Asian Journal of Scientific Research

ISSN 1992-1454

OPEN ACCESS Asian Journal of Scientific Research

ISSN 1992-1454
DOI: 10.3923/ajsr.2019.97.104

Research Article
Mesosphere-Stratosphere-Troposphere Radar Data Processing using Sparse Learning via Iterative Minimization

C. Raju and T. Sreenivasulu Reddy

Department of Electronics and Communication Engineering, Sri Venkateswara University College of Engineering, Sri Venkateswara University, Tirupati, 517502, Andhra Pradesh, India

Abstract

Background and Objective: The Atmospheric Radars can provide accurate wind parameters using various spectral estimation techniques. Existing methods for spectrum estimation, however, often fail to detect the signal at low signal-to-noise ratio (SNR) conditions and to estimate precise wind parameters. In this study, a regularized minimization approach, Sparse Learning via Iterative Minimization (SLIM) is considered for the spectral analysis. **Methodology:** SLIM, which is a high resolution semiparametric adaptive algorithm, follows an l_q-norm based minimization method for sparse signal and noise power estimation. This is applied for atmospheric data collected at National Atmospheric Research Laboratory (NARL), Gadanki, India, from the Mesosphere-Stratosphere-Troposphere (MST) radar, backscattered echoes. **Results:** The results show that SLIM gives a better SNR or high detectability. The Zonal, Meridional, Wind speeds are calculated, and validated using the real-time Global Positioning System (GPS) Sonde data. **Conclusion:** It can be concluded that SLIM has better performance when compared to the previous methods. The correlation between the wind speeds computed using GPS and SLIM for the radar data collected in February 2015 has a correlation factor of 0.94.

Key words: Spectrum estimation, MST radar, adaptive algorithm, wind speeds, Global positioning system

Received: May 26, 2018 Accepted: August 07, 2018 Published: December 15, 2018

Citation: C. Raju and T. Sreenivasulu Reddy, 2019. Mesosphere-stratosphere-troposphere radar data processing using sparse learning via iterative minimization. Asian J. Sci. Res., 12: 97-104.

Corresponding Author: C. Raju, Department of Electronics and Communication Engineering, Sri Venkateswara University College of Engineering, Sri Venkateswara University, Tirupati, 517502, Andhra Pradesh, India Tel: +91-8142488696

Competing Interest: The authors have declared that no competing interest exists.

Data Availability: All relevant data are within the paper and its supporting information files.

INTRODUCTION

Doppler estimation is essential for the detection and estimation of wind parameters from the atmospheric radar data[1]. The atmospheric radar used in the present study is MST radar established at Gadanki (13.5°N, 79.2°E), Andhra Pradesh, India. The Indian MST radar operates at 53 MHz starting from 3.5 km with a resolution of 150 m to 25.6 km above the earth's surface. The MST signals are always characterized by falling signal-to-noise ratio (SNR), from which the detection and estimation of atmospheric signals is often difficult and leads to errors. Spectral estimation algorithms are applied to the radar data to estimate the Doppler spectrum. The existing spectral estimation method used at NARL is a software package named Atmospheric Data Processor (ADP)[1]. The ADP is primarily the periodogram method. The ADP processes the data in a sequence of steps, which begins by determining the Doppler profile of the radar echoes. The Doppler frequencies can be obtained from these profiles. From the spectra, the radial velocities can be found out, which then leads to the calculation of Zonal (U), Meridional (V) and Wind Speed (W) components. However, this software is found to give satisfactory results only up to a certain height.

Bispectral estimation algorithm[2] is applied to radar at a high computational cost. The advantage of a reduction in variance in the multitaper spectral estimation[3] has been proposed and applied to the radar data. The main drawback of the algorithm is spectral peak broadening. The estimation of Doppler with certain parameters has been suggested[4] that can adaptively track the signal in the spectral range frame. Wavelets[5] and Cepstrum thresholding[6] have been introduced for Doppler estimation and cleaning of the spectrum. The uniform filter banks are used for the spectrum estimation using a polyphase approach[7]. Three different types of filter banks have been proposed, of which the overlapped filter banks have reduced variance with increased correlation among the adjacent spectral components. Principal Component Analysis (PCA) has been recommended before the spectral estimation using minimum variance and Blackman-Tukey methods[8]. All the existing methods used in spectral estimation[9,10] for atmospheric radar data comes under two estimation methods either parametric or nonparametric. The parametric methods require prior knowledge and suffer from poor resolution and have high sidelobes. This is very severe especially in case of missing data. Although some techniques can give improved estimates but are sensitive to model errors. The nonparametric approach has global leakage and local leakage problems.

