Advanced Signal Processing of Radar Wind Profiler using Wavelet Transform Techniques

M. Krupa Swaroopa Rani, P. Jagadamba, G. Kiran Kumar

Abstract--Atmospheric Signal processing has been one field of signal processing where there is a lot of scope for development of new and efficient tools for cleaning of the spectrum, detection and estimation of the desired parameters. Atmospheric signal processing deals with the processing of the signals received from the atmosphere when manually stimulated using atmospheric Radar. Removal of clutter and noise in the radar wind profiler is the utmost important consideration in radar. In this paper, we implement wavelet thresholding for removing clutter and noise from radar wind profiler data. By applying the concept of discrete multi-resolution analysis and non-parametric estimation theory, we develop wavelet domain thresholding rules, which identifies the coefficients relevant for clutter and noise and suppresses them and increases the accuracy of wind vector reconstruction.

Keywords: Atmospheric Signal Processing, Spectrum, Detection, Clutter, Wind Profiler.

I. INTRODUCTION

RADAR (Radio Detection and Ranging) is a device that sends out electromagnetic waves.These waves reflect off of objects in space, and a proportion of the original wave energy is actuallybounced back towards the RADAR. The RADAR then reads this returning signal and analyzes it. This returning signal can be processed to determine many properties about the original object that the wave reflected off of. Two examples that can be determined from the returned signal are the location of the object as well as the velocity of the object in relation to the radar.

II. CONCEPT OF RADARS

Radar itself is an abbreviation for Radio Detection and Ranging. Radar systems send out modulated waveforms using antennas in order to transmit electromagnetic energy into a specific volume of space to search for targets. Objects (i.e. targets) within a certain volume will reflect part of the energy (radar returns or echoes) back to the radar. From these radar returns, the radar receiver then extracts information such as velocity and range, angular position, and other identifying characteristics. If relative motion exists between target and radar, the shift in the carrier frequency of the reflected wave(Doppler effect) is a measure of target's relative (radial) velocity and may be used to distinguish moving targets from stationary objects. National Atmospheric Research Laboratory (NARL) at Gadanki (13.47°N, 79.18°E) near Tirupati, India has been operating a 1280 MHz atmospheric radar for studying structure and dynamics of lower atmosphere.

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The operating frequency of LAWP is 1280MHz. The phased antenna array consists of 8x8 elements occupying an area of 1.4mx1.4m.It transmits a peak power of 0.8KW.The number of coherent interations can be in the range of 4-1000.The number of fast fourier transform (FFT) points can be from 1-256.To obtain the wind speed and direction,LAWP measures data in three directions,namely zenith, north and east in one observation cycle.The typical height coverage in the clear air is 3-4Km and 10Km during precipitation.The selected parameters of LAWP are shown in table.

Specifications

Frequency	1280 MHz
Technique	Doppler beam Swinging
AntennaType	Microstrip Patch Array
ArraySize	8x8 (1.4 m x 1.4 m)
BeamWidth	9^0
BeamForm	Passive
Beams	25
Tx/Rx Type	Solid State Transceivers
PeakPower	0.8 kW
Duty Ratio	Upto 10%
PulseWidth	0.25 – 8.0 µs
NCI	4 - 1000
NFFT	32 -1024
RangeBins	1-256
Receiver	Super Hetrodyne
Detection	Direct IF Digital
Dynamic Range	70 dB
Min.Height	100 m
MaxHeight	3-5 km

Most of these RWP employ the Doppler-beam swinging (DBS) method for the determination of the vertical profile of the horizontal wind and, under certain conditions, the vertical wind component. These radars transmit short electromagnetic pulses in a fixed beam direction and sample the small fraction of the electromagnetic field backscattered to the antenna.

At least three linear independent beam directions are required to transform the measured 'line-of-sight' radial velocities into the wind vector. 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. [16] The goals of signal processing are:

– to provide accurate, unbiased estimates of the characteristics of the desired atmospheric echoes;
– to estimate the confidence/accuracy of themeasurement;
– to mitigate effects of interfering signals;
– to reduce the data rate.

