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MST Radar Signal Processing using PCA Based Minimum-Variance Spectral Estimation Method

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Abstract: The sub-space methods based on Eigen decomposition have been used for extracting relevant information from large data sets. The paper proposes, the principal component based spectrum computation by using the minimum variance spectral estimation method (PALG). In this work, we investigate the data received from the MST (Mesosphere-Stratosphere-Troposphere) radar installed at NARL (National Atmospheric Research Laboratory) Gadanki using PALG. We also tested the proposed algorithm (PALG) for broadband signal in presence of different noise levels (α). For the simulated signal, the PALG has given a superior performance while detecting the number of frequencies in extremely noise corrupted data also. Finally, the PALG is used to process the MST radar data for estimating the Doppler spectrum and thus in turn to find the Zonal and Meridional and wind velocity components from the Doppler. Compared with existing algorithms, the PALG works well at higher altitudes and the MST radar results were validated with the GPS data.

Keywords: Subspace methods, Eigenvalue decomposition, Principle component analysis, Spectrum estimation, MST Radar and GPS.

I. INTRODUCTION

MST radar gives wind data in the mesosphere-stratosphere-troposphere with a resolution of 150 m from a height of 3.5km. MST radar utilizes the Doppler Beam swinging (DBS) technique for gathering wind information in different directions (East, West, Zenith, North, and South). The radar collects the information using various beam positions with 16 µs coded pulse and an inter pulse period of 100 µs. The online data processing for Doppler spectra for each bin can be obtained by using FFT (Fast Fourier Transform). The DC removal, mean noise level estimation, incoherent integration and removal of interference are the steps that are involved in offline data processing. The correct estimation of the Doppler frequency is the vital one in the detection and estimation of the wind velocity by the radar. A package for processing MST radar data is developed by the NARL, Gadanki. It is called as Atmospheric Data Processor (ADP) [1].

The package (ADP) can be estimated Doppler frequencies accurately up to certain heights only. Since the data is highly corrupted with noise at higher range bins, so the ADP is unable to estimate wind profiles at higher altitudes. It can be seen in the literature that there are many authors introduced different strategies, techniques, and algorithms for denoising the Doppler spectrum for MST radar information, computing Doppler frequencies from the estimated spectrum and thus, in turn, finding the Zonal *U*, Meridional *V* and Wind velocity *W* components. An adaptive estimation technique is presented in [2] to estimate the Doppler spectrum. In this technique, certain parameters were used to adaptively track the radar signal in the range-Doppler spectral frame. Multi-taper spectral estimation [3] and Bispectral-based estimation [4] have been applied to MST radar data, which have broadened spectral peak and high computational cost respectively. Other algorithms also applied to the aforementioned data, such as cepstral thresholding [5] and wavelet-based denoising [6]. In signal processing, the power spectral density estimation techniques are classified as parametric and non-parametric algorithms. These techniques suffer from problems of spectral leakages. Due to this, there is a restriction in frequency resolution. Hence, there is need and scope to develop new methods and algorithms that give an accurate power spectrum, particularly at higher altitudes. In this paper, a new algorithm named as minimum variance spectral estimation based on the principal component analysis is introduced to estimate the precise Doppler spectrum for the MST radar data.

The paper is organized as follows. In Section II, we discuss the proposed algorithm. In Section III, power spectral Density for simulated signal and MST radar results are discussed and the paper is finally concluded in Section IV.

II. PROPOSED ALGORITHM

Principle Component Analysis is a mathematical process which uses an orthogonal transformation to change a set of observations of correlated variables into a set of uncorrelated variables. In PCA approach there is an advantage of dimensionality reduction. There are different spectral estimation algorithms to estimate the frequency. But in certain cases, we need to find only the amplitudes and frequencies of the spectrum. There is no need to find the entire spectrum. These are called frequency estimation methods. These techniques may employ the vectors that lie signal subspace or in noise subspace. The signal subspace techniques form a low-rank autocorrelation matrix which is incorporated into a spectrum estimation algorithm. The principal component analysis is one of the signal subspace methods. In the frequency estimation methods, the orthogonality of the signal and noise subspaces could be used to remove the frequencies of p exponentials in white noise. There are another set of algorithms which can be use vectors that lie in the signal subspace. These algorithms are based on principal component analysis of the Autocorrelation Matrix (ACM) and are denoted as signal subspace methods. The autocorrelation matrix for the input data $x(n)$ consisting of p exponentials plus noise is a sum of autocorrelation matrices due to signal s and noise n [7]. Let $\boldsymbol{R}_x$ be a $K \times K$ ACM of process that consists of p complex exponentials in the white noise.

