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Wavelet Based Methods for Improved Wind Profiler Signal Processing

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Abstract- **In this paper we apply wavelet thresholding for removing ground clutter and intermittent clutter (airplane echoes) automatically from wind profiler radar data. Using the concept of discrete multiscale analysis and nonparametric estimation theory we develop wavelet domain thresholding rules which allow us to identify the coefficients relevant for clutter and to suppress them to get filtered reconstructions.**

Key Words- Wind profiler radar, Ground and intermittent clutter, Doppler signal spectrum, Discrete wavelet analysis, Nonlinear and nonparametric estimation techniques

Introduction

Radar Wind Profiler (RWP) technology has reached a stage, where Meteorological Services consider their operational use within the Global Observing System (GOS), see [MC98]. In this paper, 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[1].

These radar systems transmit short electromagnetic pulses in a fixed beam direction and sample the small fraction of the electromagnetic field, that is backscattered to the antenna. (Due to the nature of the acting atmospheric scattering processes, the received signal is several orders of magnitude weaker than the transmitted signal.) The received signal is Doppler shifted, which is used to determine the velocity component of "the atmosphere" projected onto the beam direction. As the occupied spectrum bandwidth of the transmitted electromagnetic pulse is much larger

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[1]Under certain conditions, the vertical wind component can be measured additionally

($\propto 1/\tau \approx 100...1000$ kHz) than the Doppler shift ($f_d \approx 10...500$ Hz), the frequency shift can not be determined from the processing of a single pulse. Instead, the return of many pulses is evaluated to compute the Doppler frequency from the slowly changing (relative) phase of the received signals [BR86]. The samples at each range gate form a discrete time series which are the *raw data* of the measurement (e.g. [DZ93]). The reflected power, the radial velocity and the velocity variance (e.g. the first three moments of the Doppler spectrum) contained in this data is usually extracted using the well established 'classical' signal processing, as described by [Tsu89], among others. Finally, at least three independent beam directions are required to transform the measured 'line-of-sight' radial velocities into the wind vector.

The operational experience with these systems has shown, that the "classical" signal processing for the DBS method 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. This problem is well known within the profiler community and several methods have been proposed so far. Especially time domain processing has recently become a matter of increasing interest, probably due to the improved computational capabilities of modern Digital Signal Processors. In this contribution we deal with wavelet based techniques. Related approaches were done in the papers/works of J.Jordan et al., J.Boisse et al.. The main problem with this method is that there exist no fine-tuning procedures so far.

Generally, the purpose of radar signal processing is to extract the desired characteristics of the atmospheric echoes. The goals of signal processing are thus [KP90]:

- to provide accurate, unbiased estimates of the characteristics of the atmospheric echoes
- to estimate the confidence/accuracy of the measurement
- to mitigate effects of interfering signals
- to reduce the data rate

It must be noted, that signal processing includes all operations that are performed on the radar signal, that is analog[2] as well as digital processing[3]. However, in the following we will only concentrate on digital signal processing. The incredible development of fast digital processors opens up new opportunities to optimize this latter part of the signal processing chain.

Statement of the Problem

Classical RWP signal processing is visualized in Figure 1. So far, the currently used digital processing (at least the processing that is implemented in commercially available systems) assumes, that the signal consists of two parts: The signal that is produced by one (and only one) atmospheric scattering process and noise (different

