# Postprint: Rapid Detection and Analysis of Low-Frequency Radio Interference Using Computer Vision Algorithms

**Authors:** Gao Wenshuai^{1,2,3}, Zhao Bixuan^{1}, Guo Quan^{1}, Hong Xiaoyu^{1,2,3}

**Date:** 2023-06-07T00:00:00+00:00

## Abstract

Radio frequency interference (RFI) can lead to loss or quality degradation of astronomical observation data pertinent to scientific objectives, therefore its detection and mitigation constitutes one of the crucial steps in radio astronomy observation data processing. Low-frequency RFI primarily originates from anthropogenic activities and natural atmospheric phenomena, such as FM broadcasting, aviation communications, satellite communications, meteors, and lightning. Based on the high time-resolution (approximately 1 ms) observation mode of the single-antenna array of the 21CMA (the 21 centimeter array) at Ulastai, Xinjiang, an algorithmic software suite for rapid detection and analysis of low-frequency RFI was developed. This software utilizes signal spectrum waterfall plots as input and primarily identifies RFI signals based on the Canny edge detection algorithm and the Hough line detection algorithm. Test results demonstrate that this software exhibits low parameter dependency, with an output accuracy of approximately 90%, and its processing performance is expected to meet the requirements for real-time processing. The observational data were acquired from approximately 42 h of observations conducted during the Quadrantid meteor shower in January 2020. Through RFI detection and preliminary analysis, the results indicate that within the frequency range of 74   110 MHz, the primary source of the detected low-frequency RFI is likely reflected signals from meteor trails.

## Full Text

## Preamble

**Progress in Astronomy**, Vol. 40, No. 2
June 2022

doi: 10.3969/j.issn.1000-8349.2022.02.09

**Fast Detection and Analysis of Low-Frequency Radio Interference Based on Computer Vision Algorithms**

GAO Wen-shuai[1;2;3], ZHAO Bi-xuan[1], GUO Quan[1], HONG Xiao-yu[1;2;3]
(1. Shanghai Astronomical Observatory, Chinese Academy of Sciences, Shanghai 200030, China;
2. School of Physical Science and Technology, ShanghaiTech University, Shanghai 201210, China;
3. School of Astronomy and Space Science, University of Chinese Academy of Sciences, Beijing 100049, China)

## Abstract

Radio Frequency Interference (RFI) causes loss or degradation of astronomical observational data relevant to scientific targets, making its detection and mitigation one of the crucial steps in radio astronomical data processing. Low-frequency radio interference primarily originates from human activities and natural atmospheric phenomena, such as FM broadcasting, aviation communications, satellite communications, meteors, and lightning. Based on the high time-resolution (approximately 1 ms) observation mode of the single-antenna pods of the 21 Centimeter Array (21CMA) at Wulasitai, Xinjiang, we have developed a software pipeline for rapid detection and analysis of low-frequency radio interference. The software uses spectral waterfall plots as input and primarily employs the Canny edge detection algorithm and Hough line detection algorithm to identify RFI signals. Test results demonstrate that the software exhibits low parameter dependence and achieves an accuracy of approximately 90%, with processing performance that promises to meet real-time processing requirements. Observational data were obtained from approximately 42 hours of observations conducted during the Quadrantid meteor shower in January 2020. Through RFI detection and preliminary analysis, the results indicate that within the 74-110 MHz frequency range, the detected low-frequency radio interference most likely originates from reflected signals of meteor trails.

**Keywords:** low-frequency radio interference; low-frequency radio interferometer; image processing; computer vision algorithm
**Classification:** P161
**Document code:** A

## 1 Introduction

For low-frequency radio telescopes (operating below 300 MHz), signals generated by human activities—including radio communications, television and radio broadcasting, FM radio transmission, aviation, and satellite communications—constitute major sources of interference. Certain physical processes in the atmospheric environment also introduce radio interference, such as scattering in the troposphere causing reflection of broadcast and television signals, long-distance propagation of electromagnetic signals due to atmospheric ducting effects, reflection of low-frequency radio signals caused by ionospheric anomalies, scattering from meteor trails, and lightning. When these physical processes themselves become scientific targets, the resulting radio interference may reflect information about the underlying physical mechanisms.