$$\boldsymbol{R}_x = \boldsymbol{R}_s + \boldsymbol{R}_n \tag{1}$$

The Eigen decomposition of $\boldsymbol{R}_x$, we have

$$\boldsymbol{R}_x = \sum_{i=1}^{K} \lambda_i \boldsymbol{v}_i \boldsymbol{v}_i^H = \sum_{i=1}^{p} \lambda_i \boldsymbol{v}_i \boldsymbol{v}_i^H + \sum_{i=p+1}^{K} \lambda_i \boldsymbol{v}_i \boldsymbol{v}_i^H \tag{2}$$

Assuming that the Eigenvalues are arranged in descending order, $\lambda_1 \geq \lambda_2 \geq \cdots \lambda_K$. Since the second term in above equation is due to only noise, we can write a reduced rank approximation to the signal $\boldsymbol{R}_x$, by retaining the only principal Eigenvectors of $\boldsymbol{R}_x$.

$$\boldsymbol{R}_s = \sum_{i=1}^{p} \lambda_i \boldsymbol{v}_i \boldsymbol{v}_i^H \tag{3}$$

This approximated principal components may be used instead of $\boldsymbol{R}_x$ in case of spectral estimator such as maximum entropy method or minimum variance method. The PCA of the ACM can be used in conjunction with any of the spectral estimation methods and thus forming principle components spectrum estimation [8]. In this paper, we developed the minimum variance method for PCA based spectrum estimation. The equation of the principal component version of the minimum variance method is given by,

$$\hat{P}_{MV}(e^{j\omega}) = \frac{K}{\sum_{i=1}^{p} \lambda_i \left| \boldsymbol{e}^H \boldsymbol{v}_i \right|^2} \tag{4}$$

where $\boldsymbol{e}$ is the vector of complex exponentials orthogonal to eigenvectors $\boldsymbol{v}_i$, $i = 1, 2, \ldots, p$ and λ_i denotes eigenvalues of the covariance matrix.

Selecting the principal components

Let $\boldsymbol{R}$ be the $K \times K$ covariance matrix calculated from the mean subtracted data $x(n)$ and $\boldsymbol{R}$ can be expressed as,

$$\boldsymbol{V}^{-1}\boldsymbol{R}\boldsymbol{V} = \boldsymbol{D} \tag{5}$$

In (5), $\boldsymbol{V}$ is the matrix of eigenvectors and $\boldsymbol{D}$ is the $K \times K$ diagonal matrix of eigenvalues of a covariance matrix $\boldsymbol{R}$.

$$\boldsymbol{D}[p,q] = \begin{cases} \lambda_m; \, p = q = m \\ 0; \, p \neq q \end{cases} \tag{6}$$

here λ_m denotes the m^{th} eigenvalue. The eigenvalues represent the energy distribution of source data among each of the eigenvectors. The cumulative energy content $\boldsymbol{E}$ of the m^{th} eigenvector is the sum of the energy content across all the eigenvalues from 1 through m.

$$\boldsymbol{E}[\mathrm{m}] = \sum_{q=1}^{m} \boldsymbol{D}[q,q], m = 1, \ldots, K \tag{7}$$

Taking the first M columns of $\boldsymbol{V}$ and representing it as $K \times M$ matrix $\boldsymbol{W}$

$$\boldsymbol{W}[p,q] = \boldsymbol{V}[p,q], \quad p = 1, \ldots. K; q = 1, \ldots, M \tag{8}$$

where $1 \leq M \leq K$. The cumulative energy $\boldsymbol{E}[\mathrm{m}]$ can be used as guide in choosing an appropriate value of M. The smallest value of M is chosen such that it gives a high value of energy $\boldsymbol{E}[\mathrm{m}]$ on a percentage basis. We have to choose M, so that the cumulative energy $\boldsymbol{E}[\mathrm{m}]$ is greater than 90%. The smallest value of M is selected such that,

$$\frac{\boldsymbol{E}[m = M]}{\sum_{q=1}^{K} \boldsymbol{D}[q,q]} \geq 90\% \tag{9}$$

thus, the number of principal components to be selected.