[2] amplification, mixing and matched filtering

[3] after A/D conversion

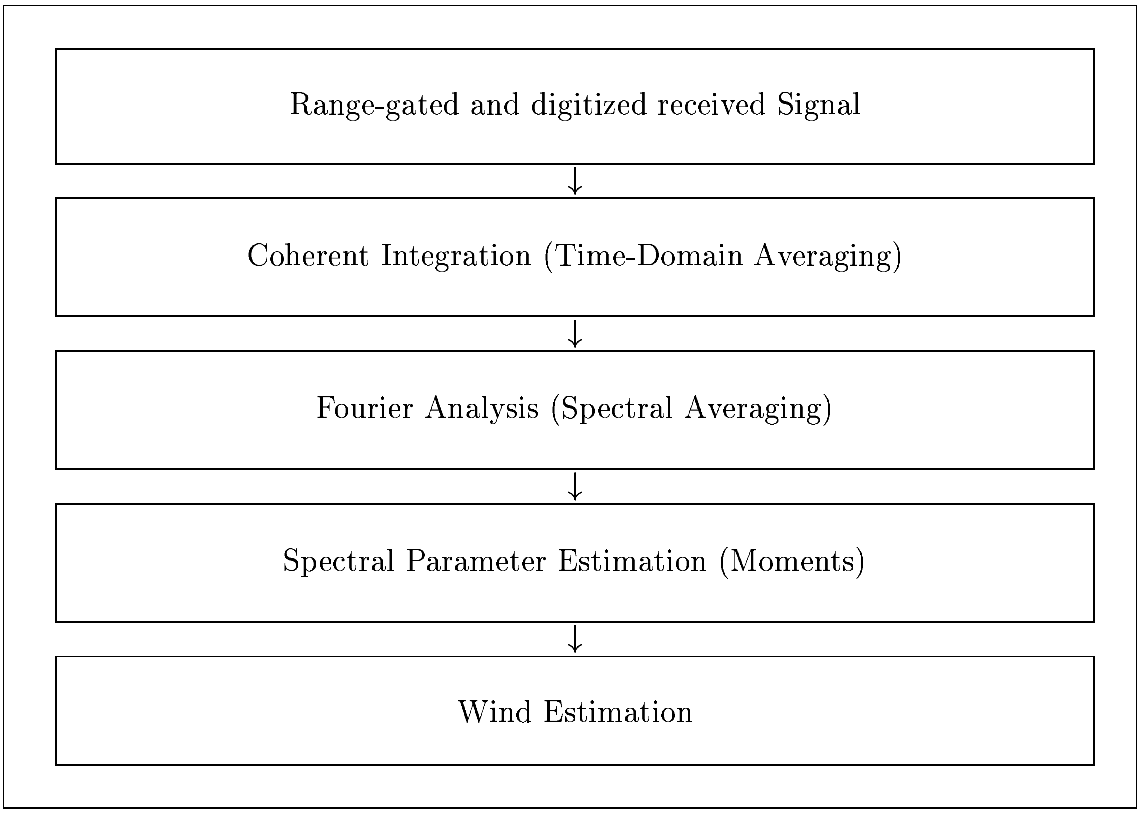

Figure 1: The figure shows the flow diagram of 'classical' digital signal processing.

sources, mainly thermal electronic noise and cosmic noise). This is certainly not true. Additional signal contributions emerge from ground clutter echoes due to antenna imperfections, i.e. sidelobes, intermittent clutter echoes due to fliers (planes, birds) both in the main lobe and in the sidelobes of the antenna and occasionally spurious Radio Frequency (RF) signals of internal or external origin. Especially at UHF, the atmospheric signal itself can be the result of two distinct scattering processes (at least at times), namely scattering at inhomogenities of the refractive index and scattering at particles like droplets or ice crystals. So, even the desired atmospheric signal may have different characteristics. However, here we will concentrate on the clutter problem and demonstrate this by one typical example, where the standard signal processing yielded erroneous wind data.

The 482 MHz wind profiler whose data are used in this study was installed at the Meteorological Observatory Lindenberg in Summer 1996. The system is the prototype for three additional profilers, which will be installed in Germany to supplement the aerological network of DWD. A summary of the main characteristics of the system is given below. For a more detailed description, the reader is referred to [SDE$^+$98]. The system is operated quasi continuously using a five beam configuration. All the main parameters can be freely programmed, for special investigations. In particular, for the investigation of the detrimental clutter signal that was present in the systems East beam from the 30th November to the 1st of December 1999, the profiler was operated for a short period using this beam (and low mode) only, while the huge amount of timeseries data was stored for further investigation (namely the Wavelet filtering). We now substantiate the radar parameter settings, that were used in collecting the radar raw data.

