Efficiency of Atmospheric Radar Signal Processing Using Eigen Value Decomposition Method

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(Dated: 30 May 2012)

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Abstract

From the beams synthesized at different pointing directions for wind profiling by Postset Beam Steering (PBS) technique on multi receiver data, the Doppler power spectra are obtained from model based spectral estimation method i.e. Eigenvector (EV). EV, one of the subspace methods, uses eigen-analysis to decompose the signal into two subspaces as signal subspace and noise subspace. Also, the power spectrum produced by sub-space methods like EV has a unique advantage of de-noising atmospheric radar signals from noisy environment. In this artcile, the advantages of EV are mainly focused for profiler radars. Such advantages are much useful to improve and estimate the spectrum parameters and thereby complete wind profiling about 20 km with temporal resolution less than 1 min.

1. Introduction

Post beam steering (PBS) and digital beam forming (DBF) is getting greater interest in radar signal processing community with its advantage in detecting the target with better temporal and spatial resolution. This is supported by advanced signal processing approaches and complex algorithms being developed in the recent past with the availability of high power computers at a cheaper cost. Generally atmospheric signals are very weak and contaminated with noise. Retrieving the signal information in the noise background is always an issue. Various techniques and quality checks have been used to extract these signals. In this paper a study has been carried out for de-noising the atmospheric signal using sub-space based method on the data received from middle and upper atmospheric (MU) radar at Shigaraki, Japan. MU radar is a monostatic pulsed phased array radar operates at 46.5 MHz with a peak power of 1 MW. The array is configured as circular array of 475 crossed Yagi elements which are grouped and formed by 25 different receiver channels for observational purpose. Array is also capable of steering the beam electronically using phase shifters in transmit and receive path. The experiment was conducted with full array of transmission (beam width 3.6^{o}) in vertical direction. The data collected is subjected to PBS [4] to synthesize new beams within transmit beam volume by capon method [8]-[9]. The EV method has unique advantage of looking the signals (beam) distinctly on to signal sub-space and noise sub-space for a given steered direction. Result shows that in the power spectral distribution, the signals only visible by completely removing noise fluctuations. This approach has shown distinct advantage in identifying the atmospheric signals from a noisy environment. The wind velocity estimated through this approach is compared with other estimation algorithms and shown excellent agreement. Study also reveals that the technique is an excellent tool to identify signals in disturbed condition of the atmosphere and having bi-modal characteristics like occurrence of clear air and precipitation echoes side by side.

Several approaches [1]-[2] were presented to overcome the lack of spectral resolution and to identify overlapped echo in the power spectrum. Again, the study [1] showed that subspace based spectral estimation method, applied to the autocorrelation function, appears to be a good alternative to Fourier-like techniques when echoes are buried in noisy environment, with a possible real time implementation. Fourier based spectral estimation methods has limitation in identifying spectrum parameters in low SNR cases. But, the advantage of Fourier based spectral estimation methods has been revealed to estimate the spectrum width in a better way compared to other model based spectral estimation methods [1]. Meanwhile, recently developed model based spectral estimation methods [1], [6]-[7] have shown greater spectral resolution and SNR improvement. For this, EV has been analyzed to identify and trace the spectrum parameters in noisy environment. EV derived from Multiple Signal Classification (MUSIC) [6]-[7] is used to detect the frequency components from the synthesized time series signal. EV assumes a statistical model for the signal through Eigen-decomposition. In subspace method, the normalized power spectrum is sharply peaked (line/pseudo spectrum) at the frequencies of the sinusoidal components of the signal. This may cause a serious problem in turbulence study using atmospheric radars. So, a simulation study was carried out not only to estimate spectrum parameter through de-noising, SNR improvement, etc and also possibility of Doppler frequency and spectrum width. However, the simulation results are not discussed in this article but the implementation on atmospheric radar signals are focused to show the advantages for profiler community. The main importance of EV is revealed through this paper such that atmospheric signals are identified distinctly from a noisy environment. So, EV removes the statistical uncertainties from power spectrum estimations so as to improve the quality of the calculations of spectrum parameters and then wind estimation. Thus, the EV technique may potentially overcame some of the difficulties that standard Fourier based techniques face in low SNR conditions, and also, may improve the temporal resolution of the estimations which is of importance for atmospheric and weather studies.

