Doppler Feature Based Classification of Wind Profiler Data

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Abstract. Wind Profilers (WP) are coherent pulsed Doppler radars in UHF and VHF bands. They are used for vertical profiling of wind velocity and direction. This information is very useful for weather modeling, study of climatic patterns and weather prediction. Observations at different height and different wind velocities are possible by changing the operating parameters of WP. A set of Doppler power spectra is the standard form of WP data. Wind velocity, direction and wind velocity turbulence at different heights can be derived from it. Modern wind profilers operate for long duration and generate approximately 4 megabytes of data per hour. The radar data stream contains Doppler power spectra from different radar configurations with echoes from different atmospheric targets. In order to facilitate systematic study, this data needs to be segregated according the type of target. A reliable automated target classification technique is required to do this job. Classical techniques of radar target identification use pattern matching and minimization of mean square error, Euclidean distance etc. These techniques are not effective for the classification of WP echoes, as these targets do not have well-defined signature in Doppler power spectra. This paper presents an effective target classification technique based on range-Doppler features.

1. Introduction

Wind Profiler (WP) radar is a ground based remote probing instrument to study the dynamics of the earth's atmosphere. These are pulsed and coherent radars working in the VHF and UHF bands. These radars perform the Doppler analysis of the received signal and present the data in form of Doppler Power spectra. The spectral parameters like signal power, Doppler shift and spectral width are available from this data. Products like wind velocity, wind direction and turbulence intensity at various heights can be derived from these parameters. Main purpose of the wind profiler is to get wind information at various heights. By setting radar parameters to different values, echoes from different regions of the atmosphere can be obtained. Each region has different atmospheric targets; as an example it is possible to get precipitation in troposphere, meteoric echoes in mesosphere, and magnetic activities in ionosphere. Most of the radars are operated in long sessions and generate a large volume of data. Approximate rate of data generation is 4 Megabytes per hour. For a systematic study, a researcher is required to analyze data volumes of 100 of Gigabytes. For effective use of the data, it must be classified according to the above target types. Traditionally this job is done by human experts. However, in order to process large volume of data, it would be highly desirable to have a fast and robust automated processing method. An algorithm with this functionality has been developed.

A quick overview of historical developments presents early efforts towards the target classification and the rationale behind the work in the field. Initial efforts were directed towards accurate estimation of the spectral moments. In 1970s systematic reporting on the wind profiler echoes was done by Žrnić...
Sato [3] presented a method that determines wind velocity by computing first spectral moment and wind turbulence by second central moment of the Doppler spectrum. This led to the development of the methodology of weather modeling from combined observation of Doppler weather radar and wind profiler [4]. The accuracies of the spectral parameters were also estimated in the WP data [5]. A reliable estimation of spectral noise power was established [6]. This was followed by use of appropriate thresholds in weather parameter [7]. These efforts established the relation of spectral parameters wind velocities. However, the determining the atmospheric phenomenon was largely done by human experts.

The Doppler Power Spectra is a representation of the radar echoes on two dimensional range-Doppler plane. Surveillance and imaging radars use techniques like sum of differences, Euclidean distance, and signature correlation for target identification [8]. Signature correlation method works well if the target structure is distinct [9]. In case of strategic radars, the targets are classified into a few known structures. In such cases, techniques of changing radar waveforms followed by seeking consensus are used [10]. However, these techniques are effective for the targets having well defined signatures, e.g. aircraft. Echoes from atmospheric targets do not possess even loosely defined range Doppler signatures. This is expected as the received WP signals from atmospheric targets are not wide sense stationary! Therefore, the classification or the identification of the target types can only be done by methods based on statistical criterion or soft computing techniques. One of the early reports on statistical technique was by Silverstein [11]. This technique uses the concept of catalog target representations and match quality distance function. This concept was later formalized as fuzzy logic approach and was used in ground surveillance and acoustic radars [12][13][14]. In such techniques, feature definition for each target class is critical step. Hui-Lin [15] presented feature definition and extraction on time frequency plan in the context of ground penetrating radars.

Systematic work using fuzzy logic and neural network techniques started at the National Center for Atmospheric Research (NCAR), Boulder, Colorado; Cormman [16]. Morse presented improved version of NCAR Improved Moment Algorithm (NIMA) technique capable of identifying the echoes from various wind profiler targets like clear wind, precipitation, clutter and radio frequency interference (RFI) [17]. Ostrovsky [18] presented neural network technique for the classification of the different types of precipitation echoes. The NIMA technique considers each spectral point separately and analyses 5 to 7 features like power spectral density, velocity slope, velocity curvature, gradient etc. The method defines appropriate membership functions like Gaussian, sigmoid, trapezoidal etc. and computes the membership values for each feature. A weighted sum of these values is subjected to a threshold to decide whether the data set belongs to a particular weather phenomenon. NIMA method and associated variations are robust and give precise results. However, the parameters of the membership functions and the thresholds require prolonged observations, statistical analysis and fine tuning. These efforts are often radar specific and computation intensive.

