Improved Moments Estimation for Ground-Based K-Band Doppler Radar Using Cost Function Method

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ABSTRACT An improved moments estimation algorithm used in a newly developed K-band wind profiler to obtain accurate 3-D profiles of wind velocity along the altitude is described. The signal-to-noise ratio (SNR) of turbulent echoes detected by millimeter-wave radar is usually low, making it becomes a challenging task to determine accurate Doppler profiles. And if wind profilers can provide quick estimates of wind, they will have greater applicability in automated, real-time environments. The improved method combines the concepts of adaptive Doppler windows and profile chain construction, reduces the search range of prospective spectral peaks by using adaptive Doppler windows, and designs new multiparameter cost functions to determine velocity profiles by studying the wind shear in the surface boundary layer. The algorithm can effectively identify the atmospheric echo components of each range bin even under the condition of low SNR, and the computational time is decreased by at least 18% compared with the previous algorithms. The proposed method is tested on the real wind radar datasets to verify its robustness and reliability. The wind information obtained by four different algorithms is compared with the data obtained from the meteorological mast of the Gaoyou wind farm in China. The comparison results indicate that the proposed method shows a nicer match with the data of the mast, and it derives the winds more accurately in the atmosphere of the surface boundary layer.

INDEX TERMS Moments estimation, wind profiler, surface boundary layer, adaptive Doppler window, profile chain building.

I. INTRODUCTION

Wind information is an important resource. Reliable atmospheric wind field measurement is of great significance in fields such as wind power, aerospace, climate and meteorology [1]–[3]. Wind profilers have the characteristics of high temporal and spatial resolution which can provide continuous wind information from different heights [4]–[6]. And the Doppler beam swing (DBS) technology has been widely used in Doppler-based remote-sensing instruments to measure the radial wind velocity [7], [8]. According to the definition of inertial sub-range and the Bragg scattering principle, the wavelength of the wind profilers should be greater than the internal scale of turbulence in the required detection height and Bragg scatter occurs when refractive index gradients with a size of half of the radar wavelength will scatter with constructive interference [9]. Traditional wind profile radars mainly work in the wavelength range of decimeters and meters to detect the atmosphere of boundary layer or troposphere, but they usually ignore the refined measurements of the atmosphere in the surface boundary layer. Some studies have shown the importance of the knowledge of air dynamics in the lower atmosphere, such as urban micrometeorology described in [10], and replacing meteorological mast to provide wind resource assessment for wind farms [11]. At present, anemometer, sodar, and lidar are usually used for the measurement of the wind field [12]. But the anemometer can only achieve single-point measurement; Sodar is easily affected by the noisy environment, and sodar noise itself is not easily accepted by nearby residents; Lidar may be

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Anandan et al. proposed an adaptive moments estimation algorithm (AME), which utilizes the information of SNR and wind shear from the previous range bin to estimate the wind velocity of the current range bin [26]. The profile tracing starts from the lowest range bin and identifies five spectral components in the Doppler windows which define the range of all possible values. After three iterations, the profile in the range-Doppler spectrum can be tracked adaptively by setting the SNR threshold, Doppler window and the wind shear threshold. Compared with the SPP method, the adaptive moments estimation algorithm can extract atmospheric information in a higher range, especially under the condition of low SNR without interference and ground clutter [27].

Sinha et al. proposed the multiparameter cost function method (MPCF) to estimate the wind profile [28]–[30]. The MPCF algorithm selects the spectral components corresponding to five possible peaks from the entire range of each range bin. Then, it discards traces which exceed the maximum allowable wind shear and allocates cost for each of the remaining traces. The MPCF is defined as the function of two weighted items. The first term is relative spectral power, and the second term is a nonlinear function of differential wind shear. And finally, the trace with the maximum cost is selected as the wind velocity profile.

Note that both the AME method and the MPCF method have been proven to be effective techniques for extracting Doppler profiles. However, the issue here is to implement a more rapid framework that is suitable for measurement of the atmosphere of the surface boundary layer.