Site name	Lindenberg 482 MHz Profiler
Latitude	52.21 N
Longitude	14.13 E
Altitude	103 m msl
Frequency	482.0078 MHz
One-way beamwidth	3 degrees
Number of beams	5
Zenith distance	15 degrees
Effective antenna area	140 m^2
Pulse peak power	16 kW
Altitude Range	0.5 - 8.0 km (Low Mode)
Beamdirection	East (Azimuth:79 Elev. 75)
InterPulsePeriod (IPP)	61 μs
Pulsewidth	1700 ns (Low Mode)
Delay to first gate	4800 ns
Gate Spacing	1700 ns
Number of gates	30
# of coherent integrations (NCI)	144
# of spectral integrations	1 (none)
# of points on online FFT	2048
System Delay (w/ 1700 ns pulse)	1550 ns

Table 1: Specification of RWP.

From the table of the radar's parameter settings, we find that the spacing of the timeseries data is $\Delta t = NCI * IPP = 8.784\ ms$. This corresponds to a Nyquist frequency of $f_N = 1/2\Delta t = 56.92\ Hz$, which gives in turn the maximum resolvable radial velocity $v_R = \lambda f_d/2 = 17.6$ m/s.

Clearly visible in figure 2 is the detrimental impact of ground clutter at the heights around 1400 m and 3000 m. The computed winds are obviously wrong and we will therefore look in detail into the problem. The gap in the data shown above was caused by this detailed investigation as the radar was programmed to store time series data for about 30 minutes in the East beam only, thus no wind computations were possible for that period of time.

A more detailed look into the raw data (I/Q-Timeseries) of Gate 17 and 11 and the resulting power spectra (Figure 3) shows 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, compare also [MS98]. 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 [BKA99]. This transient almost completely covers up any atmospheric signal in the power spectrum.

