A Novel Direction Noise Detection Method of HFSWR Based on Space-Time Multi-eigenvalue Synthesis

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Abstract. High Frequency Surface Wave Radar (HFSWR) is one of the main emerging technologies in the field of modern ocean exploration and monitoring remote sensing. However, with the increasing complexity of the HFSWR detection environment, the spatial distribution of its external environmental noise intensity presents a directional distribution, called directional noise. Directional noise has a complex source, and its noise base will be elevated by 10 to 15dB. Accurate detection of directional noise is pivotal for enhancing the detection performance of HFSWR. The eigenvalue is used as a measure to characterize directional noise. In this paper, a directional noise detection method based on space-time eigenvalue synthesis is proposed. The construction of the space-time covariance matrix relies on sample selection within the local processing region (LPR) of the angle-doppler joint domain and the accumulation of multiple snapshot samples in the range units. Subsequently, the detection statistics are formulated based on the eigenvalue distribution characteristics of the space-time covariance matrix. Finally, the effectiveness of the proposed algorithm in locating directional noise is validated using measured data.

Keywords: HFSWR · Directional noise · Eigenvalue detection · Direction detection

1 Introduction

High frequency surface wave radar (HFSWR) has been widely used in ocean information acquisition with small propagation attenuation, large observation range, all-weather detection, low cost and over-the-horizon detection capabilities. It has great development potential in military and civilian applications [1]. Currently, hundreds of HFSWR systems have been deployed, most are located along the coastline. However, the development of social economy, advancements in science and technology, and increased human activities have led to the generation of substantial harmful electromagnetic environmental noise. Especially, in the high-frequency (HF), the sources of external environment noise received by the antenna are complex and diverse, and vary with the change of location, time, frequency and radar parameters. The target detection performance of

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HFSWR is closely related to the distribution of external environment noise [2]. While previous studies often modeled high-frequency external environment noise as a gaussian model, assuming omnidirectional distribution and no directionality, the reality involves directional noise. However, due to bad weather (such as thunderstorms and typhoons) or human factors (such as industrial or wind farms) [3], the spatial distribution of external environmental noise intensity is directional, which is called directional noise [4]. For high frequency radar systems, the total noise entering the receiver is affected by the directivity of the antenna beam and the directional noise. Understanding the spatial directivity distribution of noise is crucial for HFSWR design [5].

Since the 1930s, atmospheric noise measurements at HF bands have been conducted in Europe. However, due to equipment limitations and the absence of standardized measurement methods, it is difficult to compare the results with each other. Additionally, most existing research primarily focuses on the temporal and statistical characteristics of HF external environmental noise, neglecting its spatial directional distribution [6]. In contrast, the observation results from the antenna array show clear spatial directivity distribution. In 1990, The International Telecommunication Union (ITU) published a standard HF noise model, relying on limited high-frequency noise measurements [7]. Kotaki enhanced the ITU model by integrating data on global lightning strike activity [8]. Regrettably, neither the ITU nor the Kotaki model considers the directional distribution properties of noise. In 2002, Coleman proposed a high frequency directional noise model based on global lightning strike distribution data combined with ray-tracing propagation methods [4]. Subsequently, in 2016, Pederick proposed a more precise high-frequency noise model based on Coleman's model, incorporating background ionospheric information and ionospheric absorption data [9].