Recently, a high-resolution spectral estimation algorithm i.e., Sparse Learning via Iterative Minimization (SLIM)[11,12] have been developed. The "l_q-norm" based regularized minimization method for sparse signal recovery and noise power estimation is presented. This is referred to as SLIM. This regularized minimization algorithm with the sparsity-promoting constraint can provide precise and sparse estimates. For complete and incomplete data, the algorithm can attain exceptional spectral performance under different environments. However, for the spectral estimation of high dimensional data, SLIM is computationally expensive. In the present study, SLIM is used to estimate the spectrum of MST radar data collected from NARL. The proposed algorithm is found to give excellent results for real-time atmospheric radar data.

MATERIALS AND METHODS

The MST radar data collected from the NARL is a uniformly spaced complex baseband signal consisting of in-phase (I) and quadrature (Q) phase components. The spectrum of the radar data will have one or more frequencies which explain the need sparse signal recovery algorithms for spectral estimation.

Let us consider the problem of spectral estimation with complex-valued data samples. Assume that there is a finite number of measurements and the signal vector x is sparse which is an N×1 column vector. This constraint is necessary since, the linear system has many solutions indefinitely.

Let x_n(n = 0, 1,..., N-1) be the complex amplitude at the n-th frequency grid point of the spectrum and a_n (n = 0, 1,..., N-1) be the normalized contribution of the n-th frequency grid point to the available N data samples.

Then the complex data signal can be represented as:

$$y = Ax+n \quad (1)$$

where, y is an M×1 vector that represents the received signal and n is an M×1 vector that denotes the additive white Gaussian noise components. Assume that the signal x is sparse and there is limited number of measurements (M<N):

$$x = [x_0, x_1,..., x_{N-1}]^T \quad (2)$$

and:

$$A = [a_0, a_1,..., a_{N-1}] \quad (3)$$

where, x is a column vector that represents the spectrum to be estimated and A is referred to as the steering matrix.

Sparse learning via iterative minimization (SLIM): The regularized minimization criterion for sparse signal recovery is:

$$(\hat{x}, \hat{\eta}) = \min_{x,\eta} g(x, \eta)$$

Where:

$$g(x,\eta) \triangleq M \log\eta + \frac{1}{\eta}\| y - Ax \|_2^2 + \sum_{n=1}^{N} \frac{2}{q}\left(| x_n |^q - 1\right) \quad (4)$$

The vectors x, y and η represent the complex-valued signal, the received signal and the noise power respectively. The user parameter q value lies between 0 and 1. This approach is termed to as sparse learning via iterative minimization (SLIM).

The former part of the function $g(x,\eta)(\text{i.e.}, M \log\eta + \frac{1}{\eta}\| y - Ax \|_2^2)$ is the fitting term and the next part of the function $g(x,\eta)(\text{i.e.}, \sum_{n=1}^{N} \frac{2}{q}(| x_n |^q - 1))$ is the penalty term. Moreover, the penalty term will become $2\|x\|_1$-2N, if q = 1 and is similar to the l_1-norm constraint.

If q→0, the penalty term will become $2\sum_{n=1}^{N} \log x_n$ instead of l_0-norm constraint. Interestingly, when x_n→0, log x_n→-∞ and the term $2\sum_{n=1}^{N} \log x_n$ promotes sparsity.

The SLIM algorithm can be seen as a maximum a posteriori (MAP) approach.

The Bayesian model for Eq. 1 is considered as follows:

$$y|x,\eta \sim CN(Ax, \eta I), \quad f(x) \propto \prod_{n=1}^{N} e^{-\frac{2}{q}\left(|x_n|^q - 1\right)}, \; f(\eta) \propto 1 \quad (5)$$

where, f(x) is a sparsity promoting prior for $0 \leq q \leq 1$ and f(η) is an improper prior which means that η has equal probability over the range [0, ∞). When q = 1, then $f(x) \propto e^{-2\|x\|_1}$ which is a Laplacian prior and has the finite peak at 0. When q→0, the prior distribution becomes $f(x) \propto \prod_{n=1}^{N} (1/|x_n|^2)$, which has an infinite peak at 0. The smaller q has a sharper peak at 0 and gives the sparse Bayesian inference estimation.