This paper is presented as follows. The spectral estimation of EV method is given in section-2. System description is given in section-3. Result analysis with discussion and conclusion are given in the section-4 and section-5 respectively.

2. Spectral estimation

Frequency estimation is the process of estimating the complex frequency components of a signal in the presence of noise. Now, let us consider the time series signal of radar array output in a vector form as

$$\mathbf{Y} = [Y(t_1)\ Y(t_2)\ Y(t_3) \cdots Y(t_m)]^T \quad \text{(or)} \quad \mathbf{Y} = [Y(1)\ Y(2)\ Y(3) \cdots Y(m)]^T \tag{1}$$

In subspace methods, spectral estimations are based on eigenanalysis of the autocorrelation matrix. Generally, a natural estimate of the sample auto covariance matrix **R** is given as

$$\mathbf{R} = \frac{1}{m}\sum_{k=1}^{m} \mathbf{X}(k)\mathbf{X}^H(k) \tag{2}$$

The Subspace based spectral analysis distinguishes the information in a correlation or data matrix, assigning information to either a signal subspace or a noise subspace. Let us now consider that the time series signal vector **Y** has number of complex sinusoids in additive Gaussian white noise. Autocorrelation matrix **R** for this system can be written as the sum of the signal covariance matrix ($\mathbf{P'}$) and the noise covariance matrix (**Q**) as described in Eqn (2).

$$\mathbf{R} = \mathbf{P'} + \mathbf{Q} \tag{3}$$

There is a relationship between the eigenvectors from signal and noise subspaces. The eigenvectors **v** of $\mathbf{P'}$ spans the same signal subspace as the signal vectors. If the system has the required signal and the order of the autocorrelation matrix is p, eigenvectors $\mathbf{v_2}$ through $\mathbf{v_{p+1}}$ span the noise subspace of the autocorrelation matrix. To generate their frequency estimates, eigenanalysis methods calculate functions of the vectors in the signal and noise subspaces and the resulting estimate has sharp peaks at the frequencies of interest. The power spectrum for MUSIC is given as

$$\mathbf{P}(f) = \frac{1}{\mathbf{e}^H(f)\left(\sum_{l=p+1}^{m} \mathbf{v}_l \mathbf{v}_l^H\right)\mathbf{e}(f)} = \frac{1}{\sum_{l=p+1}^{m} \left|\mathbf{v}_l^H \mathbf{e}(f)\right|^2} \tag{4}$$

where complex sinusoid vector e(f) is $\mathbf{e}(f) = [1\, e^{(j2\pi f)}\ e^{(j2\pi f \times 2)} \cdots e^{(j2\pi f \times (m-1))}]$

v represents the eigenvectors of the signal correlation matrix. $\mathbf{v_l}$ is the l[th] eigenvector. The eigenvectors corresponding to the smallest eigenvalues span the noise subspace (p is the size of the signal subspace). The expression $\mathbf{v}_l^H \mathbf{e}(f)$ is equivalent to a Fourier transform. This form is useful for numeric computation because the Fourier transform can be computed for each $\mathbf{v_l}$ and then the squared magnitudes can be summed. The EV method weights the summation (shown in Eqn.12) by the eigenvalues of the correlation matrix as

$$\mathbf{P}(f) = \frac{1}{\sum_{l=p+1}^{m} \frac{\left|\mathbf{v}_l^H \mathbf{e}(f)\right|^2}{\lambda_l'}} \tag{5}$$

In the case of atmospheric radar signals, the normalized eigenvalues *(λ')* of auto covariance matrix (Eqn. 2) are sequenced in descending order. The response curve is obtained by taking gradient on the normalized eigenvalues. The valley point is identified such that magnitude of gradient of eigenvalues increases abruptly (10 dB and above) and also the order (p) is minimum. Since sub space methods assume the signal into signal sub space and noise subspace, p numbers of eigenvalues and corresponding eigenvector sets (sinusoids) are assigned into signal sub space and rest of things are assigned into noise subspace. During simulation, it was observed that MUSIC, one of the subspace methods, can be useful to de-noise the signal (like atmospheric radar signals) and may not be useful for parameter (spectrum width) retrieval. Though EV is derived from MUSIC through eigenvalue weighting, its performance in obtaining parameters is observed to be efficient due to the contribution of eigenvalues which are not uniform or zero valued numbers for atmospheric radar signals**.** It is noted that there exists much uncertainty in parameters if the number of sinusoids are chosen lesser or greater than p. It is observed that number of sinusoids less than p leads to line spectrum and that more than p leads to unwanted multiple peaks within spectrum width.