Radio interference signals are typically at least 10 times stronger than astronomical signals, though their duration is usually relatively short. Taking 21CMA as an example, its optimal operating band is 70–200 MHz, with the primary scientific goal of detecting cosmic reionization signals. The strength of neutral hydrogen signals from the cosmic reionization epoch is on the order of ($1 \times 10^{-3}$ to 0.1) K. In our actual observations, the dominant component is the low-frequency radiation from the Galaxy itself, with intensity around 100 MHz of 1–100 K, which is 4–5 orders of magnitude stronger than the cosmic reionization signal. Radio interference in this frequency range is typically another 2 orders of magnitude higher than the Galactic radiation. Due to their distinct identification features, manual annotation of RFI in data is feasible when data volumes are modest. However, the single-antenna pods of 21CMA used in this study, while observing with only one or two pods at a time, generate 32 MB of data per second per antenna due to the high time resolution (approximately 1 ms). A 24-hour observation yields 2.76 TB of data, and with 81 antenna pods in total, full operation would produce 440 TB daily—far exceeding the current data processing capacity of the telescope backend. Therefore, in this experiment, we used only two pods for continuous observations totaling 42 hours, obtaining 4.6 TB of data. Even so, manual identification of RFI in these observations has become inefficient and unsustainable. Additionally, human-generated RFI signals typically have relatively narrow bandwidth, fixed frequencies, and sometimes exhibit clear modulation structures—characteristics that facilitate identification of specific low-frequency RFI sources.

Existing RFI identification software in the astronomical community does not fully meet current requirements. For instance, VarThreshold is unsuitable for detecting extremely close and sharp RFI signals. Algorithms based on Singular Value Decomposition (SVD) perform exceptionally well in detecting periodic RFI but struggle with frequency-varying signals. AOFlagger is a software package that detects, flags, and removes RFI based on signal morphology, designed with detection and labeling accuracy as primary considerations at the expense of processing speed—AOFlagger requires approximately 1 second to process $10^6$ data points, while a single 21CMA pod samples about $8 \times 10^6$ points per second. Furthermore, AOFlagger does not support the data format of 21CMA' s single-antenna modules.

This work leverages computer vision algorithms to rapidly extract millisecond-timescale RFI sources and characterize RFI signals in observational data, with the ultimate goal of building an RFI sample database for studying the physical mechanisms of RFI generation. This paper is organized into four sections:

Section 1 introduces the background and significance; Section 2 describes the observational data and software framework; Section 3 presents the test results; and Section 4 provides summary and discussion.

## 2.1 Data

The data used in this work were obtained from 21CMA, located at Wulasitai in Xinjiang at an altitude above 2,650 m, surrounded by mountains exceeding 3,000 m that serve as natural barriers blocking electromagnetic radiation from surrounding regions. The observational equipment consisted of two single-antenna pods, E5 (East 5) and E9 (East 9), with a time resolution of 1 ms and frequency range of 50–200 MHz. Observations were conducted on January 3, 4, and 5, 2021, with a cumulative observation time of 42 hours and total data volume of 4.6 TB. The data format is a time-varying waterfall plot (spectrogram) with frequency (in MHz) on the horizontal axis and time (in ms) on the vertical axis. Field measurements indicate that the primary RFI sources around the 21CMA site are low-orbit satellite data transmission (137 MHz) and civil aviation communications (121 MHz), with no persistent FM broadcasting interference, making it an excellent site for low-frequency radio astronomy.

[Figure 1: see original paper] shows the spectrogram of received signal power distribution over time and frequency. Note: The upper portions of panels a) and b) display waterfall plots of frequency signals over time, while the lower black lines show the averaged spectral distribution over the same time period. Panel a) shows weaker RFI appearing between 87–111 MHz in the lower subplot, with the red line representing the spectrum of the subplot and green lines indicating local FM broadcast bands.

**Figure 1** Power distribution of signals received by the E9 antenna pod at two different moments. The upper portion of panel a) shows RFI signals identified through manual inspection, with the corresponding RFI signals magnified in the inset of the lower portion. The black line in the lower portion of panel a) represents the average power over 2,000 ms, the red line shows the average over 250–500 ms, and green lines mark regional FM broadcast frequencies (China National Radio: 88.7 MHz; Uyghur Language Station: 90.6 MHz; Xinjiang People' s Radio City Broadcast: 92.9 MHz; Xinjiang People' s Radio Traffic Broadcast: 94.9 MHz; Xinjiang People's Radio News Comprehensive: 96.1 MHz; Urumqi Traffic Radio: 97.4 MHz; News Music Radio: 99.0 MHz; Travel Music Radio: 106.5 MHz). During this period, weaker RFI appeared between 87–111 MHz, with the corresponding signals shown in the inset of the lower portion, while strong interference was detected at 137 MHz. Panel b) shows no RFI signals, with the black line representing the average over 2,000 ms. No weaker RFI like that in panel a) appeared between 87–111 MHz, but strong interference at 144 MHz was detected, likely from walkie-talkie communications.

