Postprint: A Study on Methods for Reducing Background Noise in the Chang' e-4 Low-Frequency Radio Spectrometer

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Abstract

The Chang' e-4 lander will be equipped with a low-frequency radio spectrometer to conduct low-frequency radio astronomical observations on the far side of the Moon. The observation band of this spectrometer ranges from 0.1 MHz to 40 MHz. According to Electromagnetic Compatibility (EMC) test results from microwave anechoic chamber tests at the China Academy of Space Technology, the lander platform itself generates extremely strong noise within this frequency band, with intensity sufficient to overwhelm most signals from solar bursts, thereby hindering the detection of valid signals and the achievement of anticipated scientific objectives. This study investigates the effectiveness of three noise elimination methods—spectral subtraction, adaptive filtering, and Wiener filtering—through simulation analysis, aiming to identify a more effective noise cancellation approach and provide a foundation for data processing in the on-orbit detection mission of the low-frequency radio spectrometer.

Full Text

Preamble

Research on Background Noise Reduction Methods for the Very Low Frequency Radio Spectrometer on Chang' E-4

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Abstract

The Chang’ E-4 lander will carry a Very Low Frequency Radio Spectrometer (VLFRS) to conduct low-frequency radio astronomical observations on the far side of the Moon. The spectrometer’ s observation band spans 0.1 MHz to 40 MHz. According to Electromagnetic Compatibility (EMC) test results from the microwave anechoic chamber at the China Academy of Space Technology, the lander platform itself generates extremely strong noise within this frequency band, with intensity sufficient to overwhelm most signals from solar bursts and making effective signal detection and achievement of scientific objectives difficult. This paper analyzes through simulation the effectiveness of three methods—spectral subtraction, adaptive filtering, and Wiener filtering—for eliminating lander noise, thereby selecting the most effective noise reduction approach to provide a basis for data processing during the VLFRS in-orbit detection mission.

Keywords: Very Low Frequency Radio Spectrometer; Chang’ E-4; improved spectral subtraction; Wiener filtering; adaptive filtering
Classification: P161

0 Introduction

In 1930, the renowned American engineer Karl Jansky first observed radio emissions from the Milky Way using his self-constructed “merry-go-round” antenna, thereby launching extensive research in radio astronomy. Astronomical studies have revealed that different celestial bodies produce electromagnetic radiation across various wavebands due to differing radiation mechanisms. Consequently, conducting all-sky observations across the full electromagnetic spectrum is of great scientific significance. However, Earth’ s atmosphere prevents many radio band signals, particularly very low frequency signals below 10 MHz, from penetrating to the ground. Nevertheless, low-frequency band detection is crucial for studying the evolution and origin of celestial objects.

To fill this observational gap in very low frequency bands, numerous countries and organizations have launched satellites for space-based observations, such as WIND and Ulysses. However, space-based low-frequency radio observations also face challenges from electromagnetic interference generated by Earth and numerous orbiting satellites. Because the Moon itself can shield radio interference from Earth, the radio-quiet zone on the lunar far side represents an ideal observation location. The European Space Agency (ESA) proposed the FARSIDE mission in January 2015, which aims to launch a lander equipped with a low-frequency radio spectrometer to the lunar far side by 2025. China has proposed the Chang’ E-4 lunar exploration mission—Chang’ E-4 is the world’ s first spacecraft to achieve soft landing and roving exploration on the lunar far side. On May 21, 2018, the Chang’ E-4 relay satellite “Queqiao” was successfully launched, with the lander and rover scheduled for launch later that year. The lander carries a scientific payload, the Very Low Frequency Radio Spectrometer, enabling humanity’ s first low-frequency (0.1 MHz–40 MHz) observations of the universe and the Sun from the lunar far side.

According to EMC test results for the complete lander system in the microwave anechoic chamber, although external signal interference can be effectively shielded, the electronic equipment and other payloads onboard the lander itself generate electromagnetic interference that affects low-frequency observations. Since engineering modifications to the platform are not feasible, interference can only be eliminated through data processing. Currently, three primary methods exist for noise reduction in speech signal and radar signal processing: spectral subtraction, adaptive filtering, and Wiener filtering. This paper will compare and analyze the signal enhancement effectiveness of these methods in the context of the VLFRS scientific objectives to identify the optimal approach, providing a basis for data processing during the VLFRS in-orbit detection mission.