We now briefly outline the proposed method. Our main goal is to reduce the computational complexity while maintaining detection capability in low SNR conditions. The improved moments estimation algorithm proposed in this paper draws on the concept of adaptive Doppler window of the AME method. It adaptively adjusts the position of the Doppler window according to the previous information to narrow the search range of the prospective spectral components in each range bin. Meanwhile, due to the low computational complexity of the MPCF method, the cost function is used to ensure the final profile from all possible wind traces. In particular, the method incorporates the echo characteristics of the atmosphere in the surface boundary layer and improves the composition of the cost function. The cost function is formed by two new parameters, the normalized SNR value and the wind shear between adjacent range bins.

The organization of the rest of this article is as follows. Section II introduces the system architecture of the VORTRAD and explains the basic processing of echo signals performed on the Field Programmable Gate Array (FPGA). In Section III, the improved moments estimation using cost function method is explained in detail. Section IV introduces the results of this algorithm on data sets of the K-band wind profiler and compares them with the previous algorithms. Finally, Section V summarizes the article.

II. RADAR DESCRIPTION

VORTRAD radar is a new wind field detection instrument developed by Suzhou Dufeng Technology Co., Ltd. It detects
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FIGURE 1. Photo of the VORTRAD radar with a clutter screen installed around in Gaoyou wind farm, China.

TABLE 1. Parameters relevant to the VORTRAD radar.

| Number | Parameter                        | Value                        |
|--------|----------------------------------|------------------------------|
| 1      | Transmission frequency           | K-Band                       |
| 2      | Peak Power                       | < 40 W                       |
| 3      | Pulse period                     | 2 µs                         |
| 4      | Pulse width                      | 200 ns                       |
| 5      | Operation mode                   | Doppler Beam Swinging        |
| 6      | Number of beams                  | 4 (East, West, North, South) |
| 7      | Tilt Angle                       | 15°                          |
| 8      | No. of Coherent Integration      | 150                          |
| 9      | FFT Points                       | 2048                         |
| 10     | Maximum range                    | 300 m                        |
| 11     | No. of range bins                | Optional                     |
| 12     | Maximum radial velocity          | 10.42 m/s                    |
| 13     | Radial velocity resolution       | 0.01 m/s                     |
| 14     | Weight                           | < 30 Kg                      |
| 15     | Temporal resolution              | 1 s                          |

The Doppler frequency shift produced by the turbulent particles of the near-surface atmosphere to measure the wind profile. Fig. 1 shows a picture of the radar tested in a wind farm and a temporary clutter screen was installed around to mitigate the ground clutter observed in the spectra.

The VORTRAD radar transmits electromagnetic pulses in four different azimuths is operating at K-Band. More related details on antenna design can be found in [31]. The repetition period of the radar is 2 µs and the radar is used to provide radial velocity measurements at a range of 300 meters. Signal generation, coherent accumulation and fast Fourier transform (FFT) of the pulse signal are all processed in the FPGA, and then the data stream is transmitted to the host computer for further processing. It processes 150 coherent accumulation and 2048 FFT points so that we get one spectrum of a beam approximately every 0.6 seconds. The maximum spatial distance between different beams does not exceed 160 m, and it can be considered that the atmosphere within the detection range of the millimeter-wave wind profile radar is moving uniformly. The radar is designed to operate in a variety of weather conditions, including precipitation and clear sky. As for most radars, data quality is typically greatest during periods of precipitation. Important specifications of the profile radar are summarized in Table 1 and data collected by the VORTRAD radar during the year 2021 are used in this study.

Fig. 2 shows contour maps of spectra of four different beams collected on 15 September 2021 (7:47) which belongs to a clear air day. The pseudo-colors represent the received power in dBm and the spectra were interpolated across direct current (DC) to mitigate the clutter signal. The radial velocity is on the abscissa and approximately extends from -2 m/s to 2 m/s. The ordinate is range above the ground in meters and extends from 40 m to 280 m. It can be seen that the variation of the radial velocity of atmospheric echoes at different heights within a few hundred meters is small, and the echo signals detected by the symmetrical beam are almost symmetrically distributed, which meets the basic requirement of wind information detection. It can also be observed that the echo power of some heights may suddenly weaken, resulting in discontinuous changes in the power amplitude, such as the...
position of the east beam at a height of about 80 m. In addition to the echo components of the target atmospheric turbulence, there are some strong power components scattered in other parts of the spectra which will cause the phenomenon of multi-spectral peaks and affect the extraction of radial wind velocity profiles.

