4.2-O **A new intermittent clutter filtering algorithm for Radar Wind Profiler**

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1. Introduction

The standard RWP signal processing usually assumes, that the received voltage signal at the receiver output $S(t)$ is the sum realization of the atmospheric scattering process $I(t)$ and the receiver noise $N(t)$. Both can be regarded as independent stationary Gaussian random processes. All terms are complex-valued base-band voltages that are obtained after demodulation at the receiver output. Stationarity can be assumed over typical dwell-times (quasi-stationarity). Under these assumptions, the stochastic process $S(t)$ is completely described by its time-independent second-order properties. The natural way to process RWP data is therefore based on a non-parametric estimation of the power spectrum (Doppler spectrum) using a discrete Fourier transform of the (usually coherently integrated) raw signal over a fixed time interval. In reality, however, there is often a third component contributing to the total signal $S(t)$, namely clutter:

$$S(t) = I(t) + N(t) + C(t)$$

Clutter is the totality of undesired echoes and interfering signals, therefore it is difficult to generalize the properties of $C(t)$. In this paper, we deal only with intermittent clutter signals, in particular those caused by migrating birds in spring and fall. The problem of bird-contamination is well-known (Wilczak et al., 1995). A first and relatively successful approach to solve this problem was made by Merritt (1995), who suggested a selective averaging method of the individual Doppler spectra based on a statistical criterion. Filtering in the time-domain was suggested by Jordan et al. (1997), who used wavelet decomposition, followed by wavelet coefficient thresholding, to remove the clutter part of the signal. The problems with the wavelet method are the a-priori unclear choice of the mother wavelet and - at least for the dyadic wavelet transform - a suboptimal signal separation in the wavelet domain. This makes an efficient thresholding difficult. The proposed method builds upon this work and addresses the difficulties outlined above.

2. Intermittent Clutter Removal

2.1. Signal Representation

Intermittency means that that the signal component $C(t)$ can be classified as highly nonstationary. It is thus tempting to try methods that were developed in the frame of nonstationary signal processing. A necessary condition for detecting and filtering the clutter contribution $C(t)$ is obviously a separation from the stationary components $I(t)+N(t)$. We therefore seek a signal representation that achieves such a separation. If this is possible, then we might be able to classify the signal components and to suppress only the clutter part. Common linear signal representations are:

$$S(t) = \sum_i \alpha_i h_i.$$

Here $\{h_i\}$ is a set of functions that must be complete to allow the expansion of $S(t)$. These functions are called "elementary signals", "atoms" or "building blocks". A special case are bases, for instance the complex exponentials for the Fourier expansion or Daubechies's orthogonal wavelets. Bases allow a very efficient signal representation and are therefore often preferred. However, in many situations non–redundant systems are too restrictive, i.e. often they do not allow an optimal representation of the signal (e.g. Gibbs phenomenon). The way out consists of introducing redundancy and arriving at highly linearly dependent (non-orthogonal) systems that allow more flexible and problem-adapted linear

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signal representations. For the problem at hand we consider the so–called Gabor frame, $h_{m,k}(t) = h(t - mT)\exp ik\Omega t$, which provides an advantageous analysis and synthesis method for discrete and finite data. The signal can then be represented as:

$$S(n) = \sum_{m=0}^{M-1}\sum_{k=0}^{K-1} a_{m,k} h_{m,k}(n),$$

The Gabor coefficients can be derived (analysis) from $a_{m,k} = \sum_{n=0}^{N-1} S(n)\gamma_{m,k}(n)$, where γ is the so–called dual Gabor frame atom. We use modulated Gaussian functions with $\|\gamma\| = 1$ as dual Gabor frame atom, they are optimally concentrated in time and frequency and provide an easy to interpret time-frequency (TF) representation of the signal in the Gabor phase space (space of the coefficients $a_{m,k}$). The primal frame $h_{m,k}$ is computed through the Wexler-Raz biorthogonality relation (Wexler and Raz, 1990). The primal–dual (or sometimes restricted to bi–orthogonal) relation ensures perfect reconstruction.