[Figure 2: see original paper] shows examples of low-frequency RFI signals identified manually. To develop effective detection methods, we first performed manual visual inspection of 30 minutes of data, finding that most burst RFI signals lasting hundreds of milliseconds or longer likely originate from forward-scattered FM broadcasts by aircraft, meteor trails, or other causes. These signals fall within the FM broadcast frequency range and can be easily identified by their frequency jitter, as FM broadcasting transmits information by modulating the instantaneous frequency of the carrier.

Note: The horizontal axis shows observation frequency, while the vertical axes represent power and time. The upper panel shows regular carrier frequency variations characteristic of scattered FM broadcast signals, with a duration of approximately 300 ms.

**Figure 2** Example of typical low-frequency RFI signals

## 2.2 Software Framework Description

Through manual visual inspection, we found that most RFI signals exhibit high power levels in frequency-time plots (waterfall plots of frequency signals over time). Therefore, we attempted to extract signals using edge detection and line segment detection algorithms common in computer vision, with the Canny edge detection algorithm and Hough line detection algorithm as the core components for RFI identification. The first step involves Principal Component Analysis (PCA) processing. The waterfall plot of frequency signals over time serves as input to the detection pipeline, which first applies PCA to identify the first principal component. The first principal component corresponds to the dominant signal component in the original data, while higher-order components correspond to perturbations. In this work, due to instrumental noise and environmental temperature variations, we found through manual inspection of relative power levels that the overall signal strength in the input data was unstable. RFI appears as transient perturbations, while the first principal component corresponds to spectral structure and variations on longer timescales. We subtract the first principal component from the original signal to remove long-timescale power fluctuations, using the residual as input for the next step. The second step applies Gaussian smoothing, which performs weighted averaging across the entire image. In the input data, an interference signal appears as a line segment with consistent gradient variations along the X or Y axis, while small random fluctuations are isotropic. Gaussian smoothing effectively suppresses minor fluctuations while preserving line segment structures. The third step introduces the Sobel operator to enhance weak interference signals. The fourth and fifth steps process the data using Canny edge detection and Hough line detection to obtain effective parameters for RFI extraction. The sixth step employs the FOF (friends of friends) clustering algorithm to identify RFI signal parameters and group them into events based on temporal and frequency correlations. By statistically analyzing the duration of all RFI signals in an event, we can determine the start/end time, frequency range, and relative intensity of each RFI event. The detection pipeline workflow is illustrated in [Figure 3: see original paper].

Note: The dashed flow represents multi-threaded data processing with simultaneous input of multiple data streams.

**Figure 3** Schematic diagram of the RFI detection workflow

### 2.2.1 Principal Component Analysis Processing

Principal Component Analysis transforms input signals through orthogonal linear transformation, projecting them onto a series of linearly independent components called principal components. Generally, the first principal component corresponds to the dominant signal component, while higher-order components correspond to perturbations. This processing step helps stabilize parameter selection for subsequent Canny and Hough algorithms. The PCA algorithm used in data processing is based on Singular Value Decomposition (SVD). We perform SVD on the spectral data X(t; ) received by the antenna over a specified time period (i.e., a waterfall plot of specified duration), where t $[t_0; t_1)$ is the signal arrival time in ms and [50; 200] is frequency in MHz (as shown in [Figure 4: see original paper]).

Note: Panel a) shows data before PCA processing, while panel b) shows the processed result. The frequency-dependent systematic noise present in the original data has been removed and normalized, while short-timescale RFI signals remain preserved.

**Figure 4** Schematic diagram of PCA processing effects

### 2.2.2 Gaussian Smoothing Filter Processing

Gaussian smoothing primarily aims to suppress false signals that appear randomly at small scales. In the 2D Gaussian filter, the smoothing width in the frequency direction is s = 5 pixels, and in the time direction is s = 21 pixels. To detect stable RFI signals, we set the time-direction smoothing width to be 4 times that of the frequency direction. For detecting shorter-timescale RFI, the time-direction smoothing scale should be reduced. Measurements show that minor variations in these two smoothing widths have minimal impact on results.