III. ALGORITHM DESCRIPTION

This section describes the estimation of wind profile across the range bins using the newly improved moments estimation (IME) algorithm in detail. Overall, the algorithm is divided into three main parts, namely, preprocessing, setting the adaptive Doppler window, and assigning cost function. For completeness, we start with the power spectra data. The flowchart of the algorithm is shown in Fig. 3.

A. DATA PREPROCESSING

1) GROUND CLUTTER REMOVAL

The zero frequency often contains DC and ground clutter which are supposed to be suppressed, and the interpolation method is usually used to remove them by replacing the average values of the adjacent frequencies. Interpolating the average values of three points around zero frequency is sufficient to remove most of clutters.

2) SMOOTHING AND FILTERING

Average filtering is able to filter transient interference and has little effect on the signal of atmosphere. Considering the resolution of the VORTRAD radar, a five-point moving average filter is selected here to remove transient interference.

3) NOISE ESTIMATION

The average noise power density (indicated by $S_n$) of each range bin of the power spectra is calculated according to the Hildebrand and Sekhon method [32]. The $S_n$ values are subtracted from each range bin of the power spectra and the negative values are supposed to be replaced with zeros to facilitate subsequent recognition of the range of spectral peaks.

B. SETTING DOPPLER WINDOWS AND SELECTING PROSPECTIVE PEAKS

The algorithm starts from the lowest range bin and searches for candidate peaks in the adaptive Doppler windows. Doppler windows are determined dynamically based on the results of the previous range bin and are set for each range bin to limit the search range of components that contains prospective peaks. While the MPCF algorithm picks the five of the most prominent spectral peaks in the full Doppler window for each range bin, the IME algorithm tends to collect fewer spectral peaks in certain Doppler windows as its reduction of the search ranges. Select the position with the largest amplitude as candidate peak, and search for the intersection points with zero of its left and right sides to determine the range of the spectral peak, calculate its radial velocity, spectral width, and SNR. If the SNR is larger than 0 dB, save the peak as a prospective peak and iterate the process to select the remaining spectral peaks until all three prospective peaks are identified or there is no spectral component with a power value greater than $S_n$ in the current Doppler window.

For the first range bin, as there is no prior information available, just identify the most prominent component as a candidate signal for the SNR is always high enough. Set its radial velocity as Mean Doppler velocity and the Doppler window is set to identify prospective peaks in the second range bin. Typically, the Doppler signal is not expected to change by more than 20% of the total coherent filter bandwidth [33]. That is to say, the width of Doppler windows should be less than 20% of the entire Doppler axis width. And then, the peak in the second range bin whose radial velocity is closest to the Mean Doppler velocity in the first range bin is set to new centra of Doppler window which constrain the component range of the third range bin. And the procedure is repeated sequentially for all range bins. This process provides a predefined range for the identification of the signal and prevents the search range of spectral peaks from being affected by noise outside the windows.
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Fig. 4 shows the selection of prospective peaks in each range bin in descending order of the level of power. The sequence number of the range bin is indicated on the y-axis, and each spectrum is plotted inside a rectangle. The y-axis in rectangles represents the power normalized to the maximum value of the spectra and the x-axis represents the radial velocity. The blue and red boxes on specific range bins respectively represent the Doppler velocity windows of the current range bin and the previous range bin. It is obvious that a lot of random noise or impossible peaks are excluded from the Doppler windows.

C. GROUPING AND ALLOCATING COST

To consider the continuity between each range bin and the adjacent range bin at the same time, this step uses the concept of chain building and assigns cost to different traces to decide the most likely profiles. After identifying all the prospective peaks of a Doppler frame, connect possible traces and assign cost functions to them. However, if we link all possible traces for N range bins, the computation will be very large as there may be up to $3^N$ trails. Therefore, it is recommended to divide the spectra data into small groups and each group should contain three or more range bins to ensure the binding force of the continuity.

After making groups, construct links from range bin to range bin and each group starts with an initial value. The initial value is set as the Doppler speed of the highest range bin of the previous group. For the first group, the initial value is supposed to be the speed of the most prominent peak. Fig. 5 shows all links in a group and $M_j^r$ indicates the jth peak of the rth range bin.

Next, the algorithm allocates costs to each trace with a cost function. Due to the low SNR of the received signal and the multi-spectral peak components, the cost function pays more attention to the continuity of wind for identification. Generally, under the premise of satisfying certain continuity, the peaks whose SNR are within a certain range are more likely to belong to the spectral component of the target echoes. Therefore, the cost function is set as a function of normalized SNR and wind shear.