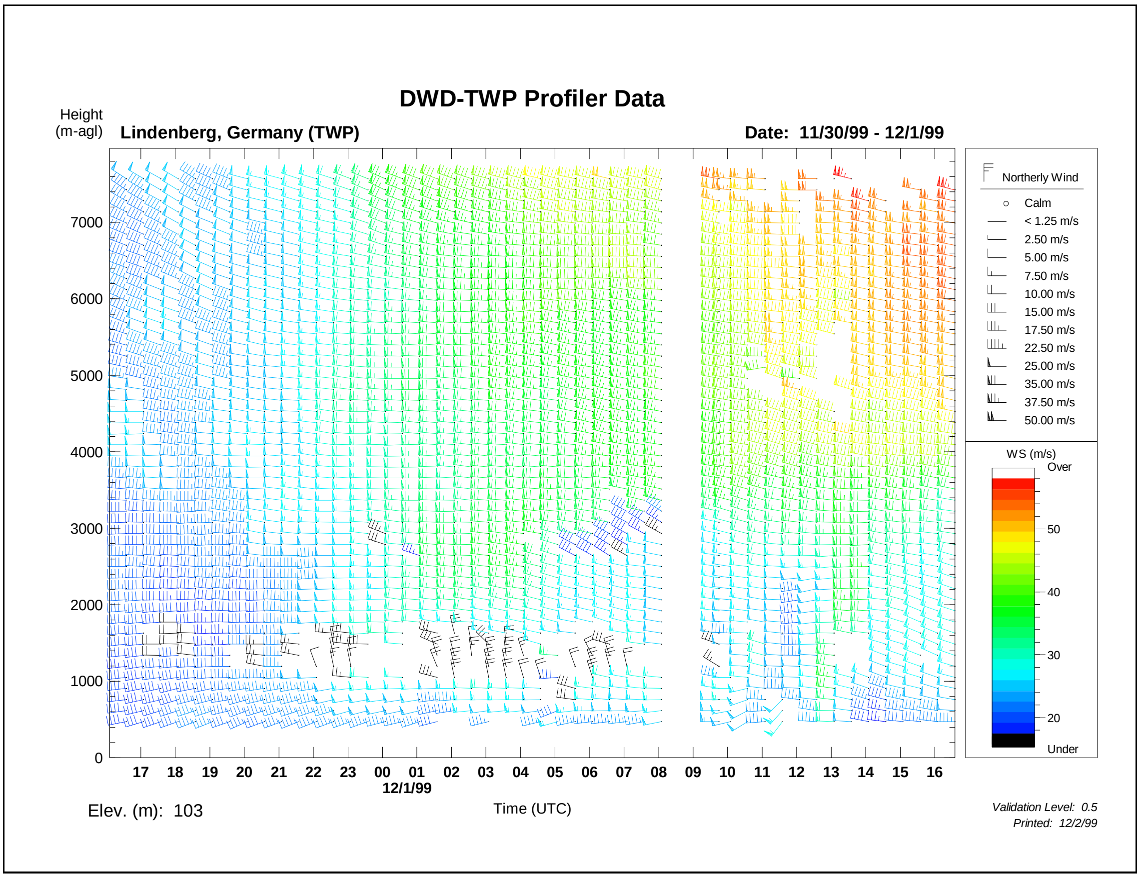

Figure 2: The figure shows the final result of the measurement with the 482 MHz RWP at Lindenberg (Germany) on the 30th November and 01st December 1999. This system is a prototype for a planned operational network of RWP's of the Deutscher Wetterdienst and is described in detail by [SDE$^+$98].

Applying Multiscale Analysis and Statistical Estimations

The main goal of the signal processing should be signal separation, i.e. a reliable extraction of signal components (noise, clutter, interference) automatically and stable. New developments in digital signal processing may be classified basically in three categories: time domain, frequency domain or wavelet domain operations.

The recently proposed algorithms in the wavelet domain aim at filtering of ground and intermittent clutter [JLC97] and filtering of intermittent clutter [BKA99]. In the time domain, the application of (digital) linear convolution filters (e.g. FIR[4] filters) (band reject) to suppress or eliminate ground clutter contribution [MS98] and out-of-band radio frequency interference [WML$^+$99] (low pass) has been published. The main purpose of all these operations is the filtering aspect, that is we intend to "clean" the raw data from contaminating signals while leaving the desired atmospheric contribution ideally intact.

Historically[5], there has been more emphasis on frequency domain processing,

[4] Finite Impulse Response

[5] Technically, the access to frequency domain data (i.e. spectra) is much easier as the data volume is significantly reduced due to the data compression effect of the periodogram computation and the spectral integration

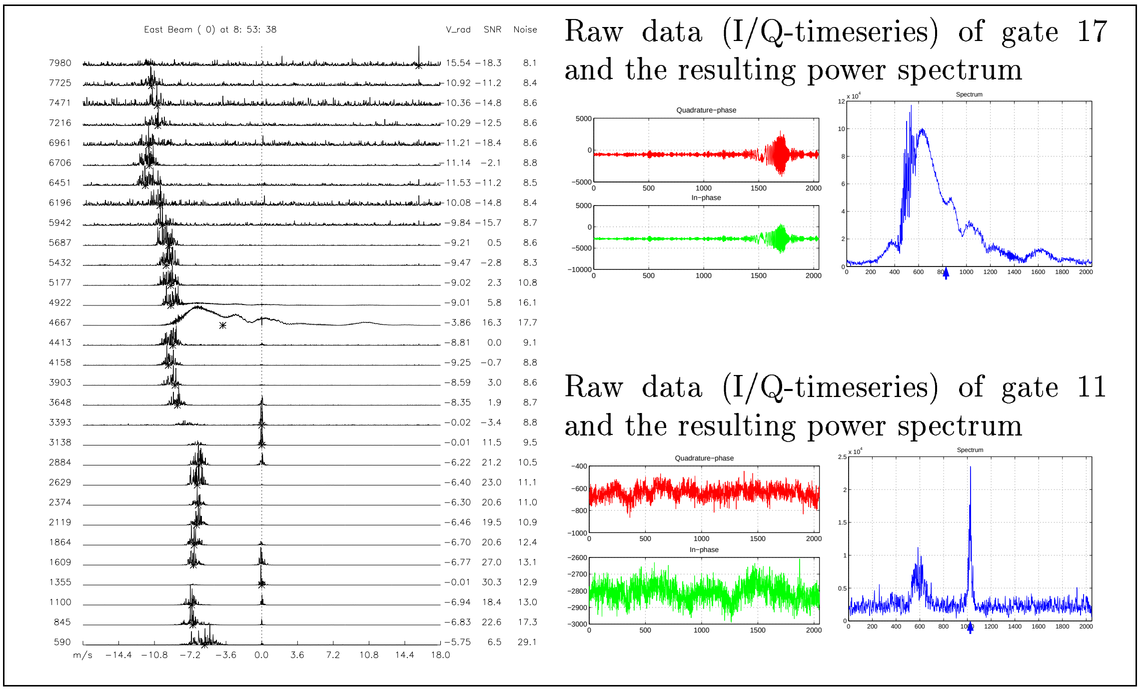

Figure 3: This figure shows the East beam and a detailed look into raw data.