III. RESULT ANALYSIS

A. Result Analysis for Simulation Data:

In this section, we apply proposed method to the data generated by using Gaussian random input to a system function. The system is designed with a transfer function such that the output data can be a broadband signal. Finally, we add noise of different levels (α) to the data generated and estimated Power Spectral Density (PSD). Let $x(n)$ be the data generated with Gaussian random input, $e(n)$ which is passed through a filter having transfer function $H(z)$, such that $H(z) = \dfrac{X(z)}{E(z)}$ as shown in Fig. 1. $H(z)$ is varied to produce different broadband signals [9].

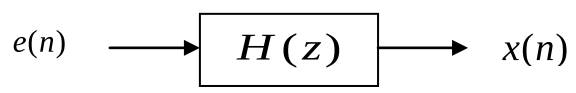

Figure1. Generation of simulated data with Gaussian random input passed through a filter.

For testing the proposed method in presence of noise, the data generated are passed through an Additive White Gaussian Noise (AWGN) channel which adds the Gaussian noise with zero mean and unit variance and let α be the amplitude associated with it. α is varied such that different levels of noise are added to data generated to produce noise signal.

$$x_1(n) = x(n) + \alpha w(n) \tag{10}$$

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The broadband nois signal is being generated using the Moving Average (MA) model and the differential equation as follows:

$$x(n) = e(n) + 0.56e(n-1) + 0.16e(n-2) \quad (11)$$

where N denotes data length and $e(n)$ is a normal white noise with zero mean and unit variance. The corresponding transfer function is

$$H(z) = \frac{X(z)}{E(z)} = 1 + 0.56Z^{-1} + 0.16Z^{-2} \quad (12)$$

for numerical simulations, N is taken as 256 samples. To test the performance of PALG in the presence of AWGN, we generated a new signal $x_1(n)$ as

$$x_1(n) = x(n) + \alpha w(n), n = 0,1,2,..., N-1. \quad (13)$$

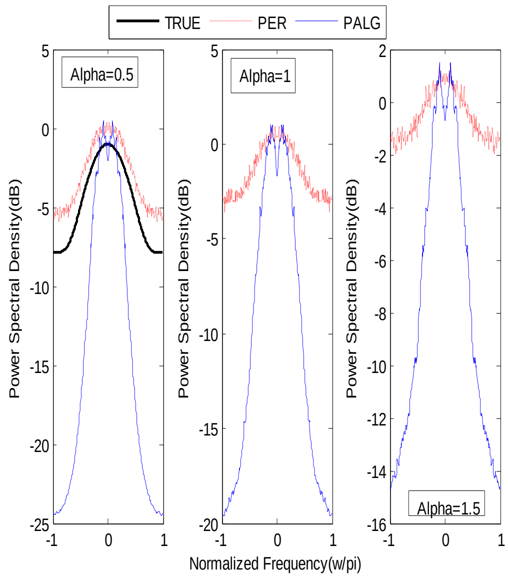

Figure2. Estimation of Power spectral density (PSDs) using PALG and PER in presence of noise associated with amplitudes α=0.5, α=1 and α=1.5.