### 2.2.3 Sobel Operator Processing

The Sobel operator, proposed by Sobel and Feldman in 1973, is a differential operator for edge detection similar to the Canny algorithm. It approximates gradients in the X and Y axes by convolving the input image with two $3 \times 3$ matrices. This paper uses the Sobel operator for preprocessing, converting the original waterfall plot into a gradient map of signal variations as input for the subsequent Canny algorithm. The Sobel operator enhances signals, making RFI more prominent relative to the background and reducing parameter dependence in the Canny algorithm, thereby stabilizing overall results (as shown in [Figure 5: see original paper]).

**Figure 5** After Gaussian smoothing and Sobel operator processing, RFI signal patterns become more prominent relative to the background

### 2.2.4 Canny Algorithm Processing

The Canny algorithm uses first-order finite differences to approximate grayscale gradients after Gaussian filtering. In images, gradients represent the magnitude and direction of grayscale changes, and edges typically occur where grayscale changes are most significant. By comparing gradients with preset thresholds, edges can be detected. The algorithm employs two thresholds, Val_{max} and Val_{min}, to determine edge detection: pixels exceeding Val_{max} are detected as edges, while those below Val_{min} are classified as non-edges. For intermediate pixels, edge classification depends on adjacency to confirmed edge pixels. In this work, Val_{min} and Val_{max} are set to 106 and 125, respectively. Measurements show that after preprocessing, Val_{min} and Val_{max} have negligible impact on final results, particularly on the total number of events (see [Figure 6: see original paper]; detailed testing in Section 3.1).

### 2.2.5 Hough Algorithm Processing

After Canny algorithm processing, the edges of RFI signals can be obtained. However, due to non-uniform noise floors, the resulting RFI structures are often discontinuous. The Hough algorithm connects these fragments into more complete RFI signal structures by transforming from 2D image coordinates to polar parameter space, converting the detection of arbitrary shapes into a peak statistics problem. We use the Hough algorithm for geometric identification of RFI signals found by the Canny algorithm, extracting information such as start time, frequency location, and frequency range. The Hough algorithm has three key parameters: threshold, which determines the minimum number of intersecting points in parameter space required to identify a line (segments below this are not considered signals); length_{{{min}}*{{line}}}, which determines the minimum signal length; and gap*{{{max}}_{{line}}}, which connects segments with gaps smaller than this value into continuous lines. The last parameter has minimal impact on RFI events as it only changes signal length and quantity by connecting short signals without generating new ones, so it was excluded from subsequent parameter convergence tests (see [Figure 6: see original paper]).

Note: The blue translucent lines represent RFI signals identified by the Hough algorithm, with the concentrated region (within the thin box) magnified in the red box at the lower left.

**Figure 6** Schematic diagram of RFI signals identified after Canny and Hough algorithm processing

### 2.2.6 FOF Classification Processing

Manual detection results show that RFI signals mostly appear in groups with temporal and frequency correlations. The previous steps can only detect individual RFI signal structures but cannot handle correlations in time or frequency. Therefore, we introduce the FOF classification search algorithm, which takes the start/end times and frequencies of RFI signals found by the Hough algorithm as input and defines groups of temporally and frequency-correlated signals as events, yielding a series of RFI events. These events and their properties are used for subsequent studies of RFI-related physical processes. Temporal correlation is measured by the linking parameter b in the FOF algorithm: larger values group signals with greater time separation into the same event, while smaller values may split closely spaced signals into different events. Testing shows b = 500 is an appropriate parameter, with variations around this value having minimal impact on the final event count (see Section 3.1).

Based on computer performance, this work divides continuous observational data into segments of $2 \times 10^4$ ms duration, runs the first five steps on each segment, and finally uses the FOF algorithm to obtain the RFI event set.

### 3.1 Program Result Stability

Our RFI detection and analysis software integrates multiple algorithms, each with several parameters, necessitating selection of an appropriate parameter set. Our primary detection targets are RFI signals with durations from tens to hundreds of milliseconds. We aim to meet two metrics: first, minimizing missed RFI signals, measured by the percentage of found signal events (q) relative to all signal events in the input data (n), i.e., q/n; second, ensuring accuracy of detected signals, measured by the percentage of genuine RFI signals (found signals minus false signals, q - f) relative to all found signals (q), i.e., (q - f)/q. Higher percentages for both metrics indicate more suitable parameters.