1 Working Principle and Noise Sources of the VLFRS

The VLFRS system consists of four receiving antennas (three 5-meter long antennas A, B, and C, and one 20-centimeter short antenna D), preamplifiers, and an electronic unit. The three long antennas A, B, and C are mutually perpendicular [Figure 1: see original paper], receiving three orthogonal components of electromagnetic signals from space. Based on electromagnetic propagation theory, the intensity and direction of the received signals can be calculated. The short antenna D lies in the same plane as long antennas B and C. According to electromagnetic wave propagation theory and the different gains of antennas with different lengths, the long antennas A, B, and C simultaneously receive both far-field signals from cosmic space and near-field signals from the lander itself, while the short antenna D, due to its short length and proximity to the lander, primarily receives near-field lander noise signals [3].

The VLFRS onboard Chang' E-4 operates across two frequency bands: low frequency (100 kHz–2 MHz) and high frequency (1 MHz–40 MHz). The main technical parameters of the spectrometer are shown in .

The electromagnetic flux density at the lunar surface is shown in [Figure 2: see original paper]. The electric field intensity near the antenna region and the output voltage from the receiver can be calculated using the following formula:

$$U_{out} = G_{preamp} G_{Receiver} IL_{coax} \frac{h_e}{1 + Z_\alpha / Z_{preamp}} E \quad (1)$$

where U_{out} is the receiver' s output voltage, G_{preamp} and $G_{Receiver}$ are the preamplifier gain and receiver gain respectively, IL_{coax} is the high-frequency cable insertion loss, Z_α and Z_{preamp} are the antenna impedance and preamplifier impedance respectively, h_e is the antenna effective length, and E is the electric field intensity at the antenna.

The parameters in Equation (1) can be obtained from the calibration report provided by the VLFRS manufacturer. Combining these parameters with Equation (1) allows the inversion of spatial electric field and flux density from the voltage data measured by the receiver. [Figure 2: see original paper] shows the flux density of various celestial bodies reaching the lunar surface. The lander noise curve in the figure was derived from high-frequency band data received by antenna A during EMC tests (Test Condition 3: lander power controller main unit, data management unit main unit, data transmission modulator main unit, payload electronic control box main unit, and VLFRS powered on and operating sequentially) conducted in the microwave anechoic chamber at the China Academy of Space Technology. The results demonstrate that the lander' s noise flux density exceeds that of typical solar bursts and is comparable to peak solar burst flux density. Without noise reduction processing of the received signals, it would be difficult to accurately reconstruct the true intensity of solar bursts.

2 Effective Signal Extraction Methods for the VLFRS

Since the target signals received by the three main antennas A, B, and C of the VLFRS all contain interference from the lander' s own noise signals, noise reduction algorithms must be applied to suppress noise and maximally separate useful signals before signal extraction and utilization. Let $x(n)$ denote the observed signal, $s(n)$ the useful signal, and $v(n)$ the noise signal. Their relationship can be expressed as:

$$x(n) = s(n) + v(n) \quad (2)$$

In the simulation conducted for this paper, a simulated signal with intensity comparable to solar bursts serves as the useful signal $s(n)$, while lander noise measured from EMC Test Condition 3 is used as the noise signal $v(n)$. Three methods–adaptive filtering, spectral subtraction, and Wiener filtering–are applied for simulation processing.

2.1 Spectral Subtraction

Spectral subtraction is a common signal enhancement method whose principle involves subtracting the noise amplitude from the amplitude of signal-plus-noise in the frequency domain to obtain the useful signal amplitude. S.F. Boll improved this method in 1979, termed the improved spectral subtraction [5]. The improved spectral subtraction uses the average power of noise during spectral subtraction, which can effectively reduce residual “musical noise.” The improved spectral subtraction can be expressed as:

$$|S(n)|^\gamma = \begin{cases} |X(n)|^\gamma - a \cdot D(n)^\gamma, & |X(n)|^\gamma \geq a \cdot D(n)^\gamma \\ b \cdot D(n)^\gamma, & |X(n)|^\gamma < a \cdot D(n)^\gamma \end{cases} \quad (3)$$

where $D(n)$ is the average amplitude of noise, γ equals 1 or 2 (1 for amplitude subtraction, 2 for power subtraction), a ($a \geq 1$) is the over-subtraction factor, and b ($b > 0$) is the compensation factor. These two parameters can be adjusted to reduce periodic errors.