Computationally simple method is required for real time handling of a large data. Also the method must not have any parameters dependent on the radar location or it operating parameters. A classification method was evolved with this motivation. This paper presents a computationally simple technique developed for the purpose of automated classification of large volume of datasets based on prominent atmospheric target. This algorithm is capable of performing near real-time classification of Doppler power spectral data emerging form wind profiler type of radars. This method mathematically formalizes human perception based classification.

Approximately 40,000 data sets of Indian MST radar and 4,000 data sets of Lower Atmospheric Wind Profiler (LAWP) were analyzed to arrive at weather features associated with specific atmospheric phenomenon. As an example, if spectral features indicating Doppler velocities between 4 ms$^{-1}$ to 12 ms$^{-1}$ and having spectral 5 times the average noise power occur consistently for the range of more than 1050 m, occurring at ranges less than 8 km are present; the data is characterized precipitation echoes. In similar manner, after extensive observations and statistical analysis, characteristic spectral features are determined for different types of atmospheric phenomenon. It may be appreciated that these features are defined in terms of atmospheric parameters like radial wind
speed, signal strength, range and the standard deviation of the radial wind speed. The spectral feature definition is independent of the radar related parameters. Therefore, this method can be implemented on any radar or WP type. The classification algorithm sequentially searches for the features of different atmospheric phenomenon.

This paper presents classification of three type of radar targets; namely the Ionospheric activity, Clear Air Turbulence (CAT) and Precipitation Echoes. The flow chart of the algorithm is given in Fig. 1. This structure makes the algorithm modular and any new atmospheric phenomenon could be added by adding one more step in the search sequence. The algorithm was implemented on the Indian Mesosphere–Stratosphere–Troposphere (MST) radar located at Gadanki, India. The operating parameters of Indian MST radar (location 13.4N, 79.17E) are as given in table 1.

Table 1. Operating parameters of MST Radar

| Parameter                  | Parameter value |
|----------------------------|-----------------|
| Transmission Frequency     | 53 MHz          |
| Average power              | 40 KW           |
| Operation mode             | DBS, 6 Beams, N10,E10,S10,W10, Zx,Zy |
| Pulse width                | 16 µs; binary coded, of 1 µs. |
| FFT points                 | 512             |
| Doppler Resolution         | 0.0305 Hz.      |
| Sampling Start (after Tx)  | 24 µs           |
| No. of range bins          | 150             |
| Starting range             | 3.6 Km          |
| Range Resolution           | 150 m           |
| Maximum radial velocity    | ±22.11 ms⁻¹     |
| Radial velocity resolution | 0.08636 ms⁻¹    |

2. Classification of different targets from Doppler Power Spectra

The WP radars segregate the echoes based on into different range bins depending on the time of flight of the received signal. The Doppler power spectra are computed at all the range bins presented by stacking them one above other as shown in Fig. 2, 3, 4. The figures are representative examples of ionospheric echoes, precipitation echoes and clear air turbulence (CAT) echoes respectively. In these figures, the abscissa gives the radial wind speed obtained by multiplying the Doppler frequency values
by $\lambda/2$. The ordinate is the range. A brief description of the classification criterion and associated mathematical conditions corresponding to each atmospheric target are given in following subsections

2.1. Echoes of ionospheric winds

The Ionosphere is an atmospheric layer that contains the charged particles like electrons ions. It surrounds the earth at altitudes between 80 km to more than 1000 km and is classified into D, E and F layers depending on the types of particles. During the day, the D and E layers become heavily ionized; thereby increasing the RF reflectivity of that layer. In spite of large distance, on the MST radar Doppler power spectra, the ionospheric echoes show good signal strength. They present themselves as prominent peaks clustered together. The spread of the ionospheric echoes is found to be less than $44\text{ms}^{-1}$. The Doppler frequency shift is according to the radial velocity of the ionospheric winds. Understanding this fact, following conditions are used to identify the ionospheric echoes.

\[
\text{If } \{ \text{R}(i)>80 \&\& \text{peakval}(i,j)>4*N(i)\&\&\text{std\_dev}(i)<44 \} \tag{1}
\]

Where, R(i) is the range of $i^{th}$ Range bin, peakval(i,j) is the amplitude for the $j^{th}$ peak selected from power spectral component, N(i) is the RMS noise level of $i^{th}$ range bin. The mathematical expressions use the symbol ‘&&’ for logical function ‘AND’. If this condition is true for more than 300 meters, more than 2 range-bins in this case, the target is identified as ionospheric winds.