mainly in the process of moment estimation. The difference with these methods is, that one does not attempt to perform any "cleaning" of data but rather to select the right signal and perform moment estimation only with them. Several criteria are used to make "an intelligent" selection of the signal. Work on frequency domain processing has been made by [CPT$^+$94, Gos97, Gri98, CGME98, STMW99, WMWW99].

Motivated by [AU96, Dau92, Teo98, VK95, BF94, Kai94, LMR98, Mey93, Koo93, Hol95, MTWW00] our purpose was to embed the filtering procedure into the known mathematical theory of wavelets. Why should wavelets be used in RWP signal processing? In general, in case of removing contamination or denoising the experience shows that more than time domain filtering and Fourier domain filtering techniques is required. Existing (and implemented) methods are frequently insufficient. But more important is the fact that contamination appears often instationary and with a priori unknown scale structure. Thus wavelet techniques seem to be more than promising. Further, in order to localize clutter components one may use a great variety of wavelet filters [Dau92, DMT00, Tes98, Sta92, DM95] i.e. to choose a certain wavelet one has to determine the properties of clutter or one select a wavelet empirically.

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 (optimization with respect to a loss function, estimation error). This reveals a objective evaluation and a self-acting filter algorithm.

Before we start, let us briefly repeat the basics of multi scale analysis. Let ϕ be some function from $L_2(\mathbb{R})$ (space of functions of finite energy), such that the family of translates of ϕ is an *orthonormal system*. We define

$$\phi_{jk}(x) := 2^{j/2}\phi(2^j x - k) \ , \ j \in \mathbb{Z} \ , \ k \in \mathbb{Z}.$$

Further we define linear spaces by

$$\begin{aligned} V_0 \ &:= \ \{f(x) = \sum_k c_k \phi(x-k) \ : \ \sum_k |c_k|^2 < \infty\} \\ &\vdots \\ V_j \ &:= \ \{h(x) = f(2^j x) \ : \ f \in V_0\} \ , \ j \in \mathbb{Z} \end{aligned}$$

Assumed that ϕ is chosen in such a way that the spaces are nested:

$$V_j \subset V_{j+1} \ , \ j \in \mathbb{Z} \ \text{ and that } \bigcup_{j \geq 0} V_j \text{ is dense in } L_2(\mathbb{R})$$

then the sequence $\{V_j \ , \ j \in \mathbb{Z}\}$ is called a multi scale analysis. This concept was introduced by [Dau92, Mal98, Mey93]. We call ϕ the father wavelet (often one requires some regularity conditions). Furthermore one may define subspaces W_j by

$$V_{j+1} := V_j \oplus W_j$$

and iterating this we have

$$\bigcup V_j = V_0 \oplus \bigoplus_j W_j \text{ and } L_2(\mathbb{R}) = V_0 \oplus \bigoplus_j W_j.$$

Assumed that our data may be described by some $f \in L_2(\mathbb{R})$ we can represent the signal as a series

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

where $\{\psi_{jk}\}$, $k \in \mathbb{Z}$ (ψ is called mother wavelet) is a orthonormal basis in W_j.

This expansion is a special kind of orthogonal series. Hence it would be useful to search in the framework of nonparametric statistical estimation theory for a applicable method to solve our problem [DNvS98, GGH97, Wu99]. In case of orthogonal series estimation the idea of reconstructing the desired atmospheric signal is simple. Primary we replace the unknown wavelet coefficients in the wavelet expansion by estimates which are based on observed data. Hereafter we need a selection procedure to select relevant coefficients.

