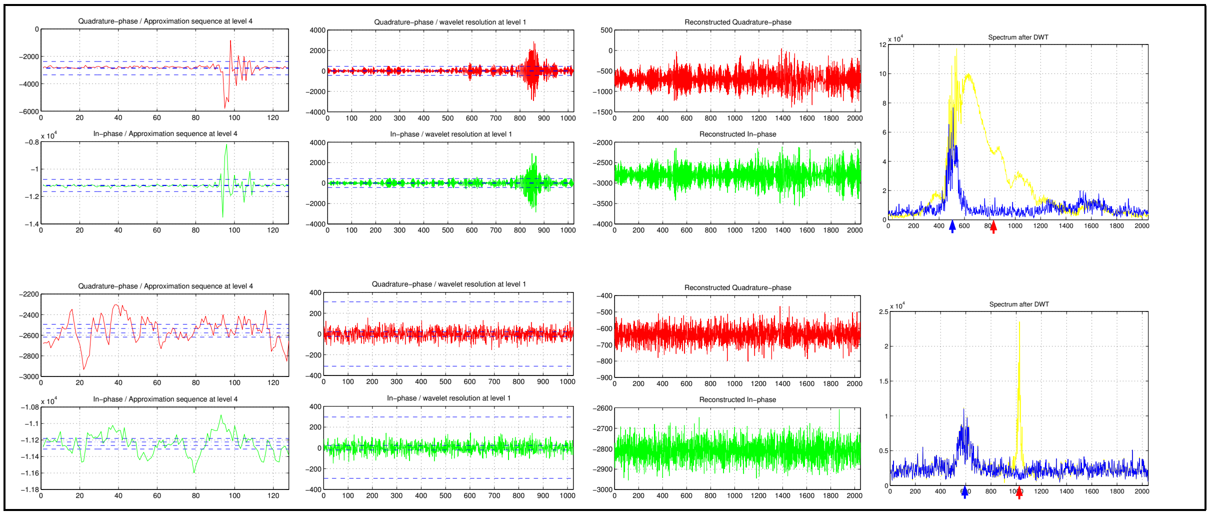

Figure 2: Decomposition (sequences of level 4), reconstruction and Fourier power spectrum of gate 17 (top) and gate 11 (below). The dark curves in the power spectra representations display the decontaminated spectra. Clearly to recognize are the differences of moment estimations, see the computed first moment before (red arrow) and after (blue arrow) the filtering step.

and Johnstone [4, 5]. Inspired by these easy to implement procedures we adjusted it to our problem.

The functions of soft and hard thresholding are given by $\eta^s(u) = (|u| - \lambda)_+ \mathrm{sgn}(u)$ and $\eta^h(u) = u\chi_{\{|u|>\lambda\}}$ respectively. Here λ is a adequate threshold. Applying this rule to our linear wavelet estimator we get a nonlinear estimator

$$\hat{f}^*(x) = \sum_k \eta^*(\hat{\alpha}_{j_0k})\varphi_{j_0k}(x) + \sum_{j=j_0}^{j_1}\sum_k \eta^*(\hat{\beta}_{jk})\psi_{jk}(x),$$

where η^* is η^s and η^h respectively.

If the threshold λ is specified according to the asymptotic distribution of the empirical coefficients, only those coefficients remain which are supposed to carry significant signal information. These are finally used for the reconstruction by the inverse wavelet transform. For the right level of significance an appropriate choice of the threshold λ is needed, which in general depends not only on the sample size n, but also on the resolution scale j and location k of the coefficients. In case of regression with non-stationary errors we have to use a both level and location dependent threshold rule [11]. For thresholds λ_{jk} satisfying $\sigma_{jk}\sqrt{2\log M_j} \leq \lambda_{jk} \leq C\sqrt{\frac{\log n}{n}}$ and for any positive constant C we have $\sup_{f\in F^s_{22}(M)} E\|\hat{f}^* - f\|_2^2 = O\left((\log(n)/n)^{2s/(2s+1)}\right)$, where σ_{jk} is the variance and M_j denotes the number of the coefficients used in the nonlinear estimator. The optimal threshold rate is attained only for the optimal threshold. But in practice this is unknown and thus we have to replace σ_{jk} by some estimation $\hat{\sigma}_{jk}$. Hence the log-term is to understand as the price for some data-driven threshold rule and it originates due to the estimation of the unknown variance $\sigma^2_{jk} = Var(\hat{\beta}_{jk})$.

Coming back to our particular dataset (see Figure 1), the problem was that gate 17 was contaminated by intermittent clutter (aircraft echoes) and gate 11 by ground clutter.

Using standard signal processing without any filtering step prior to the FFT, the spectra were significantly biased and therefore the moment estimation and in the end the wind vector reconstruction. Figure 2 exemplifies how wavelet thresholding was realized in the decomposition sequences $\alpha_{4\cdot}$ and $\beta_{4\cdot}$ of gate 11 and 17. The dotted lines may be identified with the threshold λ_4.

Result: We have demonstrated wavelet domain filtering using real wind profiler data. The ideas of discrete multiscale analysis and nonlinear estimation theory were used and developed for removing ground and intermittent clutter (airplane echoes). The presented algorithm is a step toward removing clutter automatically and stable. Real time implementation in profiler systems is required to test the new method with a substantially longer dataset, preferably in parallel with the standard processing (comparison), and to demonstrate its use for operational applications.

References

[1] J.-C. Boisse, V. Klaus, and J.-P. Aubagnac. A wavelet transform technique for removing airplane echos from ST radar signals. *Journal of Atmospheric and Oceanic Technology*, 16:334–346, March 1999.

[2] S. Dahlke, P. Maaß, and G. Teschke. Interpolating scaling functions with duals. *Report 00-08, Zentrum für Technomathematik, Universität Bremen*, 2000.

[3] I. Daubechies. *Ten Lectures on Wavelets.* SIAM, Philadelphia, 1992.

[4] D. L. Donoho and I. M. Johnstone. Minimax estimation via wavelet shrinkage. *Technical Report No. 402, Department of Statistics, Stanford University*, 1992.

[5] D. L. Donoho, I. M. Johnstone, G. Kerkyacharian, and D. Picard. Density estimation by wavelet thresholding. *Preprint, Dept. of Statitics, Stanford University*, 1993.

[6] J. R. Jordan, R. J. Lataitis, and D. A. Carter. Removing ground and intermittent clutter contamination from wind profiler signals using wavelet transforms. *Journal of Atmospheric and Oceanic Technology*, 14:1280–1297, December 1997.

[7] Louis, Maaß, and Rieder. *Wavelets.* Teubner, Stuttgart, 1998.

[8] P. T. May and R. G. Strauch. Reducing the effect of ground clutter on wind profiler velocity measurements. *Journal of Atmospheric and Oceanic Technology*, 15:579–586, April 1998.

[9] W. A. Monna and R. B. Chadwick. Remote-sensing of upper-air winds for weather forecasting: Wind-profiler radar. *Bulletin of the WMO*, 47(2):124–132, April 1998.

[10] T. Tsuda. *Middle Atmosphere Program - Handbook for MAP*, volume 30, chapter Data Acquisition and Processing, pages 151–183. ICSU Scientific Committee on Solar-Terrestrial Physics (SCOSTEP), 1989. ISAR 24.-28. November 1988, Kyoto.

[11] R. v. Sachs and B. MacGibbon. Nonparametric curve estimation by wavelet thresholding with locally stationary errors. *Preprint, Dept. of Math, University of Kaiserslautern*, 1998.