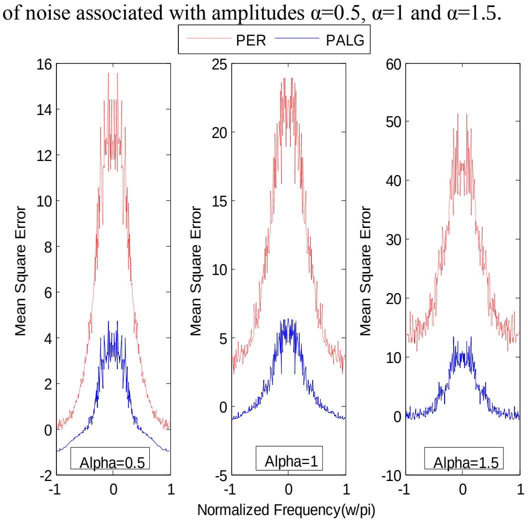

Figure3. Estimation of Mean Square Error (MSEs) using PALG and PER in presence of noise associated with amplitudes α=0.5, α=1 and α=1.5.

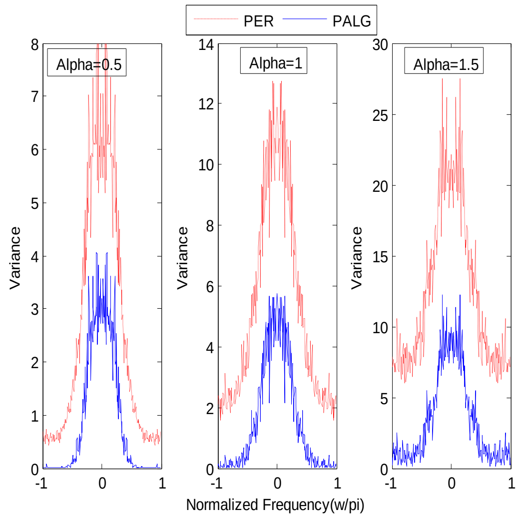

Figure4. Estimation of Variance using PALG and PER in presence of noise associated with amplitudes α=0.5, α=1 and α=1.5.

B. Result Analysis for MST Radar Data:

Atmospheric radars operate in VHF and UHF bands. The fluctuations in the refractive index of the atmosphere serve as an object (target) for those radars. We applied PALG for the data received from MST radar located at NARL Gadhanki. The MST radar data contains 150 bins; each bin has 512 complex time series data points. For a particular beam, the Doppler frequencies and Doppler velocities can be calculated by,

$$\mathbf{f} = \left(\mathbf{Index} - \frac{NFFT}{2} - 6\right) \times \left(\frac{7.56 + 7.8}{NFFT - 1}\right) \quad (14)$$

and

$$\mathbf{v} = \left(\mathbf{Index} - \frac{NFFT}{2} - 6\right) \times 0.029 \times \lambda \quad (15)$$

here NFFT is the FFT points and $\lambda = c/f_c$, c is the velocity of light and f_c is the operating frequency (53MHz).

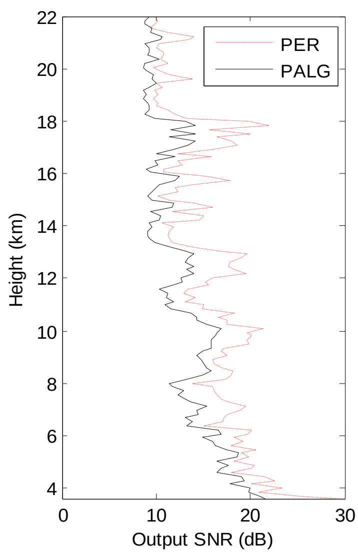

Figure5. Height profiles of SNR estimated for the east beam of radar data.

Likewise, the Doppler frequencies and Doppler velocities are computed for all six beams i.e. $\mathbf{f}_E, \mathbf{f}_W, \mathbf{f}_{Zx}, \mathbf{f}_{Zy}, \mathbf{f}_N, \mathbf{f}_S$ and $\mathbf{v}_E, \mathbf{v}_W, \mathbf{v}_{Zx}, \mathbf{v}_{Zy}, \mathbf{v}_N, \mathbf{v}_S$ respectively. The formula for calculating wind velocity components using the above Doppler velocities as follows:

$$\begin{bmatrix} \boldsymbol{v}_x \\ \boldsymbol{v}_y \\ \boldsymbol{v}_z \end{bmatrix} = \begin{bmatrix} 0.603 & 0 & 0 \\ 0 & 0.603 & 0 \\ 0 & 0 & 0.603 \end{bmatrix}^{-1} * \begin{bmatrix} 0.1736(\boldsymbol{v}_E - \boldsymbol{v}_W) \\ 0.1736(\boldsymbol{v}_N - \boldsymbol{v}_S) \\ 0.1736(\boldsymbol{v}_{ZX} - \boldsymbol{v}_{ZY}) \end{bmatrix} \quad (16)$$

where $\boldsymbol{v}_x$, $\boldsymbol{v}_y$ and $\boldsymbol{v}_z$ are the zonal *U*, meridional *V*, and vertical velocities respectively. The vertical velocity component v_z does not used in the computation of wind speed. Hence the wind speed (velocity) is computed as follows.

$$W = \left(\boldsymbol{v}_x^{\,2} + \boldsymbol{v}_y^2\right)^{1/2} \quad (17)$$

The height profiles of the SNR [10] derived from the spectrum estimated using periodogram (PER) and PALG for the east beam of data is shown in Fig. (5). From the SNR figure, it is observed that PALG yields good SNR improvement as compared to that of PER. The Doppler profiles for four scans of the east beam obtained using ADP and PALG are shown in Fig.6 (a) and (b) respectively, for the MST radar data received on Feb 10th, 2015. The mean Doppler profiles obtained by using PALG and ADP is compared in Fig.6 (c) and in the same way, the standard deviations are compared in Fig.6 (d). Until the height of 14 km, the standard deviation for PALG lies close to the zero line, but, ADP displays a clear variation from zero line.