Let us go into the details. In advance we briefly remark that in the following section we assume that our signal belongs to some Besov scale. This guarantees that functions (or signals) of manifoldly structure are covered in our considerations. A Besov scale B^s_{pq} is a function space depending on three parameters ($s > 0$ - smoothness, $1 \leq p \leq \infty$ and $1 \leq q \leq \infty$). The here used facts of estimation theory are available for a great set of these spaces [DJ92, DJKP93, JS97, vSM98, HKPT98]. If we may identify our signal as an element of one of these spaces (and indeed we can) we can adapt wavelet threshold estimators. The main advantage in this framework is that we may use existing rules for evaluating lower and upper bounds and rates of convergence for our loss function (which describes the quality of our reconstructed atmospheric signal component). Optimizing bounds and rates of convergence we get self acting algorithms.

For our utilization it is sufficient to say that $f \in B^s_{pq}$ if and only if

$$J_{spq}(f) = \|\alpha_{0.}\|_{l_p} + \left(\sum_{j \geq 0} (2^{j(s+1/2-1/p)} \|\beta_{j.}\|_{l_p})^q \right)^{1/q} < \infty.$$

We are looking for optimal reconstructions for function belonging to some subspace $F_{spq}(M) = \{f : \ J_{spq} < M\}$. For the simple case that the function is in $L_2(\mathbb{R})$ we determine $s = 0$ and $q = p \wedge 2$.

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 the X_i are on a regular grid and ε is a random variable (or more general a stochastic process). The basic idea is to replace the wavelet coefficients in the series expansion by empirical estimates

$$\hat{\alpha}_{jk} = \frac{1}{n} \sum_{i=1}^{n} Y_i \cdot \varphi_{jk}(X_i) \quad \text{and} \quad \hat{\beta}_{jk} = \frac{1}{n} \sum_{i=1}^{n} Y_i \cdot \psi_{jk}(X_i),$$

where the X_i are timestamps and the Y_i are observations. A straightforward linear estimation is given by the projection onto a subspace V_{j_1}

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

To appraise this estimator it is known that one may solve the expected loss or the risk (in L_2 sense) $E\|\hat{f}_{j_1} - f\|_2^2$. This measure is the so-called $MISE$ (mean integrated squared error). To determine the MISE one may decompose it into $E\|\hat{f}_{j_1} - E\hat{f}_{j_1}\|_2^2$ (stochastic contribution) and $E\|E\hat{f}_{j_1} - f\|_2^2$ (deterministic contribution). Under certain conditions one may find bounds for $MISE$:

$$\sup_{F_{s22}(M)} \|E\hat{f}_{j_1} - f\|_2 \leq C_M 2^{-j_1 s} \text{ and } E\|\hat{f}_{j_1} - E\hat{f}_{j_1}\|_2^2 \leq C \frac{2^{j_1+1}}{n}$$

and hence

$$\sup_{f \in F^s_{22}(M)} E\|\hat{f}_{j_1} - f\|_2^2 \leq \tilde{C} \frac{2^{j_1}}{n} + C_M 2^{-j_1 s}.$$

A minimum of the sum is given by

$$\sup_{f \in F^s_{22}(M)} E\|\hat{f}_{j_1} - f\|_2^2 \leq \hat{C} n^{-\frac{2s}{2s+1}},$$

furthermore one can generalize this result for $p > 2$

$$\sup_{f \in F^s_{22}(M)} E\|\hat{f}_{j_1} - f\|_p^p \leq \hat{C} n^{-\frac{ps}{2s+1}}.$$

This tells us by which finite number the maximum risk is limited. It becomes smaller if the number of observation increases. For detailed computations of upper and lower bounds see [vSM98, DJKP93, DJ92, DNvS98].

Obviously this kind of linear estimation includes oscillating components, in particular the clutter components. This phenomenon occurs, 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 need a suitable selection procedure for the coefficients to perform the necessary filtering step.

We want to apply so-called hard thresholding and soft thresholding respectively. These routines were introduced and adapted to several problems by Donoho and Johnstone [DJ92, DJKP93]. Inspired by these easy to implement procedures we adjusted it to our problem.