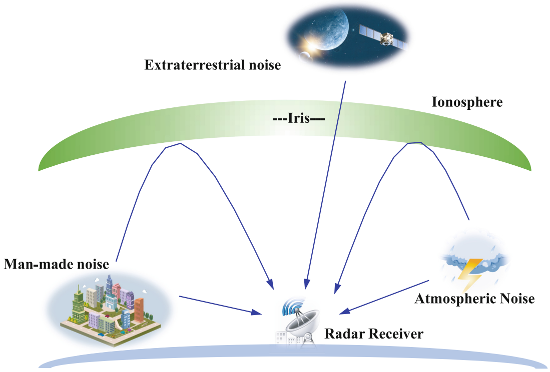

Fig. 1. Source of directional noise

Directional noise at HF primarily originates from natural sources such as lightning, the sun, and galaxies, as well as man-made sources like generators, power lines, and industrial equipment, as shown in Fig. 1. Natural sources can be thought of as coming from two parts: the local part, which the external environmental noise is propagated directly to the receiving antenna through ground waves or line-of-sight, and the ionospheric component, where electromagnetic waves generated by lightning are reflected into the ionosphere and can be received by radar receivers after secondary reflection [10]. Man-made sources mainly comprise electromagnetic pollution resulting from industrial activities, electrical by-products, etc. The high equipment density in urban areas contributes to elevated noise levels, significantly impacting HFSWR systems. The propagation of electromagnetic environmental noise caused by human factors varies depending on distance and frequency, occurring either through line of sight or the ionosphere. Another source is extraterrestrial noise, which needs to propagate across the ionosphere. Extraterrestrial noise can penetrate the ionosphere only at high frequencies. Extraterrestrial noise is received through the ionospheric "iris," a circular region in the ionosphere that is penetrable to electromagnetic waves. Extraterrestrial noise propagates to the antenna receiver through a circular region in the ionosphere called the iris. The width of the iris is related to the observed frequency and the ionospheric plasma peak frequency [11].

Detecting the direction of directional noise is pivotal in its research. In radar signal processing, determining the direction information of directional noise is essential. Directional noise is discerned from gaussian, impulse, or alpha noise, necessitating modeling based on its directional attributes. The conventional detection method currently employed is the Energy Detection(ED) method [12]. The method initially conducts pulse compression, Doppler processing, and beamforming on the radar echo data to extract clutter-free and interference-free data. Subsequently, statistical calculations are applied to estimate the noise power, facilitating the determination of the incoming direction of the directional noise. However, in the presence of correlated noise, the performance of ED algorithm decreases. Another effective approach is the eigenvalue detection method, which relies on the difference between the eigenvalues or eigenvectors of the statistical covariance matrix [13]. This method partially mitigates the impact of noise uncertainty. Classical eigenvalue detection methods include the Maximum-Minimum Eigenvalue Ratio (MME) algorithm [14], Maximum-Minimum Eigenvalue Difference (DMM) algorithm [15], among others. We proposed a novel space time eigenvalue method (STED) to detect directional noise in this paper. A fundamental distinction between directional noise and other forms of noise lies in its spatial characteristics. Samples are extracted from local processing units in the angle doppler union domain, and the statistical space-time covariance matrix is constructed in the time dimension. According to the distribution of different eigenvalues, the detection statistics are constructed to detect directional noise.

This paper is organized as follows: Sect. 2 introduces the materials and model. Section 3 provides a detailed description of the method. The analysis results are presented in Sect. 4, and the Sect. 5 concludes the paper.

2 Materials and Model

2.1 Data Model

Consider a uniform line array with N elements, where the element spacing is d, as shown in Fig. 2. Assume that the k th sample of the received echo $\mathbf{x}(k)$ consists of four components, as illustrated:

$$\mathbf{x}(k) = \mathbf{s}(k) + \mathbf{c}(k) + \mathbf{n}_o(k) + \mathbf{n}_d(k) \tag{1}$$

where $\mathbf{s}(k)$ is signal, $\mathbf{c}(k)$ indicates the clutter and interference, $\mathbf{n}_o(k)$ represents the omni-directional noise and $\mathbf{n}_d(k)$ indicates the directional noise.

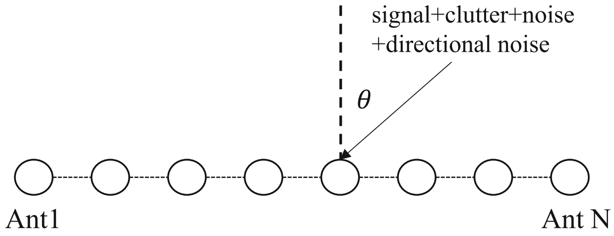

Fig. 2. Uniform linear array

Figure 3(a) shows a measured range-doppler spectrum that includes targets, clutter, noise, and other components. Figure 3(b)(c)(d) displays the range-doppler spectrum corresponding to different beam directions after applying Digital Beam Forming (DBF), respectively. It is evident that there are varying noise baseline intensities across different directions. Figure 3(e) presents the angle-doppler spectrum of the 45th range bin. Notably, directional noise is distributed across all doppler bins, occupying only a portion of the angle bins.