First, we manually inspected approximately 0.5 hours of data to compare program-identified RFI signals with manual identification. Manual comparison confirmed that the detection pipeline using the default parameter set achieves approximately 90% accuracy. The bolded entries in show the current default parameter set. Based on this, we varied one key parameter at a time and compared the resulting RFI events. Results show that our detection and analysis software output is relatively stable, with final result variations within 10% across different parameter choices. The most influential parameter is length_{{{min}}*{{line}}}, which determines the minimum signal length detected. Increasing this value reduces the number of short-timescale RFI signals found, and careful comparison confirmed that length*{{{min}}_{{line}}} only affects some faint RFI events.

**Table 1** Parameter selection for the program. Parameters 1 and 2 are for the Canny algorithm, parameters 3 and 4 are for the Hough algorithm, and parameter 5 is for the FOF classification processing. "Events" are the numbers of signal events found using approximately the first 1,000 s of data with different parameters. The last column shows the variation amplitude relative to the default event count. The default parameters for the detection and analysis framework are: val_{min} = 106; val_{max} = 125; threshold = 10; length_{{{min}}_{{line}}} = 25; b = 500.

The primary goal of this work is preliminary detection and analysis of RFI signals, focusing mainly on successful detection of structurally clear RFI signals. Optimization for faint RFI detection is not currently considered.

## 3.2 Program Performance

The entire pipeline is written in Python and operates single-threadedly except for the PCA processing. Observational data are stored on a network storage server connected at 10 Gb/s, with data read speeds of approximately 1.45 Gb/s during program execution, far below the 10 GB network bandwidth. Timing measurements show the time consumption ratios for the first five steps (PCA, Gaussian smoothing, Sobel operator processing, Canny algorithm processing, Hough algorithm processing) are 4.3:0.22:0.25:0.33:0.09. Currently, the detection pipeline requires approximately 472 seconds to process 1,000 seconds of observations, less than the duration of the observational data itself, meeting the framework validation stage target and enabling real-time data processing.

## 3.3 Detection Result Analysis

This section presents and analyzes program outputs. [Figure 7: see original paper] shows typical examples of RFI events output by the pipeline. We found some FM broadcast signals lasting tens of seconds or longer. As shown in [Figure 8: see original paper], events A, B, and C are superimposed on a few long-duration signals (about 60 s). Events A and B last approximately 100–200 ms. Event A covers more frequencies within the FM broadcast band and exists below 80 MHz, while event B covers frequencies similar to the long-duration signals, suggesting high spatial correlation between the two events. Subsequent analysis can use these correlations and temporal correlations from different antenna pods to determine the spatial location of events.

Both aircraft and meteor trails can forward-scatter FM broadcast signals. To verify whether our detected RFI signals are primarily caused by meteor trail reflections, we specifically conducted observations during the Quadrantid meteor shower outburst on January 3, 2021, and statistically analyzed the temporal variation of detected RFI signals (as shown in [Figure 9: see original paper]). We found that the detected RFI counts exhibit diurnal variation, with fewer signals around 5 AM and more around 6 PM, giving a ratio of approximately 1:3 between the two periods. This matches theoretical predictions of Earth-atmosphere-meteoroid collision probability. Due to Earth' s rotation and revolution, more meteors are observed when the Earth' s daylight side faces forward into meteoroid streams, while fewer are seen in the evening when only meteors catching up with Earth can be observed. Compared to other periods, there is a clear increasing trend in RFI counts from 10 PM on January 3 to 4 AM the next day (see [Figure 9: see original paper]b)), suggesting that the observed

RFI events likely originate from forward scattering of FM broadcasts by meteor trails.

Note: In the observational data, a few long-duration signals (about 60 s) have three additional events superimposed: A, B, and C. Events A and B are magnified in the middle and lower portions of the figure.

**Figure 8** Example of mixed RFI events

**Figure 9** Temporal variation of detected RFI signal counts. Panel a) shows RFI event counts over 42 hours of observational data. The red dotted and green dashed lines represent approximately 12-hour observations by the E5 antenna on January 3 and 4, respectively, while the black solid line shows 16 hours of E9 antenna observations. The light purple shading marks the approximate peak time of the 2021 Quadrantid meteor shower. The E5 antenna had no daytime data on January 4 due to technical issues. Panel b) compares RFI event counts from the evenings of January 3 and 4 aligned by the same time of day. The evening of January 3 during the Quadrantid meteor shower shows significantly higher RFI counts than the evening of January 4 for both E5 and E9.