The functions of soft and hard thresholding are given by

$$\eta^s(u) = (|u| - \lambda)_+ \mathrm{sgn}(u) \text{ and } \eta^h(u) = u\chi_{\{|u|>\lambda\}} \text{ respectively.}$$

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 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 [vSM98]. The resulting non-linear estimator does not only provide local smoothers, but in very many situations achieves the near-minimax L_2-rate for the risk of estimation, i.e. [vSM98] for (random) thresholds λ_{jk} satisfying $\sigma_{jk}\sqrt{2\log M_j} \leq \lambda_{jk} \leq C\sqrt{\frac{\log n}{n}}$ for any positive constant C

$$\sup_{f\in F^s_{22}(M)} E\|\hat{f}^* - f\|_2^2 = O\left((\log(n)/n)^{2s/(2s+1)}\right),$$

where σ_{jk} is the variance and M_j denote the number of the coefficients used in the nonlinear estimator. The optimal threshold rate $(1/n)^{2s/(2s+1)}$ is attained only for the optimal threshold. But in practice this is unknown. Therefore we have to replace σ_{jk} by some estimation $\hat{\sigma}_{jk}$ and this results in random thresholds $\hat{\lambda}_{jk} = \hat{\sigma}_{jk}\sqrt{2\log M_j}$. 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 $\sigma^2_{jk} = Var(\hat{\beta}_{jk})$.

We conclude that we may adapt an estimation rule for our desired atmospheric signal component where the quality is measurable in the sense of L_2-risk. This means the used procedure displays upper and lower bounds for our reconstruction and we may easily determine the rate of convergence. The calculation of the wavelet coefficients can be done by using the fast wavelet algorithm which is very pleasant for implementing.