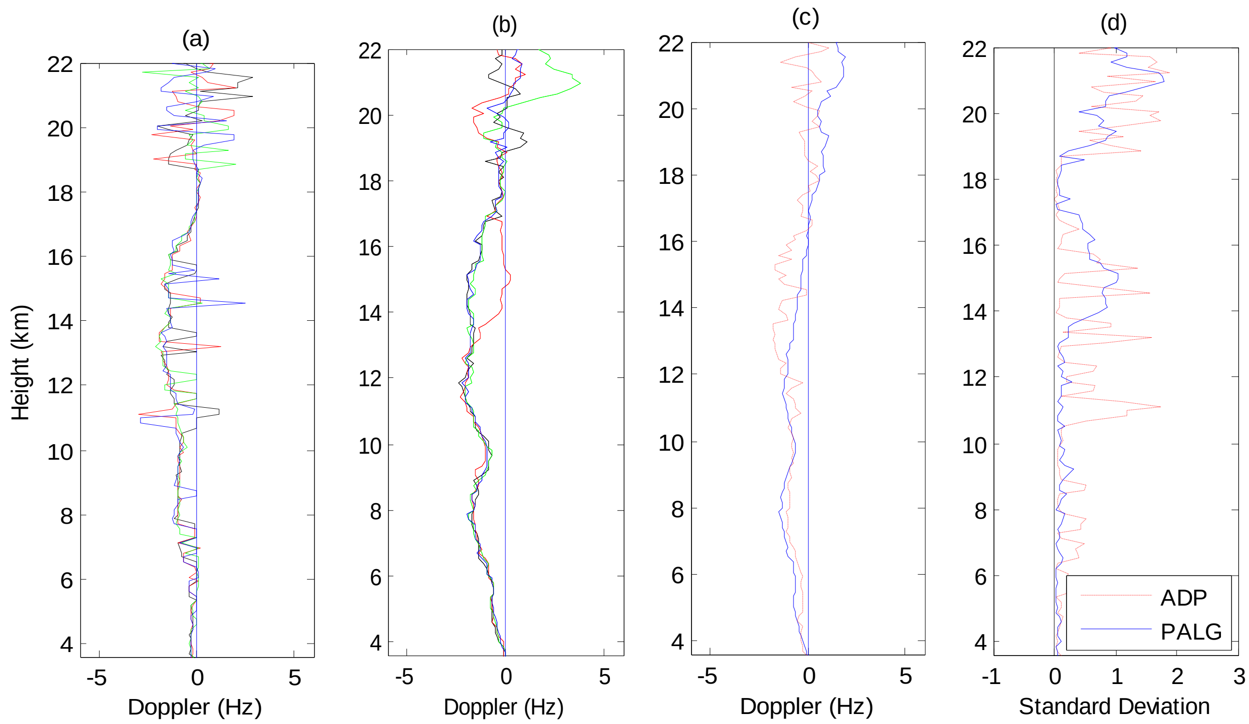

Figure6. Doppler height profiles for four scan cycles of the east beam using (a) ADP and (b) PALG. (c) Mean Doppler profile. (d) The standard deviation for the east beam of MST data Feb 10th, 2015.

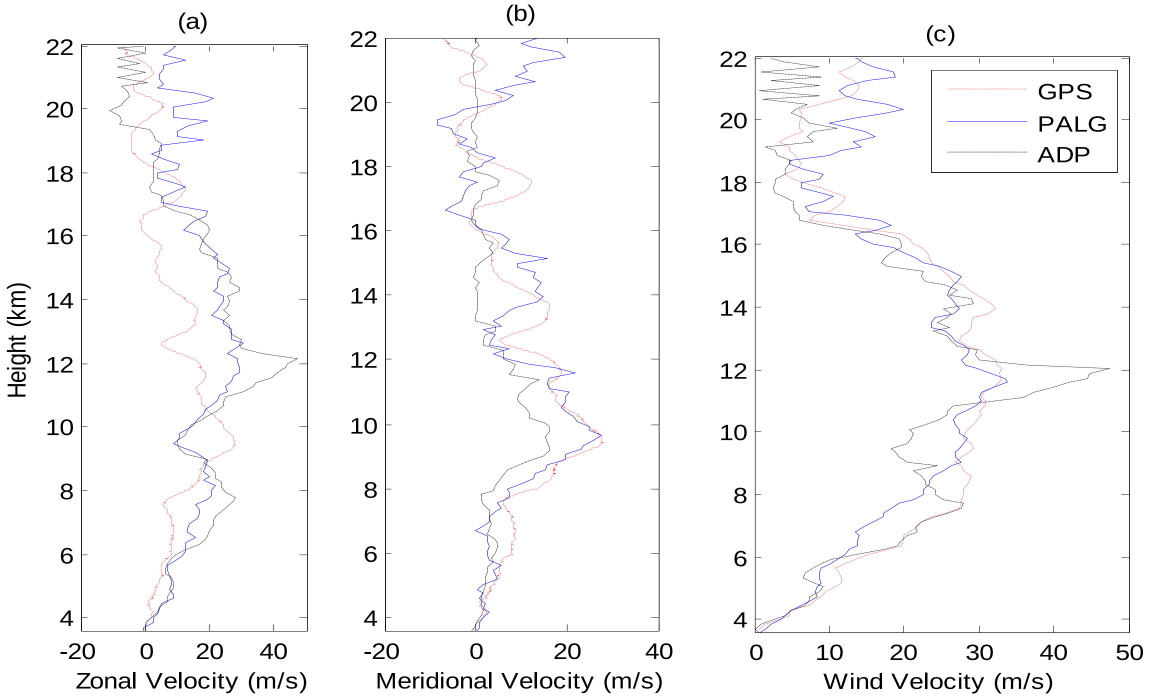

Figure7. Wind speed comparisons for the radar data collected on Feb 10th, 2015 using ADP, PALG and GPS.

The zonal (v_x), meridional (v_y) and wind velocities computed using GPS [11], PALG and ADP are shown in fig.7. This has been executed for the data collected on Feb 10th, 2015 to show the consistency of the PALG. From the fig.7, it can be noted that the wind speed profiles obtained using PALG are following the path of those calculated using GPS measure particularly in the altitude range of 10-12km. The scatter graph of fig.8 displays the correlation between ADP, PALG and GPS. By using PALG, We get a correlation coefficient of 0.93054 which is better than ADP with 0.86626.