The MAP approach for estimation of x and η are given in Eq. 6:

$$\max_{x,\eta} f(y|x,\eta) f(x) f(\eta) = \frac{1}{(\pi\eta)^M} e^{-\frac{1}{\eta}\|y - Ax\|_2^2} \times \prod_{n=1}^{N} e^{-\frac{2}{q}\left(|x_n|^q - 1\right)} \quad (6)$$

Applying the negative logarithm to Eq. 6, the equation will be equivalent to Eq. 4.

The cyclic minimization (CM) and majorization-minimization (MM)[13] methods are applied to solve the optimization problem iteratively. The first given estimates of x and η are assumed and by using the cyclic optimization technique the estimates of x and η are found. The optimization of x keeping η fixed and the optimization of η keeping x fixed are the two steps used for iteration. The updated SLIM formulae are as shown below:

- For i-th iteration, let x(i) and η(i) be the intermediate estimates of x and η, respectively. We need to minimize the function g(x, η) with respect to x

The derivative $(d/dx^H)g(x, \eta(i))$ is put to zero and solve for x(i+1) that leads to the nonlinear Eq. 7:

$$\begin{gathered}(d / dx^H) g(x, \eta(i)) = 0 \\ \frac{1}{\eta(i)} A^H A x - \frac{1}{\eta(i)} A^H y + P^{-1} x = 0\end{gathered} \quad (7)$$

Where:

$$P = \begin{bmatrix} p_1 & 0 & \dots & 0 \\ 0 & p_2 & \dots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & \dots & p_N \end{bmatrix}$$

and $p_n = |x_n|^{2-q}$.

Since, P is a nonlinear function of x, it is difficult to solve for x(i+1). We use a heuristic approach.

Put P = P(i), where P(i) = diag{p(i)}, p(i) = $[p_1(i), p_2(i), \dots, p_N(i)]^T$ and $p_n(i) = |x_n(i)|^{2-q}$.

Then Eq. 7 becomes:

$$[A^H A + \eta(i)(P(i))^{-1}]x - A^H y = 0 \quad (8)$$

The solution to Eq. 8 is simple and as follows:

$$x = [A^H A + \eta(i)(P(i))^{-1}]^{-1} A^H y$$

Finally, the (i+1) th iteration is given as:

$$x(i+1) = [A^H A+\eta(i)(P(i))^{-1}]^{-1} A^H y$$
$$x(i+1) = P(i)A^H (AP(i)A^H+\eta(i)I)^{-1} y \quad (9)$$

Let us define covariance matrix $R(i) = AP(i)A^H+\eta(i)I$ then:

$$x(i+1) = P(i) A^H R^{-1}(i)y \quad (10)$$

- Next, the function $g(x, \eta)$ is minimized with respect to η. Setting $(d/d\eta)\, g(x(i), \eta)$ to zero leads to:

$$\eta(i+1) = \frac{1}{M} \| y - Ax(i+1) \|_2^2 \quad (11)$$

The algorithm is initialized by applying a matched filter, so that $p_n(0) = |a_n^H y / a_n^H a_n|^2$, for n = 1, 2,..., N, where a_n is the n-th column of A and $\eta(0) = (1/M) \| y - Ax(0) \|_2^2$ where x(0) is obtained from $\{p_n(0)\}$. It finds the local minimum of the cost function (Eq. 4) and converges rapidly.

The convergence criterion for the algorithm is $\|x(i)-x(i-1)\|_2/\|x(i)\|_2<\Delta$, where, Δ is a small positive number and it shows no significant improvement after 15-20 iterations. The summary of the SLIM algorithm is given in Table 1.

RESULTS AND DISCUSSION

The atmospheric data is collected from the MST radar on July 2, 2014 and February 9-12, 2015 at 1737 LT to 1757 for all six beam directions. The NARL provides MST radar data in the form of range bins, scan cycles. Each range bin contains 512 complex data time series sample points. The power spectrum is estimated using the Fast Fourier Transform (FFT) algorithm for each bin of time-series data and from the FFT spectrum of each bin data, the frequency component is estimated by using maximum peak detection technique. The same would be repeated for all range bins as well as all six beams. After obtaining Doppler frequency profiles for all six beams, the Doppler velocities (v_E, v_W, v_{ZX}, v_{ZY}, v_N, v_S) are found by multiplying each of the frequencies with $c/2f_c$, where c is light velocity and f_c is the operating frequency of the Doppler radar. The three wind velocity components are calculated by using Doppler velocities of six beam directions (v_E, v_W, v_{ZX}, v_{ZY}, v_N, v_S), as follows:

$$\begin{bmatrix} v_x \\ v_y \\ v_z \end{bmatrix} = \begin{bmatrix} 0.603 & 0 & 0 \\ 0 & 0.603 & 0 \\ 0 & 0 & 0.603 \end{bmatrix}^{-1} \times \begin{bmatrix} 0.1736(v_E - v_W) \\ 0.1736(v_N - v_S) \\ 0.1736(v_{ZX} - v_{ZY}) \end{bmatrix} \quad (12)$$

Since, the Zenith-X and Zenith-Y beams are in the vertical direction, they have no role in the determination of the wind velocity.

The Wind speed W is calculated as:

$$W = \left(v_x^2 + v_y^2\right)^{1/2} \quad (13)$$

The wind speed thus obtained is then compared with the corresponding wind speed collected from the Global Positioning System (GPS) radiosonde.

Figure 1a and b shows the output SNR estimated from power spectrum using periodogram[1] and SLIM (q = 0) for the east and south beams respectively for the MST radar data collected on February 9, 2015. The output SNR is obtained by using the method proposed[14]. The comparison of average SNR values in dB for six beams on February 9 and 10, 2015 for the periodogram and SLIM algorithms is given in Table 2.

Table 1: Summary of SLIM algorithm

Step	Operation
I	Obtain the initial power and noise estimates $x_n(0)$ and $\eta(0)$ as $p_n(0) = \|a_n^H y / a_n^H a_n\|^2$ for $n = 1,2,...,N$ $x(0) = P(0) = \mathrm{diag}\{p_n(0)\}$ $\eta(0) = (1/M) \\| y - Ax(0) \\|_2^2$
II	Compute $p_n(i) = \|x_n(i)\|^{2-q}$
III	Compute the covariance matrix $R(i) = AP(i)A^H+\eta(i)I$
IV	Using the above values, update the following $x(i+1) = P(i)A^H R^{-1}(i)y$ $\eta(i+1) = \frac{1}{M} \\| y - Ax(i+1) \\|_2^2$
V	Check if $\\|x(i)-x(i-1)\\|_2/\\|x(i)\\|_2<10^{-5}$, If this condition fails then iterate steps II to IV, else STOP

Table 2: Comparison of average SNR (dB) for periodogram and SLIM algorithms

Date	Algorithm	East	West	Zenith-Y	Zenith-X	South	North
Feb 9, 2015	Periodogram	19.47	18.23	17.98	18.45	21.57	20.14
	SLIM	23.96	23.17	22.02	23.21	24.28	22.82
Feb 10, 2015	Periodogram	22.35	23.41	19.81	20.85	17.86	18.56
	SLIM	25.61	23.98	23.12	24.54	18.94	20.31