Digital signal processing in a system using an analog receiver starts with the sampling of the in- and quadrature phase components of the received signal at a rate that is determined by the pulse repetition period T . [1], [3], [27] To reduce the data rate for further processing, hardware adder circuits perform a so-called coherent integration adding some N (typically ten to hundred) complex samples together.[8], [9], [19] If the radar system uses pulse compression techniques (e.g. phase coding using complementary sequences), then the next step is decoding.The coherently averaged and decoded samples are then used to compute the Doppler spectrum using the Windowed Fourier Transform (FFT) and [16] the Periodogram method.In our system, a Fourier transformed Hanning-window is convolved with the result of the FFT. [21] A number (typically some ten) of individual Doppler spectra is then incoherently averaged to improve the detectability of the signal.

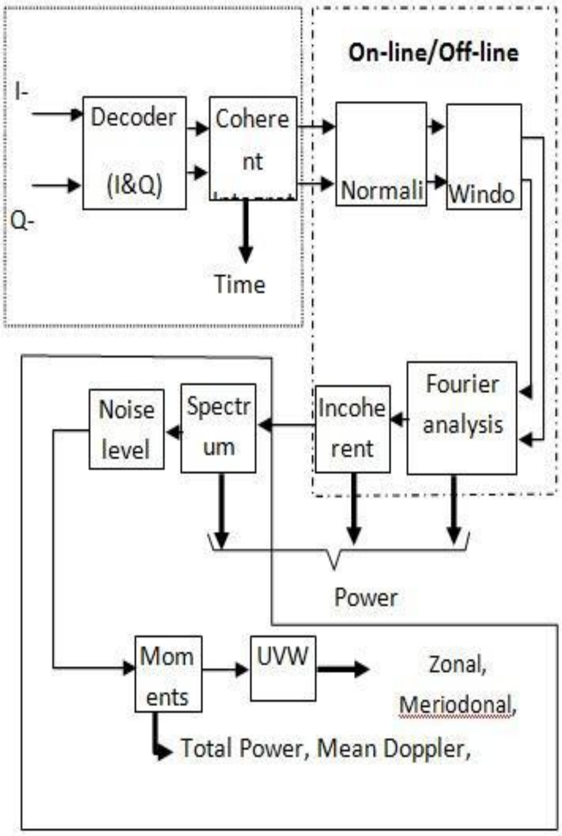

Fig 1: Data Processing Steps of Radar Wind Profiler

[12] Finally, the noise level is estimated with the method proposed by Hildebrand and Sekhon , and [18] the moments of the maximum signal in the spectrum are computed over the range where the signal is above the noise level.The problem with this type of signal processing is the underlying assumption that the signal consists of only two parts: the signal, that is produced by one atmospheric scattering process, and noise (different sources, mainly thermal electronic noise and cosmic noise). [10], [11]This is certainly not true, especially at UHF, where the desired atmospheric signal itself is often the result of two distinct scattering processes, namely scattering at inhomogenities of the refractive index (Bragg scattering) and scattering at particles, such as droplets or ice crystals (Rayleigh scattering). Therefore, even the desired atmospheric signal may have different characteristics. But, as experience shows us, the most serious problems are caused by the following contributions to the signal:

Ground Clutter. Echo returns from the ground surrounding the site, which emerge from antenna's sidelobes.

Intermittent Clutter. Returns from unwanted targets, such as airplanes or birds, from both the antenna's main lobe and the side lobes.

