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Doppler Estimation of RADAR Signals using Complex Wavelets

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Abstract

This paper discusses the application of complex wavelet transform (CWT) which has significant advantages over real wavelet transform. CWT is a form of discrete wavelet transform, which generates complex coefficients by using a dual tree of wavelet filters to obtain their real and imaginary parts. In this paper we implement Selesnick's idea of dual tree complex wavelet transform where it can be formulated for standard wavelet filters without special filter design. We examine the behaviour of 1 dimensional signal and implement the method for the analysis and synthesis of a signal. Analysis and synthesis of a signal is performed on a test signal to verify the CWT application on 1D signal. The same is implemented for the MST radar signal. In this paper, CWT with custom thresholding algorithm is proposed for the estimation of Doppler profiles. The proposed algorithm is self-consistent in estimating the Doppler of a MST RADAR signal, in contrast to existing methods, which estimates the Doppler manually and failed at higher altitudes.

***Keywords*— Signal processing, MST radar, Doppler Estimation, Complex wavelets, custom thresholding.**

INTRODUCTION

RADAR can be employed, in addition to the detection and characterization of hard targets, to probe the soft or distributed targets such as the Earth's atmosphere. Atmospheric radars, of interest to the current study, are known as clear air radars, and they operate typically in very high frequency (30–300 MHz) and ultrahigh-frequency (300 MHz–3 GHz) bands. The turbulent fluctuations in the refractive index of the atmosphere serve as a target for these radars. The present algorithm used in atmospheric signal processing called "classical" processing can accurately estimate the Doppler frequencies of the backscattered signals up to a certain height. However, the technique fails at higher altitudes and even at lower altitudes when the data are corrupted with noise due to interference, clutter, etc. Bispectral-based estimation algorithm has been tried to eliminate noise [1]. However, this algorithm has the drawback of high computational cost. Multitaper spectral estimation algorithm has been applied for radar data [2]. This method has the advantage of reduced variance at the expense of broadened spectral peak. The fast Fourier transform (FFT) technique for power spectral estimation and "adaptive estimates technique" for estimating the moments of radar data has been proposed in [3].

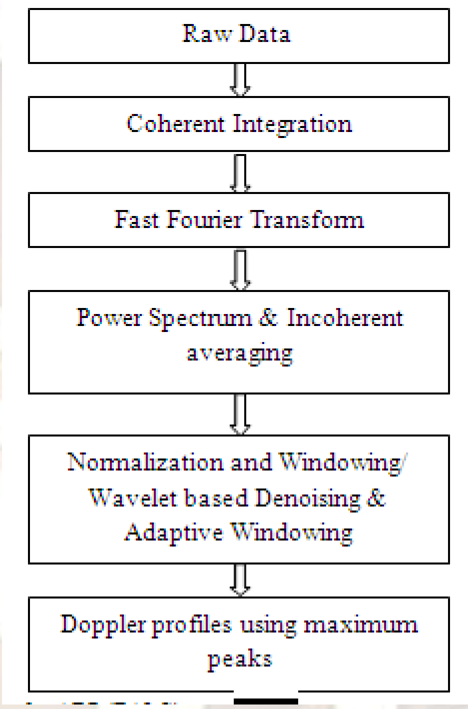

Fig.1. Flow chart for ADP (EALG)

This method considers a certain number of prominent peaks of the same range gate and tries to extract the best peak, which satisfies the criteria chosen for the adaptive method of estimation. The method, however, has failed to give consistent results. Hence, there is a need for development of better algorithms for efficient cleaning of spectrum.

II. Existing Method

The National Atmospheric Research Laboratory, Andhra Pradesh, India, has developed a package for processing the atmospheric data. They refer to it as the atmospheric data processor [4]. In this paper it is named as existing algorithm (EALG). The flowchart of EALG is given in Fig. 1. Coherent integration of the raw data (*I* and *Q*) collected by radar is performed. It improves the process gain by a factor of number of inter-pulse period. The presence of a quadrature component of the signal improves the signal-to-noise ratio (SNR). The normalization process will reduce the chance of data overflow due to any other succeeding operation. The data are windowed to reduce the leakage and picket fence effects. The spectrum of the signal is computed using FFT. The incoherent integration improves the detectability of the Doppler spectrum. The radar echoes may be corrupted by ground clutter, system bias, interference, etc. The data is to be cleaned from these problems before going for analysis. After performing power spectrum cleaning, one has to manually select a proper window size depending upon the wind shear [6], etc., from which the Doppler profile is estimated by using a maximum peak detection method [3].