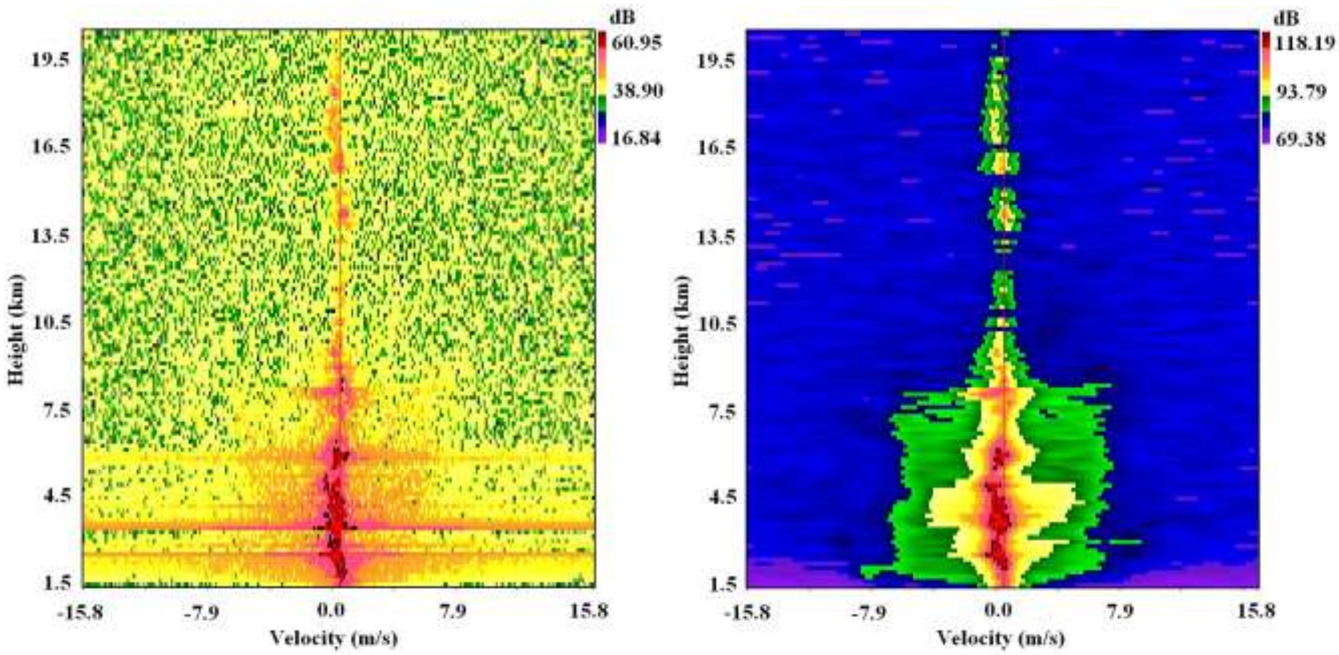
3. System description and data processing

MU radar located in Shigaraki, Japan ($34 \cdot 85°N, 136 \cdot 10°E$) has a large circular antenna array of 110 m in diameter with 475 crossed Yagi elements, the peak transmission power of 1 MW, and the bandwidth of 3.5 MHz. This frequency band is divided into five overlapping sub bands with the interval of 0.25 MHz and the bandwidth of 1.65 MHz. These sub bands are alternatively switched by pulse-to-pulse manner for obtaining phase information about targets. For receiving, the antenna array can be separated to 25 sub-arrays (channels) that have independent signal processing and storage units for spatial interferometry. The observation is conducted with full array of transmission (beam width 3.6^o) in vertical direction for PBS technique. A $1\ \mu s$ transmitted pulse is used for 150 m range resolution. The sampling time including all coherent integrations is set to be 0.1024 s and each record of 256 time series points are obtained for 25 channels.