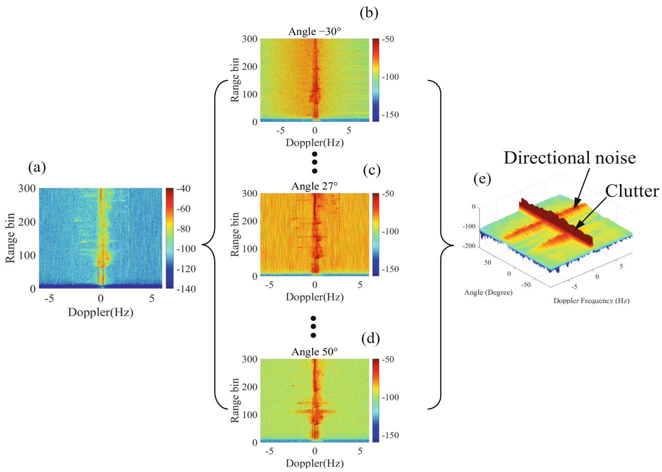

Fig. 3. Directional noise multi-dimensional distribution

2.2 Data Sets

The measured data used in this paper were collected from the HFSWR system situated in Weihai, China. The system consists of a uniform linear array with 32 transmitting and receiving antennas. The primary antenna parameters are provided in Table 1. Additionally, the origin position of the antenna array and the coverage area of the beam are depicted in Fig. 4 illustrates the origin of the antenna array and the coverage area of the beam. Multiple beams cover the radar's detection angle range. The solid red line indicates the direction of the beam in different directions, and the dashed red line indicates the beam center. Notably, the radar's positive beam extends over a portion of the land area, that surrounds many industrial power plants, as well as other man-made sources of high-frequency noise. This observation strongly correlates with the generation of directional noise.

Table 1. HFSWR system parameters.

Properties	Specification
Number of elements	32
Coherent integration time	144 s
Signal waveform	FMICW
Frequency resolution	6.94 mHz

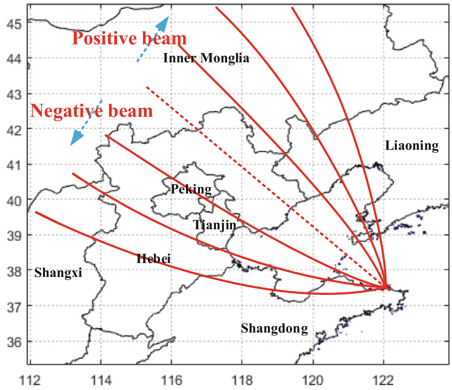

Fig. 4. Direction of the beams and radar sites.

3 Methods

3.1 Energy Detection

For subsequent analysis, the echo data underwent pulse compression, doppler processing, and DBF to obtain range-doppler spectrum across various beam directions. Theoretically, directional noise exists in all radar echo data components; however, in most cases, it is not a major component. Specifically, when directional noise originates from the target's direction, it substantially elevates the noise floor, significantly impacting the detection performance of HFSWR. To facilitate more precise extraction and analysis of directional noise properties, and to mitigate errors stemming from other factors in calculations, we selected data samples devoid of clutter and interference, containing only directional and omnidirectional noise.

The ED algorithm originates from spectrum sensing in cognitive radio. The ED algorithm employs the sample average power extracted from the echo data as its detection statistic. It is juxtaposed with a judgment criterion and compared against a predefined threshold within the algorithm to identify the direction of directional noise. Let the echo data for the n th distance cell, the m th doppler cell, and the b th beam direction be indicated as follows:

$$x(m, n, b) = s + c + n_o + n_d \tag{2}$$

According to the sample selection criteria for directional noise, the above formula is shown as follows:

$$x(m, n, b) = n_o + n_d \tag{3}$$

Assume that the sample region of directional noise selected from the range-doppler spectrum of different beam directions is PQ, the statistical average power of directional noise in the *b-th* beam direction as follows:

$$N(b) = \frac{1}{PQ} \sum_{m=1}^{P} \sum_{n=1}^{Q} x(m, n, b) \tag{4}$$

Then, for all beam directions B, the statistical average power of directional noise is calculated as:

$$\mathbf{N} = [N(1), N(2), \cdots, N(B)] \tag{5}$$

After that, the statistical noise average power $N(b)$ is compared with the threshold γ. The judgement rule is as follows:

$$N(b) = \begin{cases} < \gamma & H_0 \\ \geq \gamma & H_1 \end{cases} \tag{6}$$

where H_0 indicates that there is no directional noise in this direction and H_1 indicates that there is directional noise in this direction. The ED algorithm provides high detection efficiency and does not require prior knowledge of the signal's waveform, type, or phase. The ED algorithm exhibits low performance in detecting correlated signals and is vulnerable to noise uncertainty.

3.2 Space Time Eigenvalue Detection

The most important characteristic that distinguishes directional noise from other noise is that it has spatial information. The main characteristics of directional noise in radar echo data are evident in the range and angle dimension. Therefore, in this section, a novel detection method based on space-time eigenvalues to identify the directional noise's incoming direction from the echo data is proposed. The local processing region (LPR) is selected from the angle-doppler spectrum of the echo data, that is, the spatial covariance matrix is constructed by selecting directional noise samples from the s space-time dimension. The LPR is described in Fig. 5. The space-time covariance matrix is decomposed to obtain the joint angle-doppler eigenvalues and eigenvectors. According to the eigenvalue, it can be divided into omnidirectional noise subspace and directional noise subspace. The eigenvalues in the directional noise subspace can then represent the characteristics of the directional noise within the local unit. Since directional noise exhibits both the randomness of thermal noise and the directional nature of clutter, the information contained in the spatial covariance matrix of a single sample cannot fully captured the underlying characteristics of environmental noise. Therefore, we select multiple snapshot LPR samples from the range dimension and analyze the eigenvalue distribution characteristics of the spatial covariance matrix of directional noise using mathematical statistics. The detection statistics for directional noise are constructed based on space-time multi-eigenvalue synthesis.

The angle-doppler spectrum LPR with range bin l and beam direction b in the echo data is chosen, and subsequently column vectorization is performed. The obtained space-time column vector data can be expressed as:

$$\mathbf{X}_{LPR}^{l} = [x_1, x_2, \cdots, x_T]^T \tag{7}$$

where $T = p \times q$ denotes the size of the LPR. Here, p represents the number of the angel bins, q is the number of doppler bin.

The space-time column vector formed by LPR of the reference direction is as follows:

$$\mathbf{X}_{LPR}^{ref,l} = \left[x_{ref,1}, x_{ref,2}, \cdots x_{ref,T}\right]^T \tag{8}$$

Select L distance unit LPR samples to estimate spatial covariance matrix:

$$\mathbf{R}_{LPR}^{b} = \frac{1}{L}\sum_{l=1}^{L} \mathbf{X}_{LPR}^{l} \mathbf{X}_{LPR}^{l\ H} \tag{9}$$

$$R_{LPR}^{ref} = \frac{1}{L}\sum_{l=1}^{L} X_{LPR}^{ref,l} X_{LPR}^{ref,lH} \tag{10}$$

where R_{LPR}^{b} is the sample spatial covariance matrix with beam direction b, and R_{LPR}^{ref} indicates is the reference space covariance matrix of the reference beam direction.

Then, the sample space covariance matrix and reference space covariance matrix are decomposed respectively. The corresponding eigenvalue is $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_T$ and $\rho_1 \geq \rho_2 \geq \cdots \rho_T$. The weighted statistics of the first N eigenvalues are calculated to obtain the comprehensive eigenvalue, which represents the directional noise information in the current direction, with w denoting weight.

$$\varsigma_{LPR}^{b} = \sum_{n=1}^{N} w_n \lambda_n \tag{11}$$

$$\varsigma_{ref} = \sum_{n=1}^{N} w_n \rho_n \tag{12}$$

where ς_{LPR}^{b} is the comprehensive eigenvalue of the beam direction b, and ς_{ref} is the comprehensive eigenvalue of the direction of the reference beam.