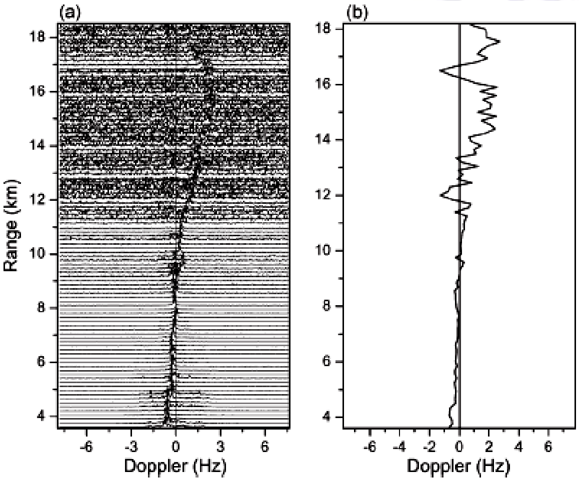

Fig.2. Typical spectra of the east beam. (a) Before Spectral cleaning. (b) Doppler profile of east beam using the EALG.

The EALG is able to detect the Doppler clearly up to 11 km as the noise level is very low. Above 11 km, noise is dominating, and, hence, the accuracy of the Doppler estimated using the EALG is doubtful as is discussed in the subsequent sections. To overcome the effect of noise at high altitudes, a wavelet-based denoising algorithm is applied to the radar data before computing its spectrum [5]. This paper gives better results compared to [4], but this method fails to extract the exact frequency components after denoising at higher altitudes. To overcome this effect we proposed a new method, where spectrum is estimated prior to denoising and then denoised using Complex Wavelet Transform (CWT) with the help of Custom thresholding method. It is named as proposed algorithm (PALG) in this letter.

III. Complex Wavelet Transform (CWT)

Complex wavelet transforms (CWT) uses complex-valued filtering (analytic filter) that decomposes the real/complex signals into real and imaginary parts in transform domain. The real and imaginary coefficients are used to compute amplitude and phase information, just the type of information needed to accurately describe the energy localization of oscillating functions (wavelet basis). The Fourier transform is based on complex-valued oscillating sinusoids

$$e^{j\Omega t} = \cos(\Omega t) + j\sin(\Omega t)$$

The corresponding complex-valued scaling function and complex-valued wavelet is given as

$$\psi_c(t) = \psi_r(t) + \mathrm{j}\psi_i(t)$$

where $\psi_r(t)$ is real and even,

$j\psi_i(t)$ is imaginary and odd.

Gabor introduced the Hilbert transform into signal theory in [9], by defining a complex extension of a real signal $f(t)$ as:

$$x(t) = f(t) + j\,g(t)$$

where, $g(t)$ is the Hilbert transform of $f(t)$ and denoted as $H\{f(t)\}$ *and* $j = (-1)^{1/2}$.

The signal $g(t)$ is the 90^{o} shifted version of $f(t)$ as shown in figure (3.1 a).The real part $f(t)$ and imaginary part $g(t)$ of the analytic signal $x(t)$ are also termed as the 'Hardy Space' projections of original real signal $f(t)$ in Hilbert space. Signal $g(t)$ is orthogonal to $f(t)$. In the time domain, $g(t)$ can be represented as [7]

$$g(t) = H\{f(t)\} = \frac{1}{\pi}\int_{-\infty}^{\infty}\frac{f(t)}{t-\tau}d\tau = f(t) * \frac{1}{\pi t}$$

If $F(\omega)$ is the Fourier transform of signal $f(t)$ and $G(\omega)$ is the Fourier transform of signal $g(t)$, then the Hilbert transform relation between $f(t)$ and $g(t)$ in the frequency domain is given by

$$G(\omega) = F\{H\{f(t)\}\} = -j\,\mathrm{sgn}(\omega)\,F(\omega)$$

where, $-j\ \mathrm{sgn}(\omega)$ is a modified 'signum' function.