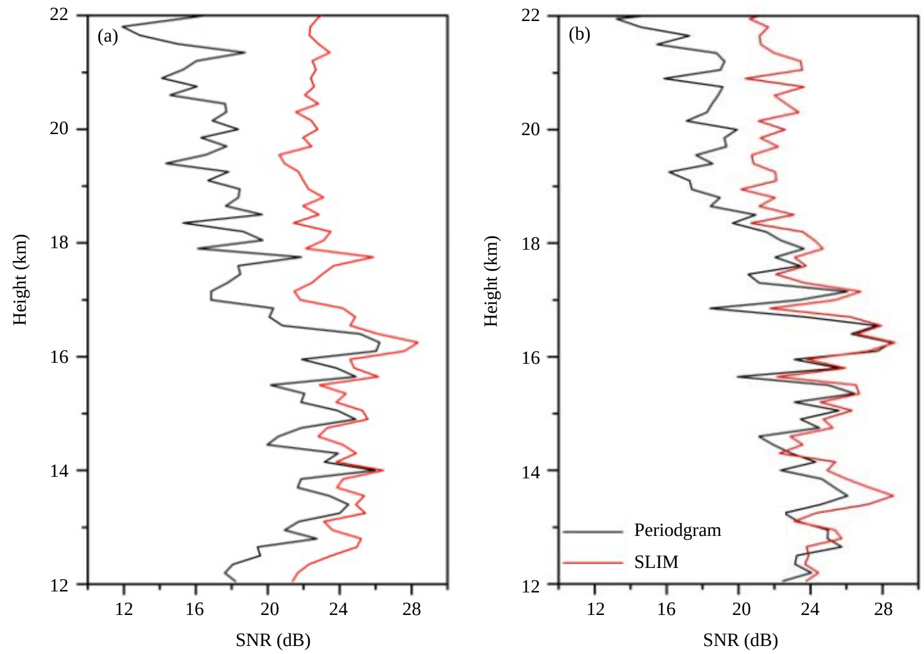

Fig. 1(a-b): Height profiles of SNR estimated (a) East Beam and (b) South Beam of February 9, 2015

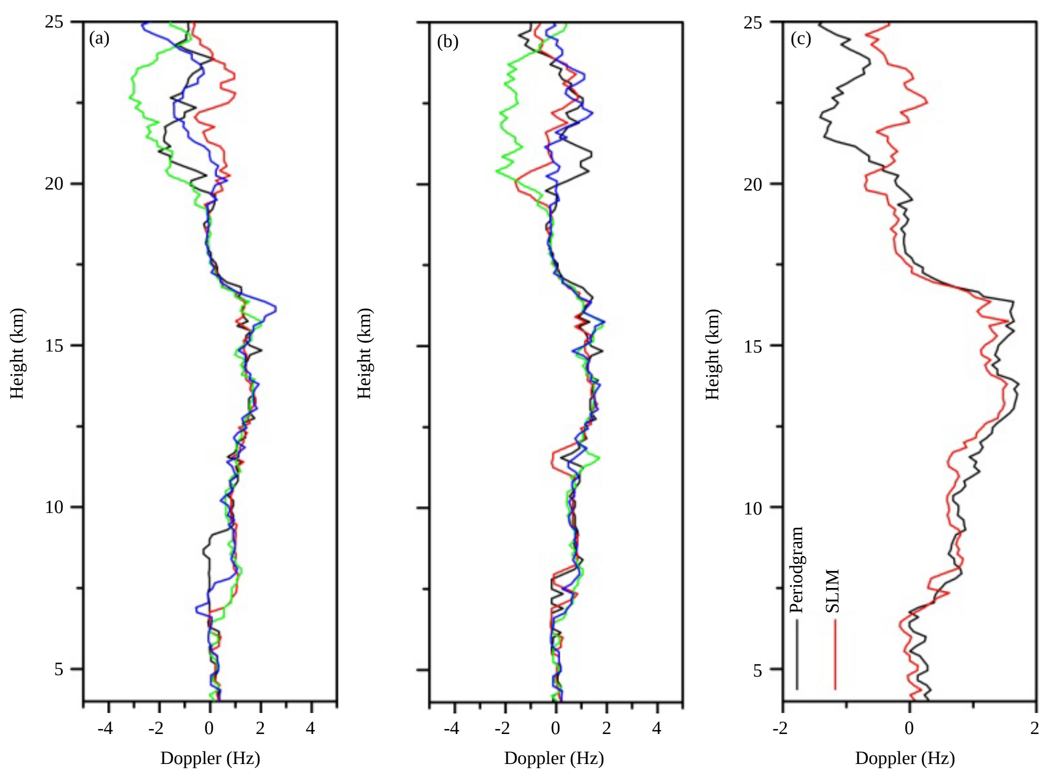

Fig. 2(a-c): Doppler height profiles for four scans of the east beam using (a) Periodogram, (b) SLIM and (c) Mean Doppler height profile of the east beam

From Table 2, it is seen that SLIM gives the better improvement in SNR values for all the six beams.

The Doppler height profiles for four scans of the east beam attained by using Periodogram and SLIM are shown in Fig. 2a and b, respectively for the radar