2.2. Precipitation echoes

Rain or precipitation is a tropospheric phenomenon and the echoes are observed at the ranges up to 6 to 8 km. The falling rain is the target-with-velocity approaching the radar. These echoes would result in positive Doppler frequency and appear on the right half of the range-Doppler plane. The terminal velocities of falling rain drops are generally between $8\text{ms}^{-1}$ to $12\text{ms}^{-1}$. Following conditions are put to identify the precipitation echoes.

\[
\text{if } \{ \text{R}(i)<8 \&\& \text{peakval}(i,j)>5*N(i) \&\& 8<\text{velocity}(i,j)<12 \} \tag{2}
\]

where, R(i) is the range of $i^{th}$ Range bin, and peakval(i,j) has same significance as in earlier section, N(i) is the RMS noise level of $i^{th}$ range bin and velocity(i,j) is the velocity of the falling rain drops in $\text{ms}^{-1}$. If this condition is true for around 1050 meters, more than 7 range bins in our case, the target is classified as precipitation echo.

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**Figure 2.** Ionospheric Echo 2D plot

**Figure 3.** Precipitation Echo 2D plot
2.3. Clear air turbulence echoes (CAT)

Occasionally, high turbulence is observed in atmospheric layers. On range-Doppler plane this presents itself as moderately strong Doppler components spread over complete Doppler range. This pattern spans over a few range-bins depending on the vertical extent of the turbulence. The CAT phenomenon generally occurs in troposphere (ranges below 12 km). The classification programme identifies the 7 highest peaks in each range bin.

\[
\text{if } \{(\text{std}_\text{dev}(i)>4 \&\& \text{peak}_\text{pos}(i,j)>1 \&\& \text{peak}_\text{neg}(i,j)>1)\}
\]

Where \(\text{std}_\text{dev}(i)\) is the standard Deviation of radial velocity of selected peaks in the \(i^{th}\) range bin. The lower limit of the standard deviation is set to 4 (in ms\(^{-1}\)), as the CAT echoes are more spread. The \(\text{peak}_\text{pos}(i,j)\) is the positive amplitude of the seven peaks selected for the \(i^{th}\) range bin and \(j^{th}\) power spectral component and \(\text{peak}_\text{neg}(i,j)\) is the negative amplitude of the seven peaks selected for the \(i^{th}\) range bin and \(j^{th}\) power spectral component. If this condition occurs for more than 300 meters, \(2^+\) range bins in our case, the target is classified as clear air turbulence.

3. Results and discussions

Previous section presents the search criteria for three target types. The algorithm was tested on 3000 sets of Indian MST radar data. The results are given in table 2. This table mentions the range and velocity limits for individual phenomenon and the percentage of match between the automated classification and the classification done by human expert.

![CAT Echo 2-D plot](image)

**Figure 4** CAT Echo 2-D plot

| Type of Atmospheric Phenomenon | No. of Data sets | Range (km) | Radial Velocity or Std Dev of radial velocity | Peak power / Noise level | Comments (% match) | Auto Vs/Human |
|-------------------------------|-----------------|------------|-----------------------------------------------|--------------------------|-------------------|---------------|
| Ionospheric (D)               | 500             | 75-80      | <44 ms\(^{-1}\)                                | 4                        | 100% match        |               |
| Ionospheric (E)               | 500             | 80-110     | <44 ms\(^{-1}\)                                | 4                        | 100% match        |               |
| Precipitation                 | 1000            | 0-8        | 4-20 ms\(^{-1}\)                               | 10                       | 90% match         |               |
| CAT                           | 1000            | 0-12       | >4 ms\(^{-1}\)                                 | 4                        | 90% match         |               |

*Table 2. Summary of the results on MST radar at Gadanki*
While implementing this algorithm the limit values need to be converted into number of range bins and number of Doppler bins. These conversion computations are done using the radar operational parameters available in the header of the data set. As example, radar operating pulse width of 1 μsec, and inter pulse period of 1 millisecond, number of coherent integration of 512 FFT points, will give range resolution of 0.15 km and radial velocity resolution of 0.0854 ms⁻¹.

4. Conclusions
The newly developed algorithm is capable of detecting the presence of 3 different types of atmospheric targets/phenomenon. This detection is done by searching range-Doppler features specific corresponding to the atmospheric phenomenon. The limit values in the mathematical conditions are finalized after studying multiple data sets. This algorithm was implemented in Matlab using simple mathematical expressions on the components of Doppler Power spectra. There is some percentage of misclassification. However, we expect that in large scale classification, such shortcomings are tolerable. This approach is capable of reliably identifying the atmospheric phenomenon as presented in earlier sections. The performance of this method does not get affected by different radar parameter settings, atmospheric conditions and the time of the day etc. The computational simplicity is the main advantage of this algorithm. It can be implemented for real time classification on any wind profiler.

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