This analytic extension provides the estimate of instantaneous frequency and amplitude of the given signal $x(t)$ as:

Magnitude of $x(t) = \sqrt{(f(t)^2 + g(t)^2}$

Angle of $x(t) = \tan^{-1}[g(t)/f(t)]$

The other unique benefit of this quadrature representation is the non-negative spectral representation in Fourier domain [7] and [8], which leads toward half the bandwidth utilization. The reduced bandwidth consumption is helpful to avoid aliasing of filter bands especially in multirate signal processing applications. The reduced aliasing of filter bands is the key for shift-invariant property of CWT. In one dimension, the so-called dual-tree complex wavelet transform provides a representation of a signal $x(n)$ in terms of complex wavelets, composed of real and imaginary parts which are in turn wavelets themselves. Figure 3 shows the Analysis and Synthesis of Dual tree complex wavelet transform for three levels.

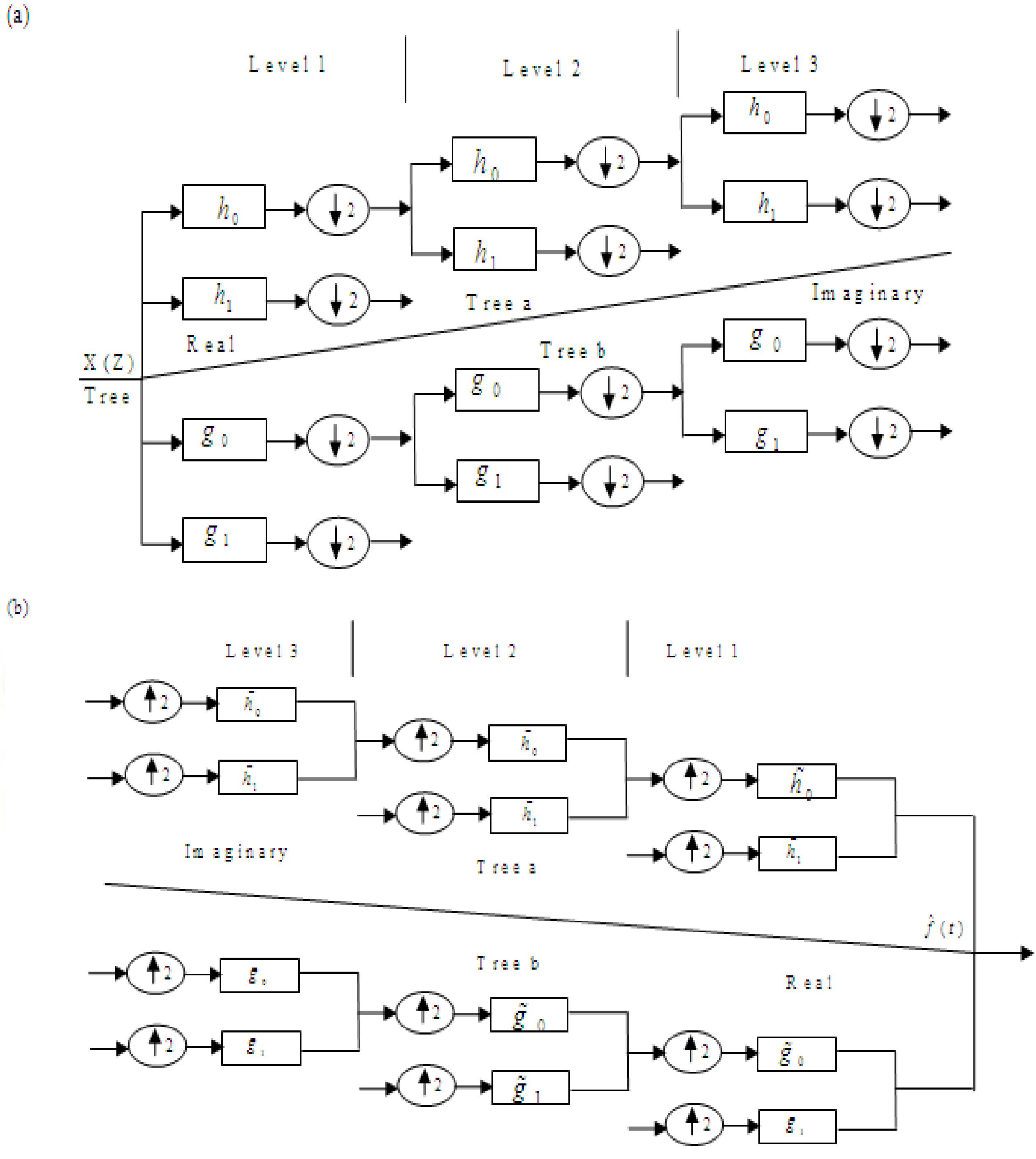

Fig.3. Three Level (a) Analysis filter bank for Dual Tree-CWT (b) Synthesis filter bank for Dual Tree-CWT

III. Custom Thresholding

To overcome the pulse broadening effect in improved thresholding function a new function called customized thresholding function is introduced. The Custom thresholding function is continuous around the threshold, and which can be adapted to the characteristics of the input signal.