2.2. Filtering by Statistical Testing

Our goal is to identify transient echoes coming from fliers. The underlying process of this echo component is rather complicated (some transient process), but signals due to atmospheric scattering and to the radar system can be assumed to be stationary Gaussian (where we note that the former has a colored Fourier power spectrum and latter a white Fourier power spectrum). We use exactly this difference of the processes to isolate the fliers (such as birds) echoes. The idea is now to argue as in Merritt (1995), but we apply the idea to the Gabor phase space representation:

For each individual fixed index m we may consider the vector $|a_{m,k}|^2$. This vector represents a time localized Frequency spectrum. Considering now the order statistics $|a_{[m],k}|^2$. Then, an averaged spectral estimate (mean value) is given by

$$\hat{a}_k^{M_k} = \frac{1}{M_k}\sum_{m=0}^{M_k-1} |a_{[m],k}|^2\ , \quad k = 0, \ldots, K-1.$$

Note that the number of averaged spectra M_k can be chosen different for each k (but,for simplicity, here is not). The number M_k determines the subset of spectra under consideration. The Gaussian statistical test implemented in Hildebrand and Sekhon (1974) is of the form

$$\frac{\mathrm{var}(|a_{[m],k}|^2 \mid M_k)}{(\hat{a}_k^{M_k})^2} \leq 1,$$

and was originally used to discriminate between radar system noise and atmospheric radar return. We use this test to identify for a fixed frequency index k_0 all a_{m,k_0}, that are affected by the fliers. In a first attempt, $|a_{m,k_0}|$ is then replaced with an estimate of the magnitude derived from the unaffected Gabor phase space coefficients.

An illustrative example is discussed in the appendix.

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3. Appendix

The performance of the method is illustrated[*] with data obtained during routine operation of the 482 MHz wind profiler radar of the Deutscher Wetterdienst at Bayreuth (Northern Bavaria). The technical data of the radar system are given in Table 1.

Center frequency	482.0078 MHz
Peak (Average) RF envelope power	16 (2.4) kW
Pulse widths (vert. resolution)	1.7 μs (250 m) 2.2 μs (330 m) 3.3 μs (500 m) 4.4 μs (660 m)
Antenna type	Phased array of 2 x 90 CoCo antennas
On-axis gain above isotropic	$\geqslant$ 34 dBi
One-way half power (3 dB) beamwidth	$\leqslant 3^\circ$
Oblique beam zenith distance	15.2°
RX type	Heterodyne (IF 60 MHz), Digital IF
LNA noise figure	$\leqslant$ 0.6 dB
A/D conversion	14 bit (@ 48 MHz)
Pulse compression	Bi-phase, complementary, max 32 bit
System sensitivity	$\leqslant$ -154 dBm
Vertical measuring range	16 km (wind), 4 km (virt. temp.)

Table 1. Technical parameters of the Bayreuth wind profiler

During bird migration in fall of 2005, full time series data of the coherently integrated I/Q signal were saved in the wind low mode (pulse-width: 1.7μs, no pulse compression). The sampling parameters (inter-pulse period IPP, number of coherent integrations NCI, total length of the time series NPts*NSP, number of range gates NHts and the range gate spacing SPAC) are shown in Figure 2, they were unchanged during the period of data recording.

Particulary significant bird migration was noted on October 13. Quite a lot of wind data were contaminated by bird returns, the effect is best seen in the top plot of Figure 3. As known, the birds migrate at night whereas the daylight time shows absolutely no signs of clutter affected winds. The operationally used intermittent clutter removal algorithm (ICRA), a particular implementation of the statistical averaging method proposed by Merritt (1995), could only alleviate the problem. Also, the operational quality control (Weber-Wuertz continuity check, not shown) was only able to flag a small percentage of the contaminated data, because the erroneous wind data exhibited the typical intrinsic consistency.

The time series data were filtered using the newly proposed algorithm and saved again in the original binary file format. This allowed a reprocessing of both the original and the filtered data using the off-line version of the operational wind profiler software, which eases comparison tremendously.

Figure 1 gives one particular example of the filtering for range gate 9 at 00:09:45 UTC (start time of the dwell). The upper-left part shows the original I/Q time series as sampled by the wind profiler. It contains the typical signature of contamination by intermittent clutter. Taking a look at this representation of the signal (the coefficients of the sampled band-limited signal - the associated basis would be the cardinal sines or sinc–functions) one would immediately identify the maxima of the envelope of the I/Q signal as two "bird events". However, the lower-left part shows the modulus of the Gabor phase-space representation of the same signal. This provides a time-frequency decomposition of the same signal. In this representation it becomes very clear that in fact the data is contaminated by three "bird-events". Two of them overlap in time and can therefore not easily be distinguished in the time representation. All bird signals are much stronger in amplitude than the atmospheric signal of interest. The latter can be seen as a line of quasi-constant frequency centered at about a frequency of 3 Hz. It is obvious that the Gabor representation provides a good discrimination of the individual signal components. In particular, non-stationary signals can be easier discriminated from stationary ones (as long as the

[*] You can use the zoom function of the Acrobat Reader software to enlarge all presented graphics

duration of the non-stationary signal component is not longer than the analyzing time interval). The filtered Gabor phase-space representation is shown in the lower right part of Figure 1. Here, the coefficients $a_{m,k}$ representing the transient (bird) contributions have been replaced by an estimation of the stationary signal component at that frequency (either noise of atmospheric signal). The upper-right part shows the reconstructed I/Q series.