## 4 Summary and Discussion

To rapidly extract millisecond-timescale RFI sources and characterize RFI signals in observational data, we have developed a fast detection and analysis software pipeline. The framework is primarily based on computer vision algorithms including Canny edge detection, Hough line detection, and Principal Component Analysis, with the FOF algorithm grouping RFI signals by temporal and frequency correlations. Preliminary verification demonstrates high processing efficiency, low parameter dependence, good consistency in detected RFI, and reduced uncertainty in RFI detection counts caused by system variations, meeting the initial goals of this work.

Future work can further optimize parameters to improve detection of faint RFI signals, such as using simulated signal data for parameter optimization, using pipeline outputs as input for machine learning, and introducing machine learning to enhance RFI detection capabilities. Additionally, comparing with other RFI software methods and referencing their advantages and disadvantages will continuously improve detection efficiency and accuracy.

Observing meteors through radio telescope reception of meteor trail reflections is a mature technique, with established radio meteor monitoring networks abroad (e.g., BRAMS). Compared to optical methods, radio telescope observations are unaffected by illumination, have low weather dependence, and can more easily detect faint meteors. Meteor observations help study the properties of cometary particle orbits and the internal structure of the solar system. Our method differs from previous radio meteor observation techniques in that it does not require a transmitter to illuminate meteor trails but uses surrounding FM broadcast signals as the "transmitter." With a comprehensive database of nearby FM broadcast information, including transmission frequencies and locations, time delays in received reflected signals could provide distance and direction information for RFI events. In addition to meteor trail reflections, tropospheric scattering, atmospheric ducting, sporadic ionospheric anomalies, and lightning can all generate RFI signals. Sometimes these signals are extremely powerful, completely disrupting the quiet electromagnetic environment of low-frequency arrays. Records show that in July 2021, 21CMA received numerous high-intensity FM broadcast signals lasting from several hours to half a day, disappearing at night, containing English and Russian content. After thorough investigation, human interference was largely ruled out. Such temporary or seasonal interference is likely related to atmospheric ducting phenomena, and continuous monitoring data will be highly valuable for studying the physical mechanisms behind these interferences.

## References

[1] Lao B Q, An T, Chen X, et al. *Acta Astronomica Sinica*, 2017, 5: 110
[2] Weiss A J, Friedlander B. *IEEE Transactions on Antennas and Propagation*, 1993, 41: 7
[3] Wang X M. Master' s Thesis. Nanjing: Nanjing University of Information Science and Technology, 2007: 72
[4] Davies K. *Ionospheric Radio*. London: Peter Peregrinus Ltd, 1990: 312
[5] Wang W. *Radio Communications Technology*, 2007, 33(2): 55
[6] Rison W, Krehbiel P R, Stock M G, et al. *Nature Communications*, 2016, 7: 10721
[7] Ciardi B, Labropoulos P, Maselli A, et al. *MNRAS*, 2013, 2: 1755
[8] Pritchard J R, Loeb A. *Physical Review D*, 2010, 82: 023006
[9] Huang Y, Wu X P, Zheng Q, et al. *RAA*, 2016, 16(2): 36
[10] Offringa A R, de Bruyn A G, Zaroubi S, et al. *MNRAS*, 2010, 405: 155
[11] Ue-Li Pen, Lister S, Jeffrey B P, et al. *MNRAS*, 2009, 394(1): L6
[12] Offringa A R, van de Gronde J J, Roerdink J B T M. *A&A*, 2012, 539: A95
[13] Zheng Q, Wu X P, Johnston-Hollitt M, et al. *ApJ*, 2016, 832(2): 190
[14] Hossain F, Kumar P K M, Abu Yousf M. *International Journal of Computer Applications*, 2015, 124: 9
[15] Patel R, Pant V, Iyer P, et al. *Solar Physics*, 2021, 296: 2
[16] Contopanagos H, Zhang L, Alexopoulos N G. *IEEE Transactions on Microwave Theory Techniques*, 1998, 46(11): 1936
[17] Sobel I, Feldman G. *Pattern Classification and Scene Analysis*. New York: Wiley, 1973: 271
[18] Meers M O, Glenn S, Elizabeth B, et al. *Geophysical Research Letters*, 2008, 35: L03102
[19] Li Z, Liu Z J, Shen J. *Meteor Trail Communication Theory and Application*. Beijing: Publishing House of Electronics Industry, 2011: 34
[20] Kaufmann W. *The Journal of the International Meteor Organization*, 2017, 45: 4
[21] Peter D, Dorotovic I, Marian V. *Proceedings of the International Meteor*

*Conference*. Rault J L, Roggemans P. Giron: International Meteor Organization, 2014: 207

*Note: Figure translations are in progress. See original paper for figures.*