Based on extensive experiments, we could see that soft- thresholding outperforms hard-thresholding in general. However, there were also cases where hard-thresholding yielded a much superior result, and in those cases the quality of the estimate could be improved by using a custom thresholding function which is similar to the hard-thresholding function but with a smooth transition around the threshold λ. Based on these observations, we defined a new custom thresholding function as follows:

$$f_c(x)=\begin{cases} x-sgn(x)(1-\alpha)\lambda & if\ |x|\geq\lambda \\ 0 & if\ |x|\leq\lambda \\ \alpha\lambda\left(\dfrac{|x|-\gamma}{\lambda-\gamma}\right)^2\left\{(\alpha-3)\left(\dfrac{|x|-\gamma}{\lambda-\gamma}\right)+4-\alpha\right\} & otherwise \end{cases}$$

where $0<\gamma<\lambda$ and $0\leq\alpha\leq1$. This idea is similar to that of the *semisoft* or *firm shrinkage* proposed by Gao and Bruce [10], and the *non-negative garrote* thresholding function suggested by Gao [10], in the sense that they are continuous at λ and can adapted to the signal characteristics. In our definition of $f_c(x)$, γ is the cut-off value, below which the wavelet coefficients are set zero, and α is the parameter that decides the shape of the thresholding function $f_c(x)$. This function can be viewed as the linear combination of the hard-thresholding function and the soft-thresholding function $\alpha.f_h(x)+(1-\alpha).f_s(x)$ that is made continuous around the threshold λ.

Note that,

$$\lim_{\alpha\to0} f_c(x) = f_s(x) \text{ and } \lim_{\alpha\to1,\gamma\to\gamma} = f_h(x)$$

This shows that the custom thresholding function can be adapted to both the soft- and hard-thresholding functions.

IV. Proposed Algorithm

The algorithm for cleansing the spectrum using CWT with custom thresholding is as follows.

1) Let *f(n)* be the noisy spectral data, for n =0, 1,...,N-1.
2) Generate noisy signal $y(n)$ using $x(n)=f(n)+\sigma z(n), \quad n=1,2,....,N$
3) Spectrum is calculated for the above signal *y(n)* as $Y(e^{j\omega})=\sum_{n=-\infty}^{\infty} y[n]e^{-j\omega n}$.
4) Input $x(n)$ to the two DWT trees with one tree uses the filters h_0, h_1 and the other tree with filters g_0, g_1.
5) Apply custom thresholding to wavelet coefficients in the two trees.
6) Compute IDWT using these thresholded wavelet coefficients.
7) The coefficients from the two trees are then averaged to obtain the denoised original signal.
8) Then variance is calculated using

$$\frac{1}{N}\sum_{k=0}^{N-1}\left(Y(k)-\sum_{k=0}^{N-1}Y(k)\right)^2$$

V. Results

The typical spectra of the data collected on December 08, 2010, for east beam before and after denoising are shown in Fig. 4. The PALG is applied to the data collected on June 9, 2006, at 1737 LT for East beams, and the respective Doppler Profile is obtained. The spectrum of the atmospheric data after performing adaptive window denoising for only the east beam is shown in Fig. 5(a).

(a) (b)

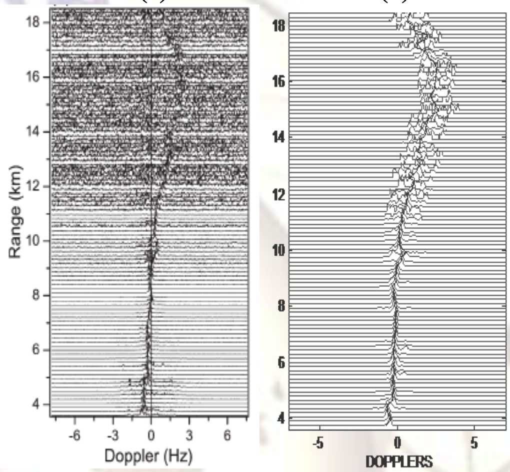

Fig.4. Typical Spectra of East beam (a) Spectra before Denoising (b) Spectra after Denoising.