An experiment was conducted to study the characteristics of wind shear in the surface boundary layer by collecting and analyzing the data of a WindcubeV2 lidar. The lidar uses DBS technology to measure wind speed at 11 different vertical heights (50, 70, 80, 90, 100, 110, 120, 140, 160, 180, 200 m) with a sampling frequency of 1Hz. The lidar gives the profile of the horizontal winds as wind speed–wind direction (WS–WD), and equations (1), (2) convert the wind data from the lidar system into zonal and meridional winds.

$$u = WS \times \sin(WD)$$
$$v = WS \times \cos(WD)$$

where $u$ represents zonal wind speed, and $v$ represents meridional wind speed. The experiment collected a total of 3996 sets of the lidar data from May 12 to July 1, 2021 which experience different weather conditions including precipitation and clear sky. Use data of the six consecutive layers (70, 80, 90, 100, 110, 120 m) to calculate wind shear value and differential wind shear value at an interval of 10 m and use data of another set of layers (80, 100, 120, 140, 160, 180, 200 m) to calculate wind shear value and differential wind shear value at an interval of 20 m. Fig. 6 shows the probability of occurrence of the wind shear value and differential wind shear value of $u$ and $v$ at different intervals. It can be seen that the probability distribution generated by $u$ and $v$ is relatively consistent, and the wind shear value seems to be changed proportionally to the interval of the range bin as more than 99% of wind shear are less than 0.5 m/s at an interval of 10 m and 1 m/s at an interval of 20 m. In this case, the wind shear is more representative than the difference wind shear as the difference wind shear value is mostly concentrated around 0.
Then, the wind shear of the radial velocity follows:

$$|\Delta v_m| \leq 0.05 \cdot \sin \theta \cdot \Delta R$$  \hspace{1cm} (3)

where $|\Delta v_m|$ refers to the maximum wind shear satisfied in most cases, $\theta$ is the tilt angle and $\Delta R$ is the distance resolution.

Generally, the smaller the speed difference between adjacent distance layers, the greater the possibility of the echo belonging to the wind. We believe that non-linear functions can better describe the distribution of wind shear, but no unique non-linear function can cover all cases exactly. For simplicity and objectivity, the characteristics of continuity of the power spectrum can be processed as a Trapezoidal function:

$$T_{r/r-1,j/j'}(x; a, b, c, d) = \max[\min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0]$$  \hspace{1cm} (4)

where $T_{r/r-1,j/j'}$ represents a partial cost associated with the trace from the $j'$ th spectral peak of the $r-1$ th range bin to the $j$ th spectral peak of the $r$ th range bin. $x$ represents the wind shear and the parameters $a, b, c, d$ determine the shape of the trapezoidal function.

Combining the above, the continuous membership function can be represented as shown in Fig. 7, then

$$T_{r/r-1,j/j'}(x) = \begin{cases} 
1, & |x| \leq \Delta v_m \\
\frac{2\Delta v_m - |x|}{\Delta v_m}, & \Delta v_m \leq |x| \leq 2\Delta v_m \\
0, & |x| \geq 2\Delta v_m.
\end{cases}$$  \hspace{1cm} (5)

The normalized SNR function is given as follows:

$$P_{r,j} = \alpha_{r,j}/\max(\alpha_r)$$  \hspace{1cm} (6)

where $\alpha_{r,j}$ represents the SNR value corresponding to the $j$ th spectral peak of the $r$ th range bin, and $\alpha_r$ represents the set of SNR of all candidate spectral peaks of the $r$ th range bin.

Then, the whole cost function is expressed as:

$$C_{r/r-1,j/j'} = w_1T_{r/r-1,j/j'} + w_2P_{r,j}, \quad \sum_{i=1}^{2} w_i = 1$$  \hspace{1cm} (7)

where $w_1$ and $w_2$ represent the weights occupied by the continuous membership function and the normalized SNR function, $C_{r/r-1,j/j'}$ is the cost from peak $M_{r-1}^{j'}$ to $M_r^j$. We set up seven sets of experiments on 1200 sets of data and the value of $w_1$ is set from 0.2 to 0.8 with a step of 0.1. The results are consistent under different times and different weather conditions including precipitation and clear sky for that the results have the highest matching degree when $w_1$ is set to 0.4.
Table 2. Parameter configuration of the algorithms.

| Parameter                  | Value          |
|----------------------------|----------------|
| Doppler window width       | 20%            |
| Range bins per range window| 5              |
| SNR threshold              | 7 dB           |
| MPCF method wind shear criterion | $(4.4 + 0.15 \times \Delta R)$ m/s |
| IME method                 |                |
| Doppler window width       | 20%            |
| Range bins per group       | 5              |

Therefore, the following experiments set relative weights of 0.4 and 0.6.