The data collected from 25 channels are subjected to PBS technique to synthesize new beams (scan [3]) at 1.5^o tilt angle with 16 equally spaced azimuth positions. The power spectra at different line of sight angles are independently obtained as mentioned in the sections II for 5 overlapping sub bands and the sequence are repeated for three times. In this way, 15 power spectra is obtained from one record itself. The spectra are integrated to improve the SNR. From the average spectrum, zeroth order (total power) and first order (mean velocity) moments [5] are calculated through adaptive moments estimation method [10]. Thus, radial velocities from corresponding line of sight angles are readily obtained. As a result, the horizontal wind components i.e. zonal and meridional velocities are derived by least squares sense.

4. Result analysis and discussion

The power spectrum obtained by Fourier and EV based methods using vertically received time series atmospheric signals are shown in Fig.1. The power spectrum has also been improved by reducing statistical uncertainties (noise) through segmentation and overlapping processes. As mentioned in section III, the time series signal has the length of 256 points. The signal length is divided into 10 segments with 25% overlapping. In this way, each segment has 32 sample points and total number of points used is 248. The enhancement in the quality of the Doppler spectrum has also been observed with integration of spectra of different sub-bands (figure not shown). The velocity spectrum is obtained by multiplying half of the wavelength with spectral components. As EV assumes a statistical model (unlike Fourier method) to the signals through eigen-analysis, it extremely suppresses the background noise in the power spectrum to improve the quality of the calculations of spectrum parameters. Again, EV overcomes some of the difficulties in obtaining spectrum parameters that standard Fourier based approaches face in low SNR conditions. Particularly the data used in Fig.1 were obtained in a time near convective process and so there exist a number of bands in lower height regions due to higher frequency (noise) spectral components. These bands are seen in the spectra obtained using Fourier based approach. Moreover, Fourier based approach is not appropriate and may introduce much uncertainty in the computation of spectrum parameters in such cases. Also, the bands are unable to eliminate in Fourier based approach. But, EV recognizes only certain signals, whichever seems not to be aliased, for power spectrum estimation by the signal model assumed through eigen-analysis (Eqn 2-5).

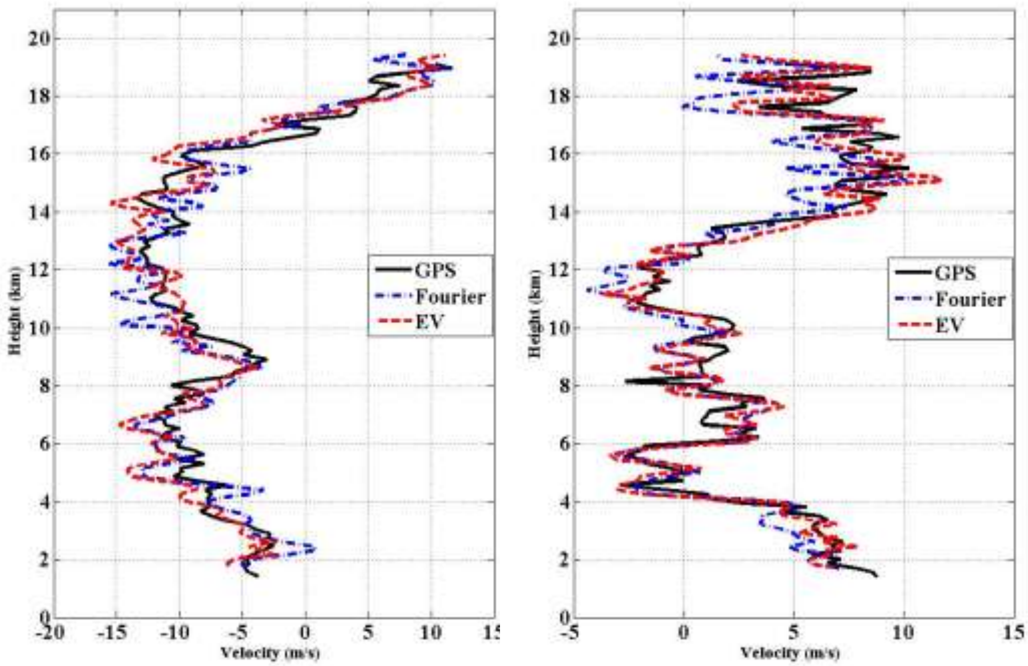


(a) (b)

Fig.1 *shows the Doppler power spectra obtained from the vertical time series data corresponding to the sub-band 46 MHz. (a) Fourier based (b) EV based. The data (time series) is obtained from MU radar on Jul 18, 2008, 0803 LT. The figure shows the characteristics of EV such as de-noising, power enhancement in comparison with Fourier method. The dB scale in the figure is arbitrary and has relevance only in comparison of background noise power with respect to signal power.*

Hence, EV not only removes the background noise (added to the radar signals) and also the statistical fluctuations (randomness of the radar and noise signals with a variance that decreases as the number of integrations increases) in the estimated spectrum.