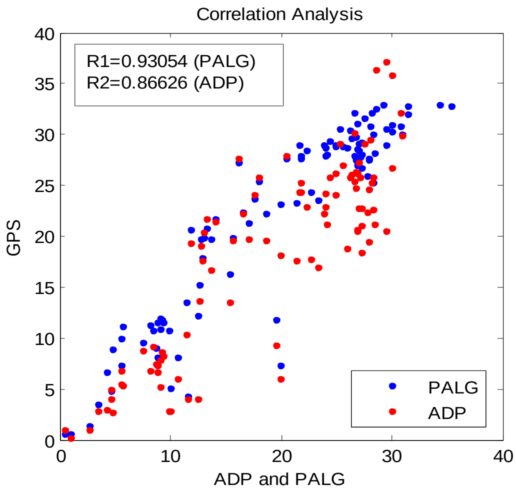

Figure8. Correlation between ADP, PALG and GPS wind speeds for MST data.

IV. CONCLUSION

We proposed principal component based spectral estimation algorithm using the minimum variance spectral method. Since the major role is only finding the Doppler frequencies from the radar echoes. By using Principal Component Analysis (PCA), the computational complexity reduces due to forming a low-rank approximation. Here we considered variance and mean square error (MSE) are the performance measures to test the PALG. The real power of PALG can be seen at higher altitudes. All the other existing methods not succeed at those heights and find the wind speed inaccurately. But it is not the case with PALG. The proposed algorithm is showing Signal-to-Noise Ratio (SNR) improvement approximately over 2.5dB overall heights. Standard deviation is also low when compared to the existing approach.

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REFERENCES

[1] Anandan V.K , Atmopheric data processor-technical user reference manual, NMRF, DOS publication, Gadanki, 2002.
[2] V.K. Anandan, P. Balamuraliddhar, P.B. Rao, and A.R. Jain, “A method for adaptive moments estimation technique applied to MST radar echoes,” in Proc. prog. Electromagn. Res. Symp., 1996.pp.360-365.
[3] V.K. Anandan, G. Ramachandra Reddy, and P.B. Rao, “Spectral Analysis of atmospheric signal using higher orders spectral estimation technique,” IEEE Trans. Geosci. Remote sens., vol. 39, no.9, pp. 1890-1895, Sep, 2001.
[4] V.K. Anandan, C.J. Pan, T.Rajalakshmi, and G. Ramachandra Reddy, “multi taper spectral Analysis of atmospheric radar signal,” Ann. Geophys., vol.22, no. 11, pp.3995-4003, Nov. 2004.

[5] T. Reddy and G.R. Reddy, “MST radar signal processing using cepstral thresholding,” IEEE Trans. Geosci. Remote Sens., vol.48, no. 6, pp. 2704-2710, Jun 2010.

[6] S. Thatiparthi, R. Gudheti, and V. Sourirajan, “MST radar signal processing using wavelet based denoising,” IEEE Geosci. Remote Sens., lett., vol.6, no. 4, pp. 752-756, Oct. 2009.

[7] Monson H, Hayes, Statistical Digital Signal Processing and Modeling, John Wiley & Sonsm 1996 .

[8] D. U. M. Rao, T. S. Reddy, “atmospheric radar signal processing using principle component analysis,” Digit. Signal Process. vol.32, pp. 79-84, Sep. 2014.

[9] P.Stoica and N.Sandgren, “Total-Variance Reduction Via Thressholding: Application to Cepstral Analysis”, IEEE Trans. Signal Process., vol. 55, no. 1, pp. 66-72, Jan 2007.

[10] D.A. Hooper, Signal and noise level estimation for narrow spectral width returns observed by the Indian MST radar, Radio sci. 34(4)(1999) 859-870.

[11] V. M. Jagannadha Rao, D. Narayana Rao, M. Venkata Ratnam, K. Mohan, and S .V. B. Rao, “Mean vertical velocities measured by Indian MST radar and comparison with indirectly computed values,” J. Appl. Meteorol., vol. 42, no. 4, pp. 541-552, Apr. 2003.

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