III. APPLYING MULTIRESOLUTION ANALYSIS AND STATISTICAL ESTIMATIONS

For the problem at hand, the goal of the signal processing should be signal component separation, i.e. an automatic, reliable and stable extraction of the different contributions to the signal (noise, clutter, interference). [5], [13], [17] Our purpose was to embed the filtering procedure into the known mathematical theory of wavelets. In general, mathematical experience concerning problems related to contamination removal or denoising shows that usually more than time domain filtering and Fourier domain filtering techniques are required to obtain optimum results. Often, most of the existing and implemented methods are insufficient. The main reasons for the particular effectiveness of wavelet analysis can be summarized as follows:

– The fact that contamination appears often instationary or transient, and with a priori unknown scale structure, favors the superior localization properties of the wavelets. [2] A wavelet expansion may allow the separation of signal components that overlap both in time and frequency .

– [4], [5], [20] In order to effectively localize clutter components, one can use a great variety of wavelet filters.To choose a certain wavelet that especially suits the desired signal component, one can determine the properties of the clutter signal; otherwise, one can select a wavelet empirically.

–[2] The wavelet expansion coefficients, _jk, drop off rapidly for a large class of signals, which makes the expansion very efficient .

–[2], [15], [17] The fast wavelet transform has a computationally complexity that is lesser than or equal to the fast Fourier transform; the algorithm is recursive. This allows for an efficient implementation on digital computers.Thus, the application of wavelet techniques to our particular problem seems to be promising. Before we start, let us briefly repeat the basics of multi-resolution analysis. Let L2(R) be the space of functions of finite energy. Let $\emptyset$ be some function in L2(R), such that the family of translates of $\emptyset$ form an orthonormal system. We define

$$\emptyset_{jk}(x) = 2^{j/2}\emptyset(2^j x - k),\ j\epsilon Z, k\epsilon Z.$$

Further, we define linear spaces by

$$V_0 = \{f(x) = \sum\nolimits_k c_k\, \emptyset(x-k) : \sum_k |c_k|^2 < \infty\}$$

$$V_j = \{h(x) = f(2^j x) : f\epsilon V_0\}, \qquad j\epsilon Z$$

Assuming that $\emptyset$ is chosen in such a way that the spaces are nested:

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

then the sequence $\{V_j, j\epsilon Z\}$ is called a multi-resolution analysis. This concept was introduced by Mallat and Meyer. $\acute{\emptyset}$ is called the father wavelet. Furthermore,one may define subspaces Wj by

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

and iterating this we have

$\bigcup V_j = V_0 \oplus \oplus_j W_j$ and $L_2(R) = V_0 \oplus \oplus_j W_j$

Assuming that our data may be described by some $f\epsilon L_2(R)$ we can represent the signal as a series

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

Where $\{\psi_{jk}\}, k\epsilon Z$ is an orthonormal basis in Wj . The function ψ is called mother wavelet.

[6] 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 an applicable method to solve our problem. In case of orthogonal series estimation, the idea of reconstructing the desired atmospheric signal is simple. Basically, we replace the unknown wavelet coefficients in the wavelet expansion by estimates which are based on observed data. For that, we need a selection procedure to choose relevant coefficients since the main emphasis of performing wavelet domain filtering is to create a suitable, i.e. problem matched, coefficient selecting procedure. To separate the atmospheric signal component, we apply statistical estimation theory. A side effect of using statistics is to obtain a measure of reconstruction quality. A typical quality measure is a loss function/ estimation error. Minimizing the error function reveals an objective evaluation and a self-acting filter algorithm. The following sub-section describes the construction of our atmospheric-signal-estimator. In advance, we briefly remark that in the following section, we assume that our signal belongs to some Besov space, i.e. a generalized mathematical function space. One special example is the previously introduced function space L2(R). But sometimes it makes more sense to suppose that the derivatives of our signal are of finite energy as well. In this and other situations, the framework of Besov spaces is an adequate mathematical tool for our application. A Besov space, denoted by ${B_{pq}}^s$, depends on three parameters: s smoothness, the number of bounded derivatives and p, q which describe the underlying function space $L_q(l_p)$. [6], [7], [14] In the following, we make use of some well-known facts of estimation theory, which are valid for almost all Besov spaces . If our signal is an element of one of these spaces (which is true for all practical signals), we can adapt wavelet threshold estimators. The main advantage of this framework is that we can use existing rules for evaluating bounds and rates of convergence for our loss function, which describes the quality of our reconstructed atmospheric signal component. By optimizing bounds and rates of convergence, we obtain self acting algorithms. For our purpose, we only need the following characterization of Besov spaces: A function f belongs to ${B_{pq}}^s$ if