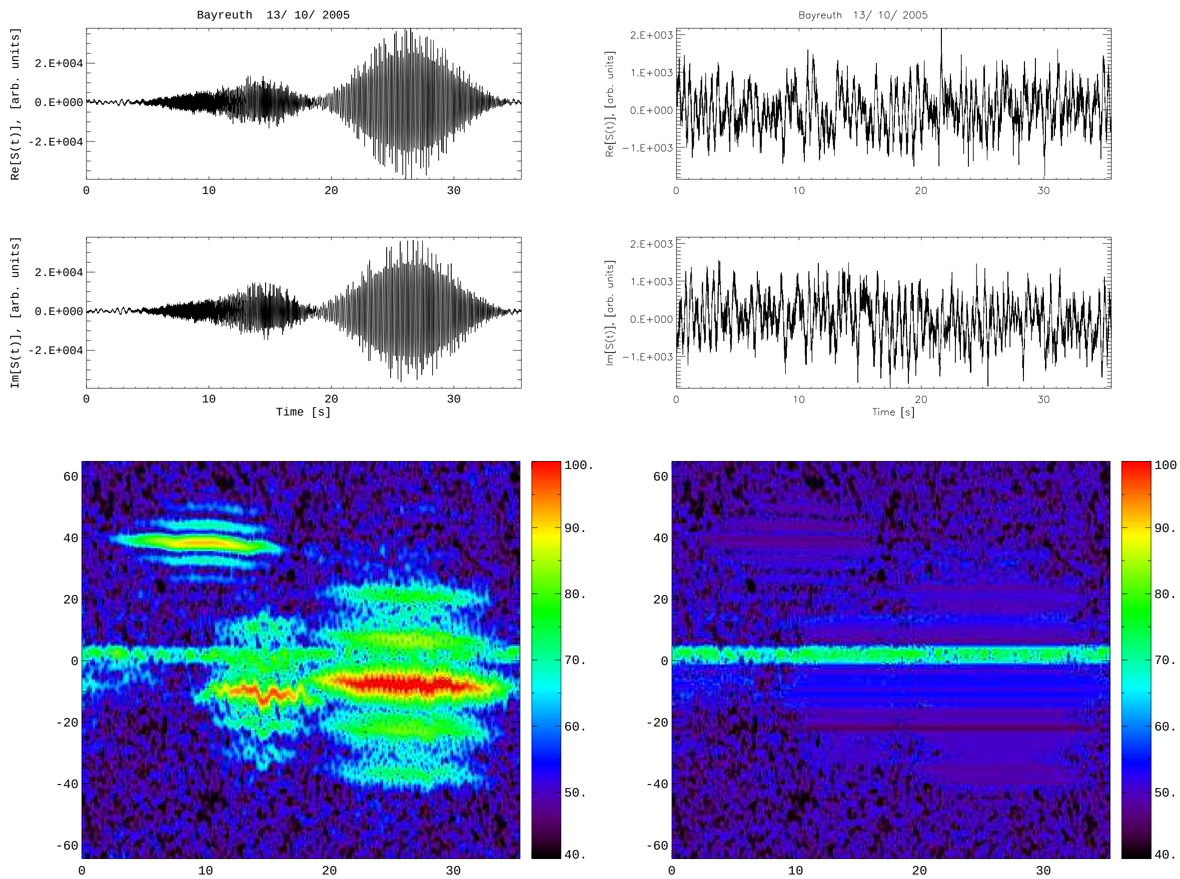

Figure 1. Bayreuth, Oct. 13, 2005 at 00:09:45 UTC, range gate number 9: From top left to bottom right: original I–Q time series, 4608 points, reconstructed I–Q time series, Gabor phase space representation, and filtered Gabor phase space representation. In the Gabor representation, the x-axis shows time (in seconds) and the y-axis frequency (in Hz).