The judgment criteria can be expressed as:

$$T_{STED} = \begin{cases} \varsigma_{LPR}^{b} - \varsigma_{ref} < \gamma & H_0 \\ \varsigma_{LPR}^{b} - \varsigma_{ref} \geq \gamma & H_1 \end{cases} \tag{13}$$

where H_0 indicates that there is no directional noise in this direction, and H_1 indicates that there is directional noise in this direction. The difference between STED and ED algorithm is that it uses the eigenvalue of the covariance matrix as the judgment basis, rather than the energy to judge. Additionally, STED has an advantage in detecting correlated signals.

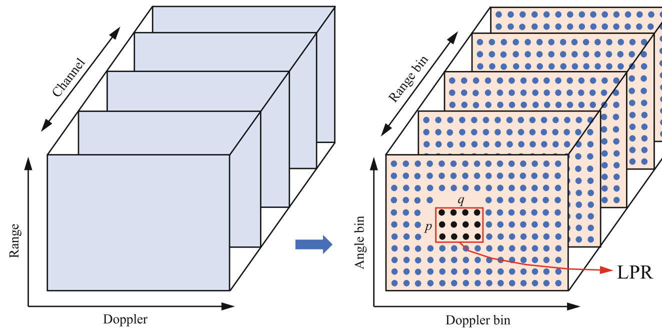

Fig. 5. Localized processing region in the STED

4 Results

In this section, we utilize measured data to demonstrate the effectiveness of the proposed algorithm. The key parameters are described as follows: the signal waveform is Frequency Modulated Interrupted Continuous Wave (FMICW), and the angle detection range is 90° centered on the normal line. The receiving antenna consists of 32 array elements and the radar operates at 5.4 MHz. After signal processing, the data is formatted as doppler-range-beam and then used in the proposed algorithm.

Figure 6(a) illustrates the angle-doppler two-dimensional spectrum of the 45th range bin, which includes clutter, directional noise, omnidirectional noise, and targets. Notably, the doppler frequency of clutter predominantly centers around $[-2, 2]$ Hz, whereas directional noise occupies all doppler bins. Employing the direction noise sample selection criteria in the ED algorithm, echo power spectrum data within the doppler frequency scope of $[-3, -7]$ Hz and range bin of [40, 100] are selected as the sample of single beam direction. Subsequently, upon traversing all beam directions, the variation in noise power with direction is depicted in Fig. 6(b). Analysis of the results reveals fluctuating noise power concerning azimuth, with the direction of maximum noise power identified at 26 °. Therefore, according to the criterion, the direction noise comes in the direction of 26 °. Despite an 18.9 dB maximum disparity in noise power across different directions, the gap between the maximum noise power and the first local maximum is merely 7 dB, potentially leading to detection errors.

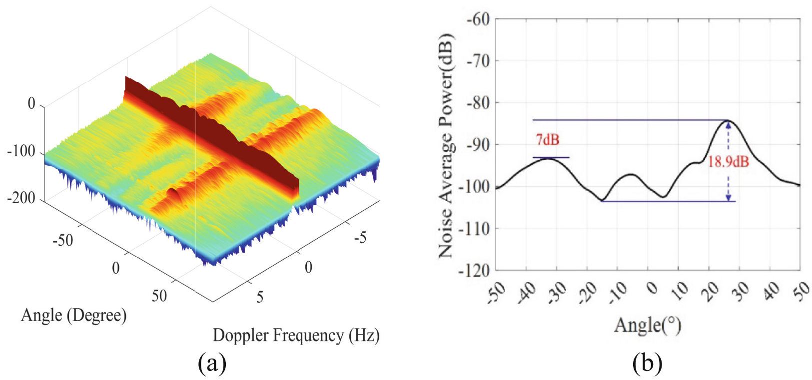

Fig. 6. Directional noise in measured data. (a) directional noise distribution in angle-doppler spectrum; (b) average power of noise in different directions calculated by ED algorithm;