$$ {J_{pq}}^s(f) = \|\alpha\|_{l_p} + (\sum_{j\geq 0} (2^{j(s+1/2-1/p)} \|\beta_j\| {l_p)}^q)^{1/q} < \infty $$

We are looking for optimal reconstructions of functions belonging to some subset
${F_{pq}}^s(M) = \{f\epsilon {B_{pq}}^s : {J_{pq}}^s < M\}$.

For our calculations, we assume that the function is in L2(R) and s is small. From given measurements (Y1, . . . , Yn), we want to estimate the function f in the simple model

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

We assume that we have the Xi on a regular grid and ε is a random variable (a stochastic process which describes all non-atmospheric components). The basic idea is to replace the wavelet coefficients in the series expansion by empirical estimates.

$\hat{\alpha}_k = \frac{1}{n}\sum_{i=1}^{n} Yi \; \varphi_{0k}(X_i)$ and

$$\hat{\beta}_{jk} = \frac{1}{n}\sum_{i=1}^{n} Y_I \, \psi_{jk}(X_i)$$

where the Xi are time stamps and the Yi are observations. A straightforward linear estimation is given by the projection onto a subspace V_{j1}

$$\hat{f}_{j1}(x) = \sum_k \hat{\alpha}_k \, \varphi_{0k}(x) + \sum_{j=0}^{j1} \sum_k \hat{\beta}_{jk} \, \psi_{jk}(x)$$

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 up to scale j1, i.e. we have not performed any filtering step thus far. In the following, we need a suitable selection procedure for the coefficients in order to perform the necessary filtering step. [6], [7] We apply a so-called hard thresholding and soft thresholding, respectively. It is based on taking the discrete wavelet transform (using a multiresolution analysis), passing the transform through a threshold (actually, the expansion coefficients are thresholded) and then taking the inverse DWT to obtain a filtered reconstruction. This type of thresholding is applied in a different way, by removing coefficients below a certain threshold in order to denoise the data().The functions for ard and soft thresholding are defined by

$$\theta^h(u) = \begin{cases} u, & |u| \geq \lambda \\ 0, & |u < \lambda| \end{cases} \qquad and$$

$$\theta^s(u) = \begin{cases} \left(u - \frac{\lambda u}{|u|}\right), & |u| \geq \lambda \\ 0, & |u| < \lambda \end{cases}$$

The modified functions for hard and soft thresholding tor clutter removal are defined by

$$\eta^h(u) = \begin{cases} u, |u| < \lambda \\ 0, |u| \geq \lambda \end{cases} \qquad \text{and}$$

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$$\eta^s(u) = \begin{cases} u, |u| < \lambda \\ \lambda u/|u|, |u| \geq \lambda \end{cases}$$

Here, λ is an adequate threshold. Applying this rule to our linear wavelet estimator, we obtain a nonlinear estimator

$$f^*(x) = \sum_k \eta^*(\hat{\alpha}_k)\varphi_{0k}(x) + \sum_{j=j0}^{j1} \sum_k \eta^*(\hat{\beta}_{jk})\psi_{jk}(x)$$

where η^* is η^s or η^h,respectively.