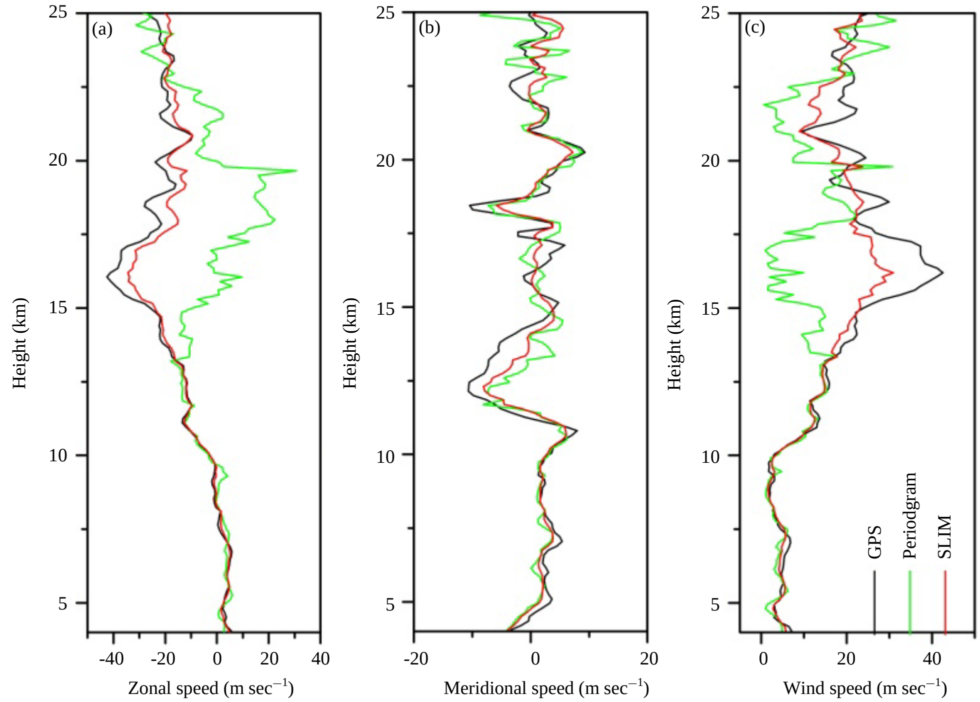

Fig. 3(a-c): (a) Zonal, (b) Meridional and (c) Wind speeds for July 2, 2014 data using GPS radiosonde, Periodogram and SLIM

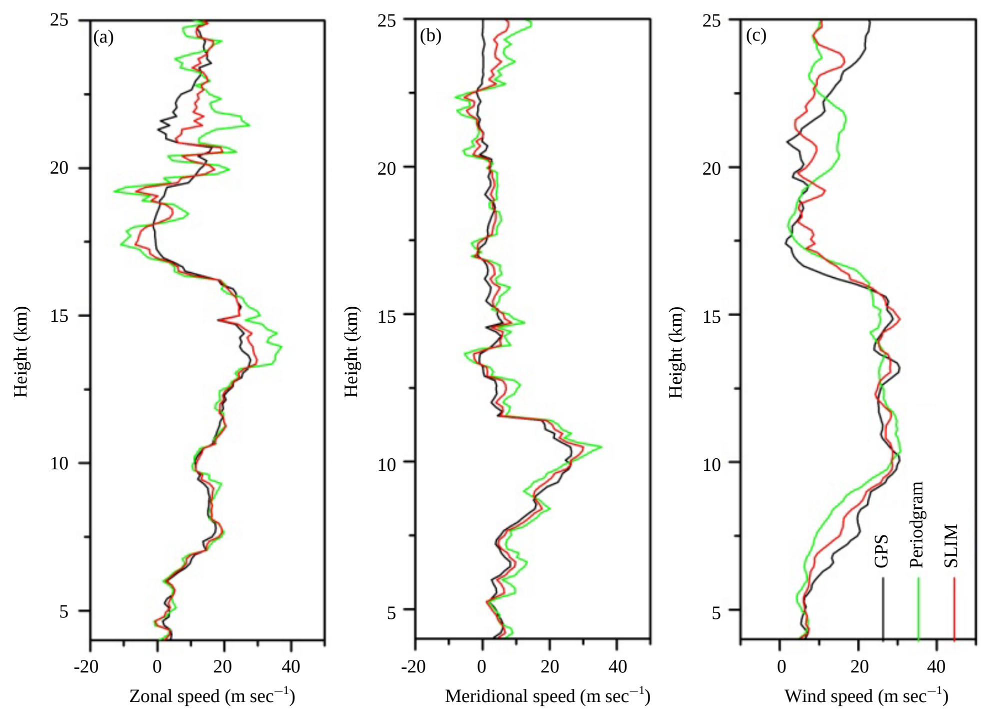

Fig. 4(a-c): (a) Zonal, (b) Meridional and (c) Wind speeds for February 9, 2015 data using GPS radiosonde, Periodogram and SLIM

data collected on February 9, 2015. The compared mean Doppler profiles are shown in Fig. 2c.