The Doppler profile obtained after processing the radar data using the PALG is shown in Fig. 5(b). From Fig. 5(b), it is evident that the Doppler could be obtained even at higher altitudes, in the presence of atmospheric noise.

(a) (b)

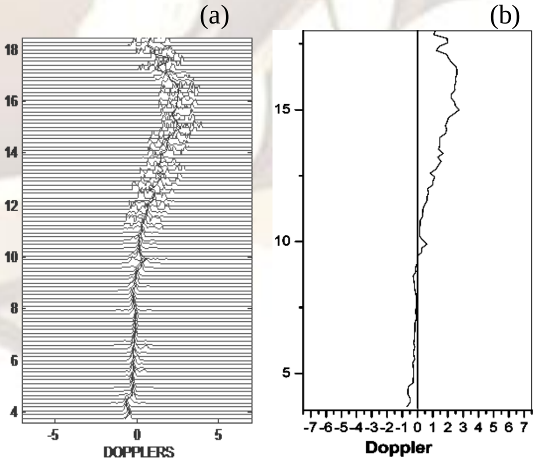

Fig.5. Typical Spectra of East beam. (a) Spectra after denoising. (b) Doppler Profile after Denoising.

To decrease the probability of filtering out the genuine peak and to improve the detectability of the signal, bin wise denoising is used instead of applying single denoising for the entire frame of data.

The Doppler profiles for the four scan of east beam are shown in Fig. 6(a), mean and standard deviation are shown in Fig. 6(b).

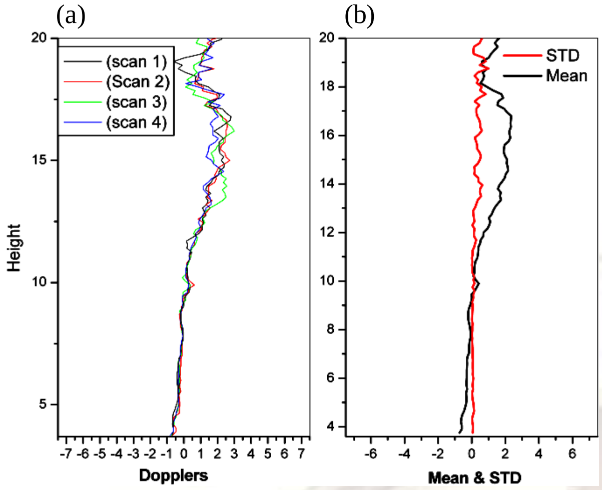

Fig.6. Typical Spectra of East Beam (a) Doppler profiles for 4 scans. (b) Mean and Standard Deviation of Doppler Profiles for 4 scans.

Finally the results were compared with the GPS sonde data and are shown in Fig. 7. From Fig. 7 it is evident that the results from the PALG are better and consistent compared to EALG.

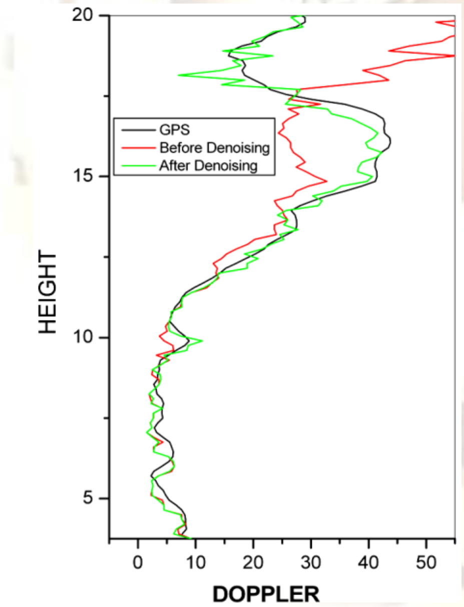

Fig.7. Mean Velocity Profiles for GPS, Raw Data and PALG

VI. Conclusion

The wavelet transform allows processing of non-stationary signals such as MST radar signal. This is possible by using the multi resolution decomposing into sub signals. This assists greatly to remove the noise in the certain pass band of frequency. The PALG is self-consistent in detecting the wind speeds up to 20 km. The results have been validated against the GPS sonde data. The proposed method may be used effectively in detection, image compression and image denoising and also it is giving better results at low signal-to-noise ratio cases (even at -15 dB).

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