The time series data were used for reprocessing of the whole day with three different algorithms: 1.) without any filtering of intermittent clutter, 2.) with the Intermittent Clutter Reduction Algorithm (ICRA) originally proposed by Merritt (this is the operational standard) and 3.) with the newly proposed Gabor transform based statistical filtering. The results for one dwell (stacked Doppler spectra) are shown in Figure 2. The top plot shows the averaged Doppler spectra that were obtained without any intermittent clutter filtering (mean spectral averaging). Here, the lowest 17 range gates show spurious peaks and also large spectral widths due to the transient bird echoes. Note the discontinuity in the location of the peak (derived Doppler velocity). The middle plot shows the same data, but processed with ICRA. The effect of the birds has been drastically reduced, however, there are still range gates that show spurious peaks. Here, ICRA was unable to reduce the clutter energy completely. The bottom plot shows the same data processed with the newly suggested filtering algorithm. The spurious remnants of the bird clutter as seen in the middle plot are almost completely gone. The spectral peak is now continuous and the spectral width values are largely unaffected by the clutter.

Finally, the horizontal wind vector data derived from the measurements are shown as arrows in Figure 3. The color coding is due to the wind speed (magnitude of the horizontal wind vector). Obviously, the clutter contamination has been drastically reduced by the new algorithm.

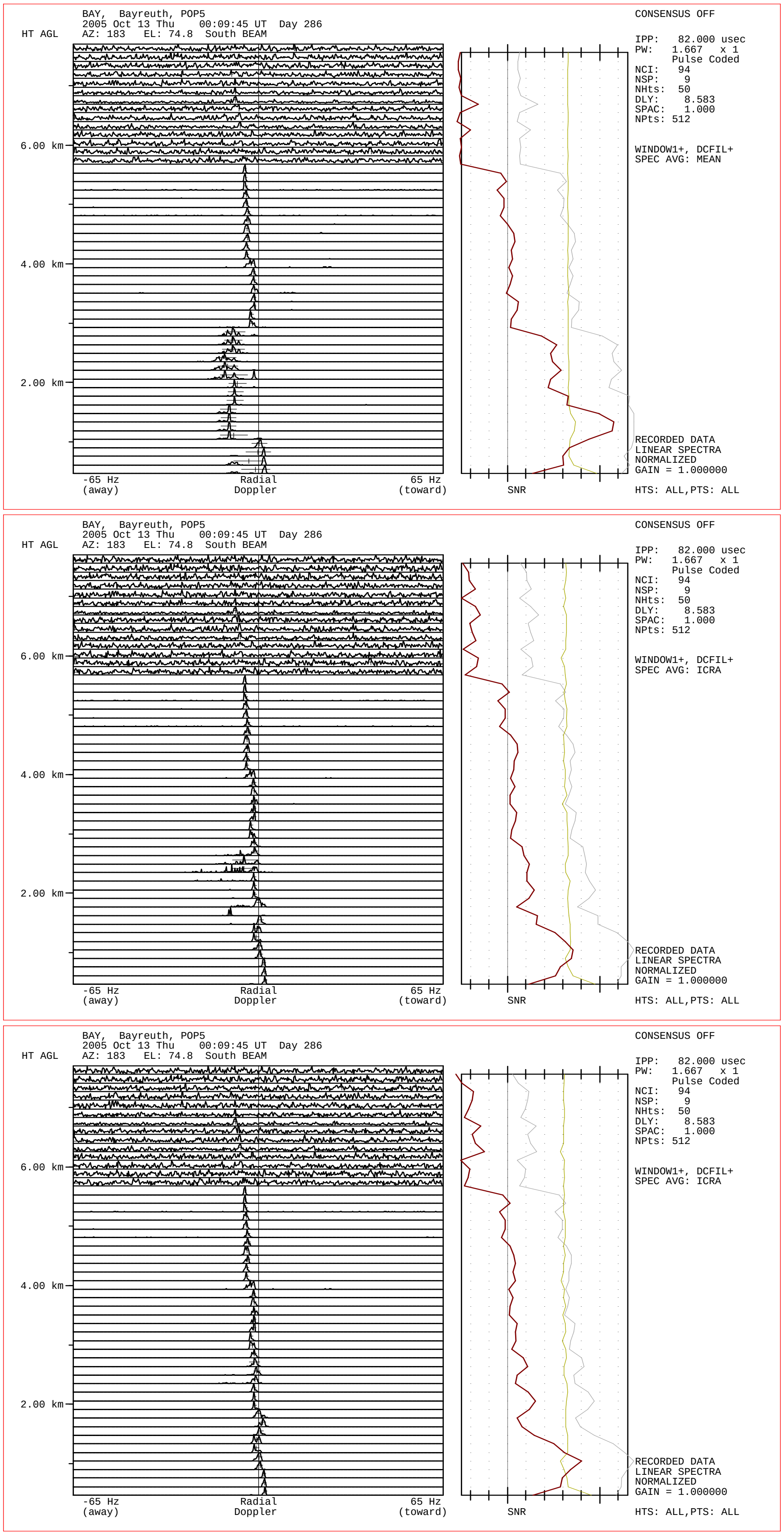

Figure 2. Stacked Doppler spectra: Bayreuth, Oct. 13, 2005 at 00:09:45 UTC From top to bottom: 1. No filtering, 2. Statistical averaging (Merritt), 3. New method.