The Zonal, Meridional and Wind speed components calculated using the GPS radiosonde, periodogram and SLIM are depicted in Fig. 3 and 4 for July 02, 2014 and February 09, 2015, respectively. It is revealed that the SLIM is following the GPS. In addition to the method used at NARL, the PCA[8] method which gives the better results than the previous

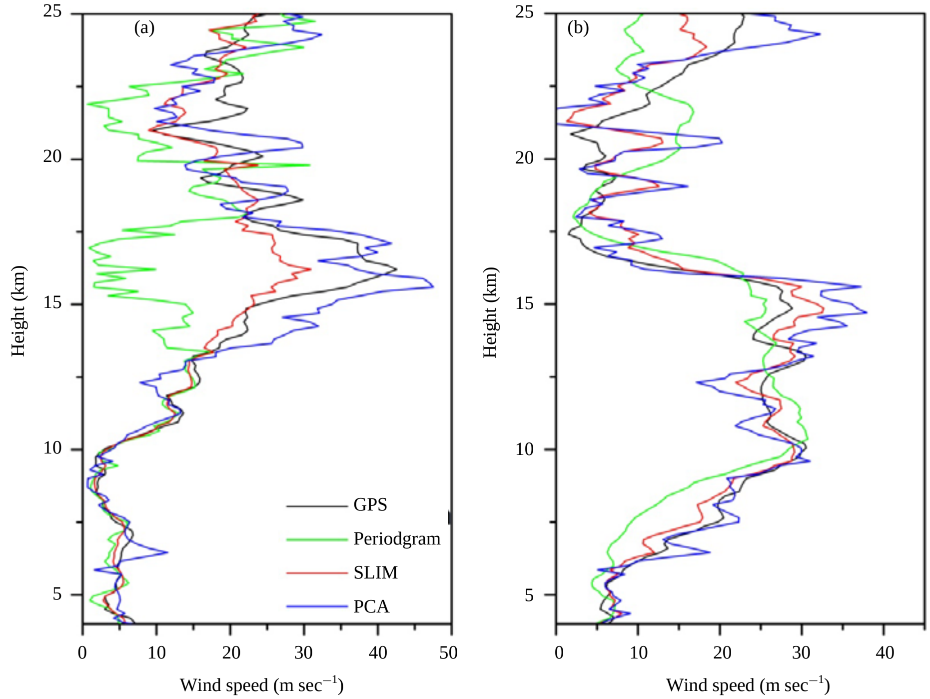

Fig. 5(a-b): Comparison of wind speed using GPS, Periodogram, PCA and SLIM for (a) July 02, 2014 and (b) February 09, 2015

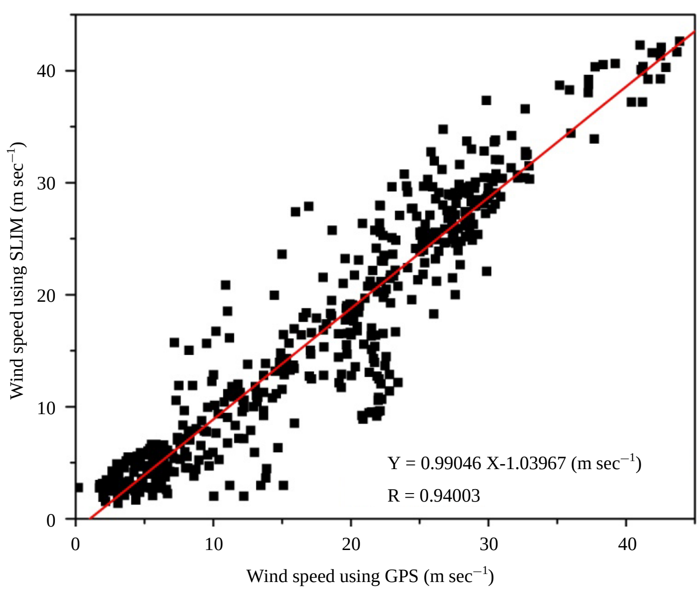

Fig. 6: Correlation between SLIM and GPS wind speeds for data during 9th-12th February, 2015

developed algorithms like Bispectral[2], Multispecrtal[3], Wavelets[5] and Cepstral Thresholding[6] is considered. The wind speed for real-time radar data collected on two different dates namely July 2, 2014 and February 9, 2015 using GPS, Periodogram, PCA and SLIM is represented in Fig. 5.