In general, the Fourier based approach is reliable to estimate spectrum width. A close agreement in spectrum width computation between Fourier and EV is observed (figure not shown). This inferred EV can be better and alternate method for atmospheric radar measurements. In weak SNR height regions, there are deviations in spectrum width calculation between both estimators due to poor performance of Fourier estimator. A better performance in SNR improvements is observed in the case of EV estimator. When compared Fourier approach, there can be better accuracy in the estimation of moments from EV produced spectrum and thereby complete wind profiling. Hence, the study reveals that EV has the advantage of (i) identifying atmospheric signal buried in noisy environment (ii) obtaining spectrum parameters (moments) (iii) cleaning the spectrum through de-nosing process (iv) improving SNR. Thus, the advantage of EV is used to estimate the spectrum parameters from the synthesized beams for PBS wind estimates. For this, the wind estimation is made with 16 equally spaced azimuth positions at the tilt angle of 1.5^{o}. The moments (radial velocities) are obtained in 16 directions and horizontal winds are derived by least square sense. The horizontal velocities derived through using both estimators are shown in Fig.7 in comparison with GPS sonde observed winds. In Fig.7, GPS sonde observation has taken the time duration of about 62 minutes for wind profiling whereas PBS based wind profiles were derived with the temporal resolution of 26 - s. The comparison between both observations methods is made with respect to height and time in Fig.7. The statistical performance of estimators, such as slope value by linear fit, correlation coefficient and Root Mean Square Error (RMSE), in PBS wind estimates is given in Table.1.



(a) (b)

Fig.7 *Vertical profile of horizontal velocity derived by PBS technique using Fourier and EV based estimators in comparison with GPS sonde observed winds (black line) (a) Zonal velocity and (b) Meridional Velocity. GPS sonde wind observation on Jul 18, 2008, 0747-0850 LT and PBS derived winds in near time.*

Table 1: *The performance of spectral estimators in PBS wind estimates (2.0 km -19.0 km) in comparison with GPS sonde observational method. Statistics correspond to the GPS sonde data observed on Jul 16, 2008, 0747-0850 LT and PBS observation (using 5 frame integrations) in near time.*

Spectral estimation method	Slope		Correlation coefficient		RMSE (m/s)	
	U	V	U	V	U	V
Fourier	0.94	0.86	0.82	0.81	2.98	2.51
EV	1.07	0.93	0.91	0.89	1.81	1.88

Similarly, the performance of estimators in PBS wind estimates in comparison with DBS observed winds are given in Table.2.

Table 2: *The performance of spectral estimators in PBS wind estimates (1.5 km -19.5 km) in comparison with BS observational method. Statistics correspond to the data observed on Jul 16, 2008, 0338 LT and PBS observation (using 5 frame integrations) at 0346 LT.*

Spectral estimation method	Slope		Correlation coefficient		RMSE (m/s)	
	U	V	U	V	U	V
Fourier	0.94	0.82	0.81	0.82	2.62	2.32
EV	1.04	0.94	0.89	0.86	1.87	2.14

From Fig.7 and the tables 1-2, it is clear that the performance of EV in PBS wind estimates is better than Fourier method. Moreover, the wind profiling with the temporal resolution of 26 - s can be reliably obtained by PBS technique with EV approach. Further, the statistics shown in tables 1-2 are in consistent with the results of wind variations reported in previous studies [10].

5. Conclusion

Various processing to improve the Doppler power spectrum is described. EV, one of the subspace methods, has shown as an alternate estimator for Fourier based method to obtain spectrum parameters from the time series atmospheric radar data. The advantages of EV have been used to improve the synthesized spectra (within transmit beamwidth) required for PBS wind estimates. Using the advantages of various signal processing techniques and EV estimator, a high temporal (26 - s) wind estimation by PBS technique is reported in detail at the first time. The obtained results have shown to be reliable and consistent with other wind observational methods. Such high temporal wind estimation with maximum height coverage (about 20 km) can be useful to study the fast changing wind fields during atmospheric convection.

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