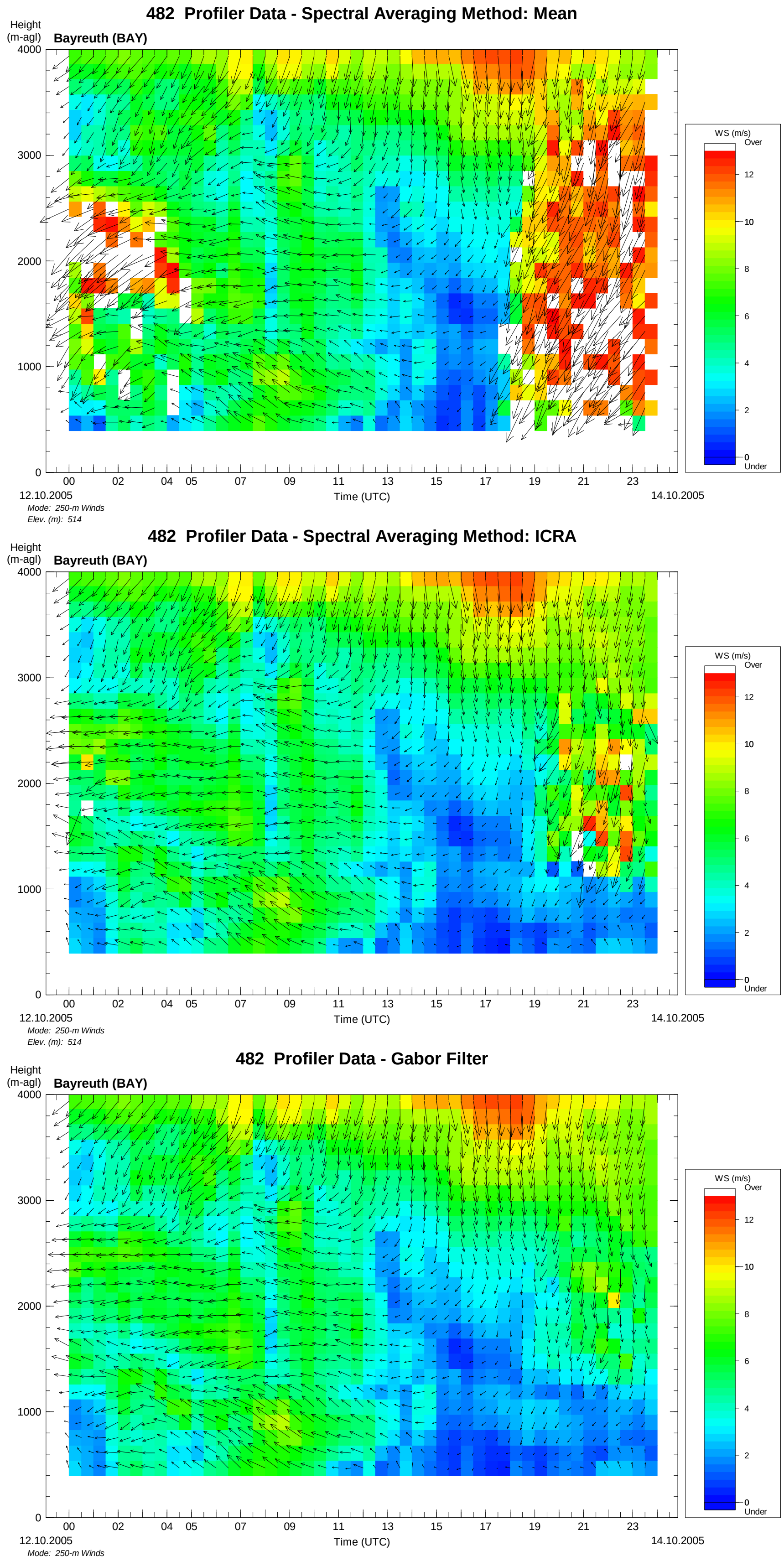

Figure 3. Horizontal wind measurements: Bayreuth, Oct. 13, 2005 - processed with three different methods. From top to bottom: 1. No filtering, 2. Statistical averaging (Merritt), 3. New method.