The consistency of the proposed algorithm is checked by calculating the correlation between GPS radiosonde data and SLIM wind speeds for the radar data collected during 9th-12th February, 2015. A significant correlation coefficient of 0.94003 is obtained between the GPS and SLIM, where as the correlation is 0.87 between GPS and PCA and 0.85 between GPS and periodogram. The high correlation factor acquired is indicating the relative accuracy of the wind speed calculated using SLIM confirming its efficiency and effectiveness. Figure 6 shows the correlation between SLIM and GPS wind speeds.

CONCLUSION

The regularized minimization approach with l_q-norm has been considered. The atmospheric parameters using SLIM is tested on data obtained from the MST radar. The obtained zonal, meridional and wind speeds are calculated and are validated using the simultaneous GPS data. The correlation between the wind speeds computed using GPS and SLIM for the radar data collected in February 2015 has a correlation factor of 0.94003. The SLIM provides improved results than the existing spectral estimation algorithms but with high computational complexity. This is because the updating process involves the computation of matrix inverse. Efficient methods can be implemented to reduce the computational complexity. In this letter, the user parameter q is chosen as 0. Further investigation can be carried for various values of user parameter.

SIGNIFICANCE STATEMENT

This study presents a data-adaptive technique that improves the signal detectability of the MST radar data even at low signal-to-noise conditions. The results can help the researchers in the area of radar signal processing.

ACKNOWLEDGMENTS

The authors would like to thank National Atmospheric Research Laboratory (NARL), Gadanki for providing radar data and Centre of Excellence, Department of Electronics and Communication Engineering, Sri Venkateswara University College of Engineering for technical assistance.

REFERENCES

1. Anandan, V.K., 2001. Atmospheric Data Processor-Technical and User Reference Manual. National Atmospheric Research Laboratory, Gadanki, India.
2. Anandan, V.K., G.R. Reddy and P.B. Rao, 2001. Spectral analysis of atmospheric radar signal using higher order spectral estimation technique. IEEE Trans. Geosci. Remote Sens., 39: 1890-1895.
3. Anandan, V.K., C.J. Pan, T. Rajalakshmi and G.R. Reddy, 2004. Multitaper spectral analysis of atmospheric radar signals. Ann. Geophys., 22: 3995-4003.
4. Anandan, V.K., P. Balamuralidhar, P.B. Rao, A.R. Jain and C.J. Pan, 2005. An adaptive moments estimation technique applied to MST radar echoes. J. Atmos. Oceanic Technol., 22: 396-408.
5. Thatiparthi, S.R., R.R. Gudheti and V. Sourirajan, 2009. MST radar signal processing using wavelet-based denoising. IEEE Geosci. Remote Sens. Lett., 6: 752-756.
6. Reddy, T.S. and G.R. Reddy, 2010. MST radar signal processing using cepstral thresholding. IEEE Trans. Geosci. Remote Sens., 48: 2704-2710.
7. Reddy, T.S. and G.R. Reddy, 2010. Spectral analysis of atmospheric radar signal using filter banks-polyphase approach. Digital Signal Process., 20: 1061-1071.
8. Rao, D.U.M., T.S. Reddy and G.R. Reddy, 2014. Atmospheric radar signal processing using principal component analysis. Digital Signal Process., 32: 79-84.
9. Stoica, P. and R.L. Moses, 2005. Spectral Analysis of Signals. Prentice-Hall, Upper Saddle River, New Jersey.
10. Hayes, M.H., 2009. Statistical Digital Signal Processing and Modeling. Wiley, Hoboken, New Jersey, USA.
11. Tan, X., W. Roberts, J. Li and P. Stoica, 2011. Sparse learning via iterative minimization with application to MIMO radar imaging. IEEE Trans. Signal Process., 59: 1088-1101.
12. Vu, D., L. Xu, M. Xue and J. Li, 2012. Nonparametric missing sample spectral analysis and its applications to interrupted SAR. IEEE J. Sel. Top. Signal Process., 6: 1-14.
13. Stoica, P. and Y. Selen, 2004. Cyclic minimizers, majorization techniques and the expectation-maximization algorithm: A refresher. IEEE Signal Process. Mag., 21: 112-114.
14. Hildebrand, P.H. and R.S. Sekhon, 1974. Objective determination of the noise level in Doppler spectra. J. Applied Meteorol., 13: 808-811.