Calculate the total cost of each link and the link with the largest cost value is supposed to be the final Doppler profile of the distance group. Then set the new initial value as the speed of the highest range bin of this group to help the formulation of profile of next group and repeat the previous process. The chain connection can better maintain the continuity of the target echo and eliminate the contamination of random noise or clutters.

This completes the description of the algorithm. These steps are repeated for each beam, and then the DBS technique is used to calculate the wind speed and direction information on each range bin by radial velocities of the final profiles.

IV. RESULTS AND DISCUSSION

This section presents some experimental results to demonstrate the performance of the proposed method. The first part of the experiments focuses on the profiles obtained by the SPP, AME, MPCF, and IME method on the range-Doppler spectra while the second part shows the comparison of horizontal wind velocities from various algorithms against the data of a meteorological mast obtained during the same period. Verification is done by using the offline data of the VORTRAD. Parameter configuration of the algorithms are shown in Table 2.

Fig. 8 shows an example of high SNR Doppler spectra of a south beam of the VORTRAD radar observed on 15 May 2021(23:01) during precipitation whose maximum SNR value is 22.85 dB and minimum value is 3.93 dB. Fig. 9(a) draws the corresponding average Doppler velocity distribution results obtained by the four methods. The Doppler spectra at each range bin have been preprocessed before applying any algorithm. All the estimated results of the SPP, AME and MPCF method mentioned in this part were programmed by author as described in [21], [26] and [30]. It is clear that the results of the four methods are similar. However, the SPP method is easily affected by strong noise as it determines the Doppler velocity profile according to the largest component in each range bin without considering any spatial and temporal continuity, such as the heights of about 156 m and 276 m. Furthermore, note that the MPCF method fails to find a profile around the top layers due to the precipitation broadens the echo spectrum, and it produced the profile only after we manually widened the wind shear criterion in the MPCF method in this case. The profile estimated by the IME method seems to be the smoothest contour results compared with the other methods. Fig. 9(b) shows the mean Doppler velocity profiles with standard deviation obtained by using 6 consecutive scans at the south beam, further illustrating the accuracy of the IME method.

Fig. 10 shows an example of low SNR Doppler spectrum of a west beam of the VORTRAD radar observed in clear sky on 27 June 2021(17:15) whose noise peaks are even larger than the atmospheric signal in quite a few range bins, and the corresponding mean Doppler velocity profile retrieved by the four methods are shown in Fig. 11(a). There is a big difference between the profiles at the heights of about 168 m and 276 m. Fig. 11(b) shows the results of corresponding standard deviations retrieved by the four methods using 3 consecutive scans of the west and east beams respectively. The SPP method can only provide reliable mean Doppler velocity profiles over very limited altitudes, and its standard deviation increases rapidly above about 100 m, reaching outside 5 m/s. The standard deviations calculated by the AME method are much smaller. However, some discontinuous strong spectral
components cause the results of the AME method to deviate from the accurate wind profile. The MPCF method even cannot produce valid profiles as the highest five spectral peaks in some range bins may belong to random noise and the candidate peaks between adjacent range bins cannot meet the wind shear criterion. The standard deviations of the IME method get the smallest value which means the error fluctuation is greatly reduced. Therefore, for the case of low SNR, the height coverage of the Doppler profile can also greatly improve with the use of the IME method.