If the threshold λ is specified according to the asymptotic distribution of the empirical coefficients, then only those coefficients remain which are supposed to carry significant signal information. These are finally used for the reconstruction by the inverse wavelet transform. [22] The resulting non-linear estimator does not only provide local smoothers, but, in many situations, achieves the nearminimax L2-rate for the risk of estimation, for (random) thresholds λ_{jk} satisfying

$$\sigma_{jk}\sqrt{2logM_j} \leq \lambda_{jk} \leq C\sqrt{\frac{\log n}{n}}$$

for any positive constant where σ_{jk} is the variance and Mj denotes the number of the coefficients used in the nonlinear estimator. The optimal threshold rate $(\frac{1}{n})^{\frac{2s}{(2s+1)}}$ is attained only for the ideal threshold. However, in practice, this is unknown. Therefore, we have to replace σ_{jk} by some estimation $\hat{\sigma}_{jk}$ which results in random thresholds $\lambda_{jk} = \hat{\sigma}_{jk}\sqrt{2logM_j}$ for clutter removal and $\lambda_{jk} = mad\sqrt{2logM_j}/.6745$ for denoising. where variance ${\sigma_{jk}}^2 = Var(\hat{\beta}_{jk})$ and mad is mean absolute deviation.

IV. CLUTTER REMOVAL AND DENOISING

In this section, we will demonstrate the performance of nonlinear wavelet filtering. For a better understanding, we have inserted the wavelet tool in the signl processing algorithm. To apply our procedure, a more substantiated algorithm flow diagram is shown in Fig. . Following the first box in the algorithm flow diagram, one has first to determine the analyzing wavelet (high and low pass filter coefficients). Usually, the decomposition of a signal in a basis (i.e. a wavelet series) has the goal of highlighting particular properties of the signal. There have been no detailed investigations thus far about the regularity properties of contaminating wind profiler signals, but there is evidence that these can be both “quite regular” (ground clutter) or “not so regular” (intermittent clutter). Thus, the Daubechies family was selected. The order of the Daubechies wavelet was chosen according to the regularity condition,

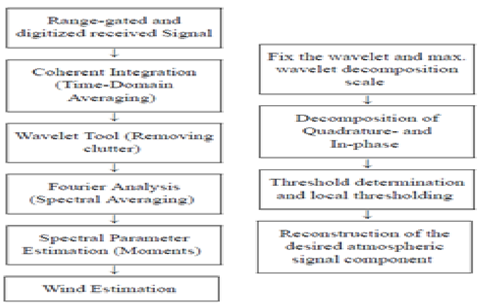

Fig 2: Left: The flow diagram using wavelet tool. Right: The wavelet algorithm flow diagram.

Which we have conservatively chosen to be rather small ($s \leq 1$)To approximate correctly a function of Bsp q ,we need to select an analyzing wavelet of regularity [s] + 1. A wavelet with regularity of the order of s = 2 and minimal In the problem of wind profiler signal filtering, the desired atmospheric signal component can be contaminated with spurious signal components. The ultimate goal is obviously to find a wavelet basis, which would allow a separation of the desired and the unwanted parts of the signal, i.e. which would have the ability to approximate the unwanted signal components (ground clutter, intermittent clutter) with only a few non-zero wavelet coefficients. In other words, the wavelet ψ has to be chosen in such a way that a maximum number of wavelet coefficients, β_{jk} are close to zero. This depends primarily on the regularity of the (contaminating) signal f , the number of vanishing moments of the wavelet ψ , and the size of the wavelets support. If f is regular and has ψ enough vanishing moments, then the coefficients β_{jk} are guaranteed to be small for small scales. If, however, the signal f contains isolated singularities, the strategy to have a maximum number of small wavelet coefficients would be to reduce the support size of the wavelet. Unfortunately, there is a tradeoff between both properties for orthogonal wavelets: if ψ has p vanishing moments, then its support size is at least 2p − 1. The best compromise between those two requirements are Daubechies wavelets, which are optimal in the sense that they have minimum support for a given number of vanishing moments. compact support is the Daubechies-2-wavelet; hence, we have chosen this one for our calculations. Mathematically, it is no problem to increase the wavelet order (regularity), but the wavelet support size and the number of filter coefficients also increases, and this will decelerate the algorithm. Finally, we note, in passing, that we have concentrated on the fast wavelet transform (multiresolution analysis), which is a special case of the discrete wavelet transform. Obviously, for an online algorithm, the number of operations per data point is limited. The fast wavelet transform is, therefore, the best choice, since it has the highest numerical efficiency (i.e. it is faster than the fast Fourier transform). This, of course, restricts the possible choices of the underlying basis wavelet. The number of decomposition scales is determined by balancing the stochastic and the deterministic part of the MISE.