Considering the structural characteristics of the VLFRS and the requirements for scientific data, the signal amplitude can be obtained by subtracting the average amplitude received by short antenna D from the average amplitude received by long antennas A, B, and C. Due to differences in length and material between antennas A, B, C and antenna D, their gains differ. Therefore, when performing spectral subtraction, the signal intensity differences caused by different gains must be compensated. Specifically, a cancellation coefficient is first calculated using signals from a short time period. Then, during subsequent processing, the average amplitude of signals received by antenna D is multiplied by this cancellation coefficient to obtain the noise amplitude. The improved spectral subtraction can be applied for noise reduction by combining the structural characteristics of the VLFRS. Taking antennas A and D as an example, this can be expressed as:

$$|S(f)|^\gamma = \begin{cases} |V_A(f)|^\gamma - P(f)^\gamma \cdot |V_D(f)|^\gamma, & |V_A(f)|^\gamma \geq P(f)^\gamma \cdot |V_D(f)|^\gamma \\ b \cdot P(f)^\gamma \cdot |V_D(f)|^\gamma, & |V_A(f)|^\gamma < P(f)^\gamma \cdot |V_D(f)|^\gamma \end{cases} \tag{5}$$

where $V_A(f)$ is the average amplitude at corresponding frequency points after Fourier transform of signals received by long antenna A, $V_D(f)$ is the average amplitude at corresponding frequency points of signals received by short antenna D, and γ is set to 1. $P(f)$ is calculated using signals received by all four receivers during a short period of quiet Sun conditions. The processing flow is shown in [Figure 3: see original paper].

Simulation results for spectral subtraction using antennas A and D are presented in [Figure 4: see original paper]. The figure displays frequency-domain signals after FFT, with the horizontal axis representing frequency (in MHz) and the vertical axis representing amplitude (in dBμV). The black curve shows the noise-contaminated signal, the blue curve shows the signal processed by improved spectral subtraction, and the red curve shows the useful signal. The results demonstrate effective noise suppression across the entire band, with noise amplitude decreasing by approximately 20 dB in the frequency band below 10 MHz and by about 10 dB in other bands. The processed signal waveform essentially restores the original useful signal, with better performance in frequency bands with lower background noise (20 MHz–40 MHz).

2.2 Wiener Filtering

From Equation (2), the objective of signal processing is to obtain the useful signal $s(n)$ without noise. However, in actual signal processing, the obtained useful signal is not exactly equal to $s(n)$ but can only be an approximation or estimate of $s(n)$. Therefore, signal processing can be viewed as estimation of $s(n)$, and the goal is to find an optimal estimator. Wiener filtering is a method for finding such an optimal estimator [6-7].

[Figure 5: see original paper] shows the schematic diagram of Wiener filtering, where $h(n)$ represents the Wiener filter parameters and $y(n)$ is the estimated value of the useful signal $s(n)$. This can be expressed as:

$$y(n) = x(n) * h(n) \quad (7)$$

According to the Least Mean Square (LMS) error criterion, minimizing $\varepsilon = E[\{s(n) - y(n)\}^2]$ yields the optimal filter parameters. Taking the Fourier transform of the above equation leads to:

$$H(k) = \frac{P_{sx}(k)}{P_x(k)} \quad (9)$$

where $P_{sx}(k)$ is the cross-power spectral density between $s(n)$ and $x(n)$, and $P_x(k)$ is the power spectral density of $x(n)$. Since the useful signal $s(n)$ and noise signal $v(n)$ are uncorrelated, $P_{sv}(k) = 0$, which yields:

$$P_x(k) = P_s(k) + P_v(k) \quad (10)$$

$$P_{sx}(k) = P_s(k) \quad (11)$$

Substituting Equations (10) and (11) into Equation (9) gives:

$$H(k) = \frac{P_s(k)}{P_s(k) + P_v(k)} = \frac{\gamma(k)}{1 + \gamma(k)} \quad (12)$$

where $\gamma(k)$ in Equation (12) is the ratio of the power spectrum of the noisy signal to the noise power spectrum at the corresponding frequency point after Fourier transform [8]. Based on data received by antennas D and A, $\gamma(k)$ can be calculated to determine the optimal filter parameters. Simulation results are shown in [Figure 6: see original paper].

The results indicate that Wiener filtering can also reduce noise effects, though its noise reduction performance is inferior to spectral subtraction. While the processed signal can basically restore the original useful signal waveform, it remains difficult to distinguish the useful signal in frequency bands with high background noise (0-20 MHz).

2.3 Adaptive Filtering Noise Reduction

Unlike Wiener filtering, adaptive filters can automatically adjust their parameters based on received signals to maximally reduce noise [9]. Adaptive filtering has been widely applied in system identification, channel equalization, signal enhancement, and signal prediction. This paper primarily utilizes its signal enhancement capability, with its structural schematic shown in [Figure 7: see original paper]. The adaptive filtering algorithm requires at least two receiving devices: one to receive the noise-contaminated signal and another dedicated to receiving noise, after which the adaptive algorithm extracts the useful signal. The VLFRS happens to have these two receiving systems.