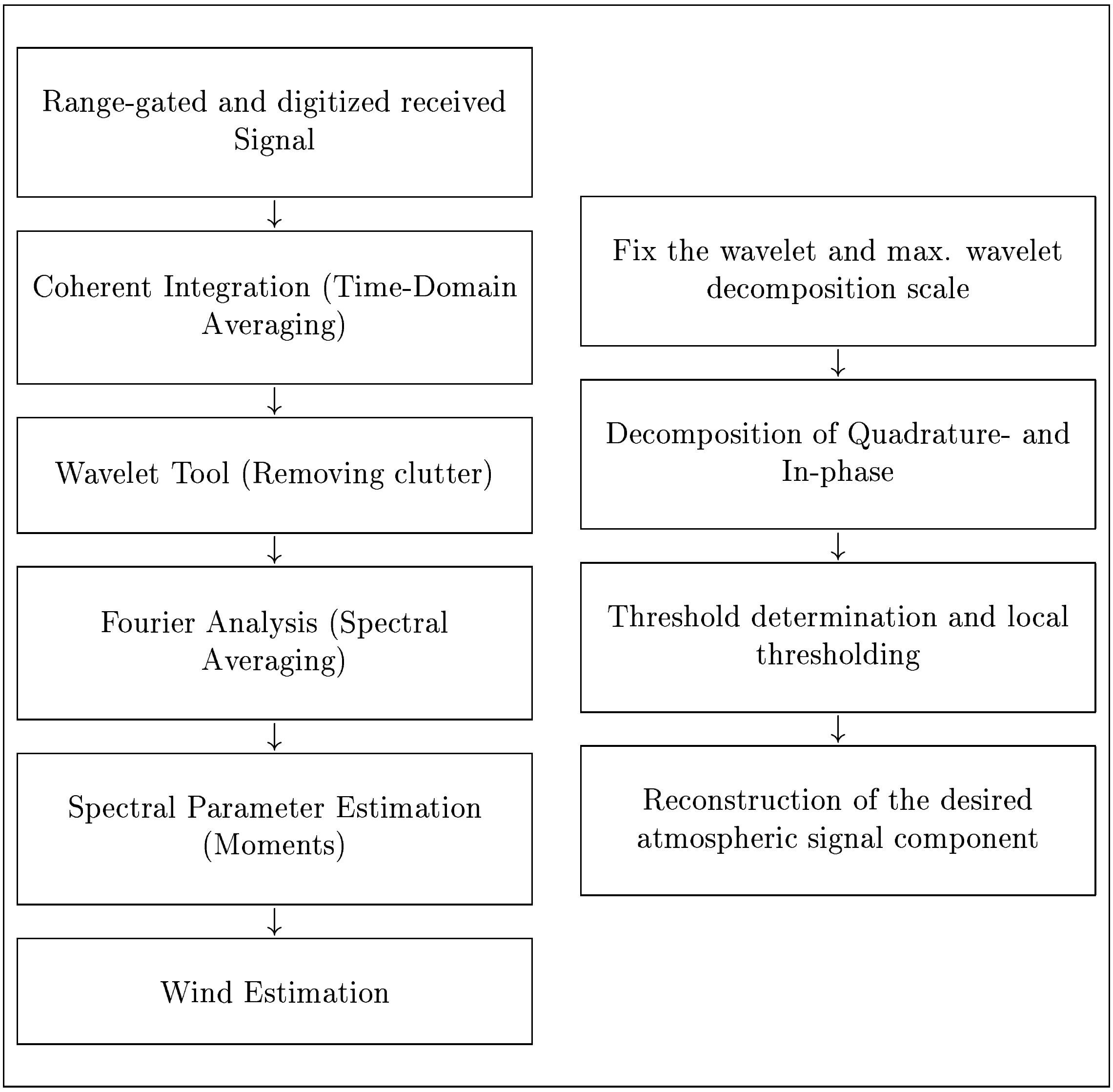

Figure 4: Left: The flow diagram extended by the wavelet tool. Right: The wavelet algorithm flow diagram.

Removing clutter

In this section we want to put the theory into practice. For a better understanding we particularize Figure 1 to see where we have inserted the wavelet tool. A more substantiated algorithm flow diagram is shown in Figure 4.

To be more practical and concrete we want to use our example (see Figure 3) to demonstrate our procedure. We are using I/Q-timeseries and resulting power spectra of gate 17 and 11. The problem was that gate 17 was contaminated by intermittent clutter (aircraft echoes) and gate 11 by ground clutter. Using customarily signal processing the spectra were significantly biased and therefore the moment estimation and in the end the wind vector reconstruction. Figure 5 shows exemplarily how wavelet thresholding was realized in decomposition sequences α_4. and β_4. of gate 11 and 17. The dotted lines may be identified with threshold λ_4.

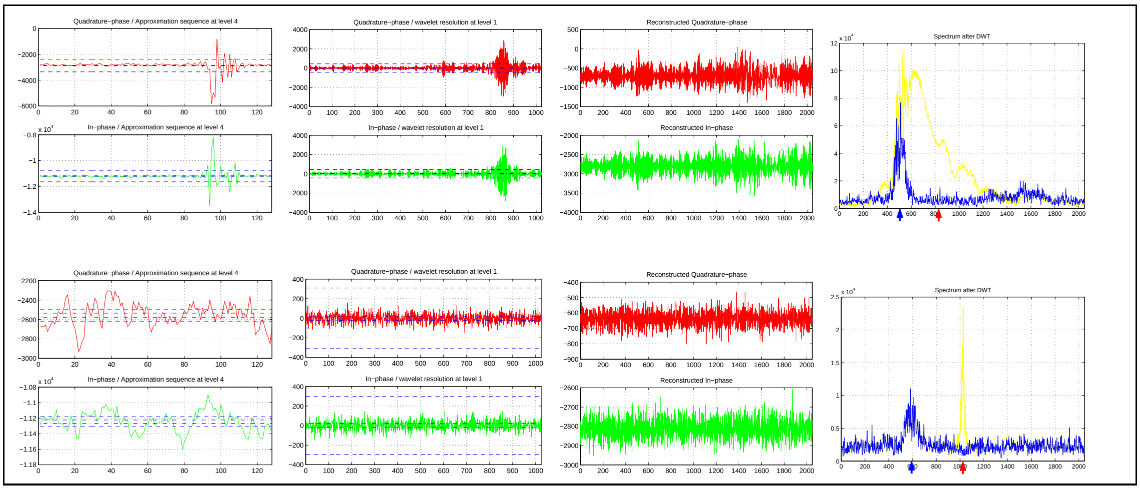

Figure 5: Decomposition (sequences of level 4), reconstruction and Fourier power spectrum of gate 17 (top) and gate 11 (below). The dark curves in the power spectra representations display the decontaminated spectra. Clearly to recognize are the differences of moment estimations, see the computed first moment before (red arrow) and after (blue arrow) the filtering step.

Conclusions

- We have demonstrated wavelet domain filtering using real wind profiler data

- Ideas of discrete multiscale analysis and nonlinear estimation theory were used and developed for removing ground and intermittent clutter (aiplane 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

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