Thus, the optimal scale may be evaluated automatically by the rule $2^{j1(n)} \cong n^{\frac{1}{(2s+1)}}$ After fixing the main parameters, one may start the wavelet decomposition of the in-phase and the quadrature-phase time series. To separate the atmospheric component, the algorithm calculates for each decomposition level the local thresholds λ_{jk}.

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V. RESULTS

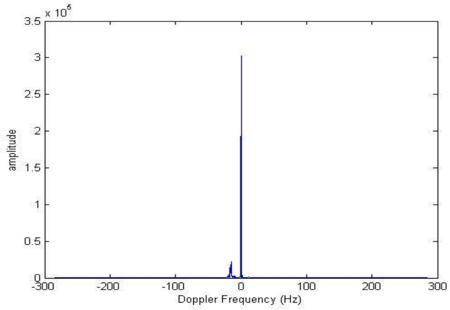

Fig 3: Signal with Clutter.

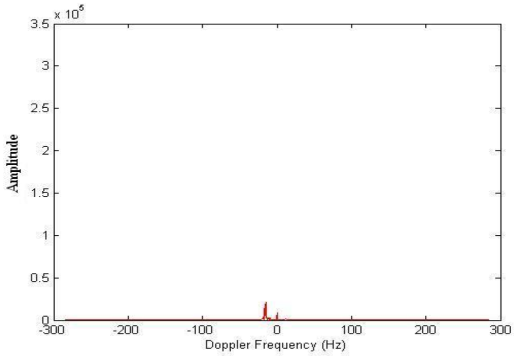

Fig 4: Signal after clutter removal

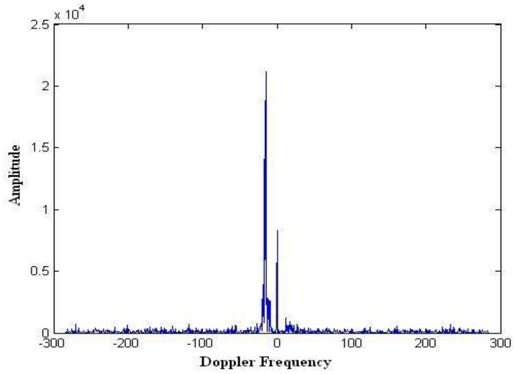

Fig 5: Signal with Noise.

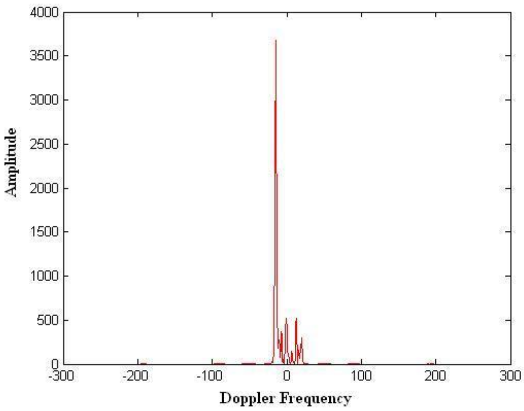

Fig 6: Signal with out Noise.

VI. CONCLUSION

This paper discusses an signal processing algorithm which implements discrete multiresolution analysis and nonlinear estimation theory for separating the atmospheric Doppler signal in Radar Wind Profiler measurements in the presence of contaminating signals.We have demonstrated that wavelet thresholding is effective in removing ground clutter and noise from the Radar Wind Profiler raw data (I/Q timeseries).

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