The meteorological mast shown in Fig. 1 provides 15-minutes average wind speed data at four heights (30, 50, 70 and 140 m) and average wind data from the VORTRAD for heights ranging from 20 m to 300 m with interval of 20 m are available. The distance between the VORTRAD and the mast is about 50 m. An example of six-day comparison results of the four algorithms between wind radar and the mast at the height of 140 m is shown in Fig. 12. The synchronous observation date is from September 28 to October 4, 2021. For the objective of comparison, no other quality control algorithms are applied here. It can be seen that using the SPP algorithm is inaccurate most of the time. The AME and MPCF algorithm has a significant improvement over the SPP algorithm, but occasionally there may be large deviations in the results. The result of the IME algorithm is the best fit with the Mast data. Fig. 13(a-d) shows the scatter plot of horizontal wind velocities obtained from the four algorithms on the VORTRAD radar and Mast data collected from 15 September 2021 to 18 September 2021 and 28 September 2021 to 8 October 2021 which are all related to clear sky. The scatter plots were generated by taking 1420 points for the height of 70 m and the color bars represent data density.

Furthermore, a statistical analysis of the results is summarized in Table 3 which compares the correlation coefficient and coefficient of determination ($R^2$) values of horizontal wind speed in different heights measured from the four methods with respect to Mast data. $R^2$ indicates the effect of the regression fitting. The larger the value of $R^2$, the denser the observation points are near the regression line. The following reasons may cause some errors in the experimental results, resulting in a decrease in the overall correlation, especially at heights of tens of meters: 1) The damping of the mechanical blade bearings used on the mast will change after long-term use, causing the measurement results error occurs; 2) The terrain of the test environment is not absolutely flat, and the
two instruments are far apart, resulting in a certain difference in wind speed information between the two locations. However, the correlation coefficients of the IME algorithm are still all greater than 0.85 and $R^2$ values are all greater than 0.72, which suggests that the horizontal wind profiles obtained from the IME method are a closer match with Mast data than results obtained from the other three methods.

While the MPCF method selects the five most significant spectral peaks within the entire power spectra, the IME method selects the three most significant spectral peaks within the dynamic Doppler windows. Thus, the computational complexity will be further decreased. The computational time to run SPP, AME, MPCF, and IME algorithms after preprocessing steps was recorded as 0.30, 0.95, 1.22, and 0.78 seconds for 1000 Doppler frames with 25 range bins and 2048 Doppler components per range bin on a computer having clock speed of 3.79 GHz using MATLAB R2020a. The computation time of the AME algorithm is slightly smaller than that of the MPCF algorithm, which might be related to the smaller number of range bins. The IME algorithm is expected to save $18\%-36\%$ of the time to estimate the Doppler profile. This will significantly reduce the computational time of the data processing.

V. CONCLUSION

In this paper, we describe a K-band wind Doppler profiler, including its technical characteristics and method of processing the received data. The radar was originally designed to provide wind speed and direction information at different distance layers for wind farms to facilitate wind resource assessment and wind energy forecasting. It is worth noting that under most meteorological conditions, measurements in the millimeter wavelength range are an effective means of wind measurement. On the one hand, compared with the traditional wind profile radar, the newly developed K-band radar makes up for the lack of fine measurement of the atmosphere in the surface boundary. On the other hand, compared with the traditional wind mast, which is expensive to build and cannot be moved, the radar has the advantages of small size, light weight, and easy installation and movement. This study proves the feasibility of millimeter-wave radar to achieve wind measuring and provides a new idea for the realization of ground-based remote sensing wind field measurement.

Meanwhile, an improved moments estimation algorithm is proposed to extract Doppler profiles. With the increasing demand for high temporal resolution and real-time data processing, the computational load of data processing is also a part of the consideration. This paper analyzes the wind shear of the atmosphere in the surface boundary layer by analyzing the data measured by the windcubeV2 lidar to adjust the composition of the cost functions, then improves the algorithm combined with the adaptive Doppler window. Compared with the previous algorithms, the computational time is decreased by at least $18\%$. In terms of the accuracy of profile extraction, this paper uses the echo spectra data collected by the VORTRAD radar in the year 2021 to compare it with the previous multi-peak detection methods. Experiments show that the present method can effectively identify atmospheric signals. The wind profiles calculated by the algorithm are compared with the average data of the meteorological mast, and the results are in good agreement. Compared with the other three methods, the correlation coefficient and $R^2$ values are all increased to a certain extent.

The present method shows a better performance in the atmosphere of the surface boundary layer, especially helping to improve the detection capabilities under low SNR.
However, the method still has certain limitations for complex weather scenarios such as convection. Further research is needed to solve the situation of multiple echoes, and more potentials of millimeter-wave radar for wind field measurement should be tapped.

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