The LPR of the 45th range bin, with the doppler frequency of 3.5 Hz and the angle scope of $[-40, 45]$ degrees in the noisy region, with the angle interval of 5 °, was selected as a sample. The spatial covariance matrix of multi snapshot data is statistically estimated along the range dimension. After performing feature decomposition, the corresponding eigenvalues are calculated and sorted in descending order. The LPR size used in the calculation is 8×8 and the number of samples selected for the range dimension is 128. Figure 7 illustrates the distribution of eigenvalues in the noisy region. It can be clearly seen that there are obvious inflection points in the eigenvalue distribution of noise in different directions. Particularly, the first five eigenvalues within the angle scope of [20, 30] ° exhibit a significantly faster rate of change compared to other directions. Subsequently, the change rate of eigenvalues in all directions tends to be stable. Consequently, under the current LPR conditions, the first five eigenvalues of the spatial covariance matrix after feature decomposition can be considered sufficient to represent the directional noise information. Thus, N is set to 5 in STED algorithm. Of course, it's imperative to note that the value of N may necessitate adaptive adjustment based on the array configuration and the LPR size.

Figure 8 illustrates the results of the STED algorithm, where the noise trend in different directions is more pronounced. The peak value of the comprehensive eigenvalue occurs at 26°. The reference beam direction is set to 0°. According to the judgment criterion, it can be considered that the directional noise comes around 26°, which is consistent with the actual noise source position. From the results, we can see that the maximum difference between the comprehensive eigenvalues in different directions is 46.3 dB, and the maximum difference between the comprehensive eigenvalues and the first local maximum is 27.8 dB. Compared with the ED method, the proposed method provides better detection conditions for directional noise detection. More precisely, the direction noise should come from an angle scope. Taking 3 dB less than the maximum comprehensive eigenvalue as the boundary, then the directional noise comes in the scope of [22,30]°. Directional noise elevates the noise baseline in radar target detection scenarios. Under the same detection threshold, the target may not be detected, which can seriously affect the performance of HFSWR. Especially when the direction of the directional noise comes from the same direction as the target, this will be a great challenge for target detection and tracking.

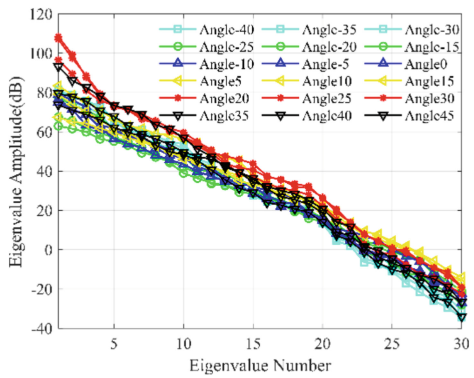

Fig. 7. Eigenvalue distribution of noise in different directions

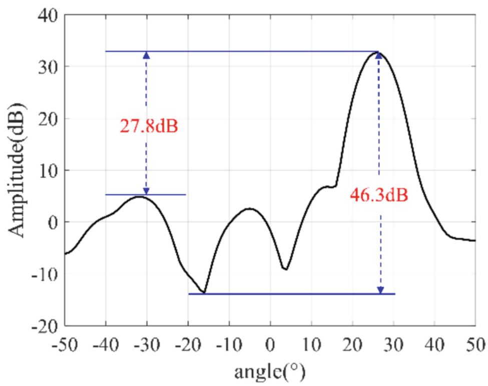

Fig. 8. Comprehensive eigenvalues calculated by STED method.

5 Conclusion

In this paper, we address the directional noise problem in HFSWR by proposing a novel detection method based on space-time eigenvalue synthesis. When estimating covariance matrix, we propose a spatial covariance matrix estimation method based on angle-doppler joint domain, which selects LPR samples and accumulates multiple snapshot samples in range domain. Then, detection statistics are derived based on the eigenvalue distribution characteristics of the space-time covariance matrix. Compared with ED algorithm, STED algorithm can express directional noise information more effectively. Experimental validation using measured data confirms the efficacy of our method. The findings not only enhance the detection performance of HFSWR but also bolster its resilience in complex electromagnetic environments.

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