As shown in [Figure 7: see original paper], the schematic diagram of an adaptive noise reduction filter includes $x(n)$ representing the signal received by the receiver (including useful signal $s(n)$ and noise signal $v(n)$), $v_1(n)$ representing the noise signal received by another receiver, and $e(n)$ representing the error signal. Their relationship can be expressed as:

$$e(n) = x(n) - \sum_{i=0}^{M-1} [w(i) v_1(n-i)] \quad (13)$$

where $w(n)$ represents the filter weighting coefficients, which can be adjusted through the Least Mean Square (LMS) criterion or the Recursive Least Squares (RLS) method by evaluating $E[e^2(n)]$ to optimize the filter to its best state [10-12]. The following simulation uses the Recursive Least Squares (RLS) method.

[Figure 8: see original paper] presents the adaptive filtering simulation results. The results show that the adaptive filtering method performs poorly, with insignificant noise reduction effects and low signal restoration accuracy. At frequency points with relatively large amplitudes in the noise signal (such as 1.73 MHz, 2.32 MHz, 2.9 MHz, etc.), the noise signal amplitude does not decrease after adaptive filtering processing.

Sections 2.1 through 2.3 have simulated lander noise processing using three different data processing methods, with adaptive filtering being a time-domain approach and improved spectral subtraction and Wiener filtering being frequency-domain approaches. provides a comparison of the signal-to-noise ratio (SNR) improvement achieved by these three signal enhancement methods.

SNR before and after data processing by three different algorithms

Data Processing Method	SNR before processing (dB)	SNR after processing (dB)	SNR improvement (dB)
Improved spectral subtraction	[value]	[value]	[value]
Wiener filtering	[value]	[value]	[value]
Adaptive filtering (RLS)	[value]	[value]	[value]

The results show that improved spectral subtraction and Wiener filtering perform significantly better than adaptive filtering, with improved spectral subtraction providing slightly greater SNR improvement than Wiener filtering. The noise reduction capability of the adaptive filtering signal enhancement system is heavily influenced by the correlation between the noise signal $v_1(n)$ at the reference input and the noise signal in the noisy signal. During the VLFRS design, the different parameters of the long antennas A, B, C and the short antenna D used for receiving lander noise signals, combined with the very low SNR of the simulated useful signal, lead to degraded adaptive filtering performance. The differences in noise signals received by antenna D and the long antennas due to their different parameters can be compensated in the frequency domain by evaluating the gain differences between the short and long antennas at different frequency points, which is why the two frequency-domain algorithms achieve better noise reduction results.

To verify the performance of the VLFRS and the data processing methods, we conducted a field test by installing the VLFRS and receiving antennas on the rooftop of the canteen building at the Miyun Observation Station of the National Astronomical Observatories, Chinese Academy of Sciences. A signal generator connected to an antenna was used to transmit simulated signals from a dormitory building approximately 100 meters away from the receiving antenna. The lander noise signal was generated using EMC Test Condition 3 results, transmitted by a 1-meter small antenna placed below the receiving antenna and connected to a waveform generator. [Figure 9: see original paper] shows the results of processing one set of test data from antenna A using the improved spectral subtraction method, where the transmitted useful signal was a 1.8 MHz point-frequency signal.

[Figure 9: see original paper] shows signals in the 1.7 MHz–1.9 MHz range. After processing with improved spectral subtraction, the lander noise is effectively suppressed, with amplitude decreasing by 10 dB, while the useful signal amplitude is not reduced. The SNR improved from -25.23 dB to -2.60 dB, representing an SNR enhancement of 22.63 dB. This demonstrates that improved spectral subtraction is also effective for reducing lander background noise signals in field experiments.

Conducting very low frequency (0.1-40 MHz) detection on the lunar far side is scientifically significant [13]. However, extracting useful signals is extremely challenging due to weak signals and low SNR in this band. This paper conducted simulation experiments using lander noise from EMC tests and target signal intensities receivable on the lunar far side by the VLFRS onboard Chang' E-4. Three common signal enhancement algorithms—improved spectral subtraction, Wiener filtering, and adaptive filtering—were applied to extract the simulated signals. Among them, improved spectral subtraction demonstrates remarkable signal extraction performance, with significant SNR improvement after processing, allowing target signal waveforms to be visually identified in the processed results. Furthermore, improved spectral subtraction shows excellent performance in processing field test data from Miyun. Therefore, improved spectral subtraction can be adopted as the primary preprocessing method for the VLFRS to achieve relatively accurate observations of solar bursts. During the VLFRS detection process on the lunar far side, environmental changes such as temperature variations may alter the cancellation coefficient. Consequently, in actual detection operations, the cancellation coefficient should be recalculated periodically based on actual environmental conditions.

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