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VSLM: Virtual Signal Large Model for Few-Shot Wideband Signal Detection and Recognition

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VSLM: Virtual Signal Large Model for Few-Shot Wideband Signal Detection and Recognition

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Abstract: Wideband signal detection and identification are crucial for military and civilian fields such as communication reconnaissance and spectrum security. This paper systematically sorts out the mainstream technologies of wideband signal detection and identification, and expounds the main current short-wave wideband signal detection and identification work from three perspectives: traditional expert feature methods, combination of expert features and machine learning, and wideband signal detection and identification based on deep learning. Particularly, this paper focuses on the processing methods of current key signals such as short burst signals and frequency hopping signals, as well as the latest deep learning methods in the past five years. Finally, the shortcomings of the existing broadband signal detection and identification methods are summarized, and the future trend is predicted.

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In the shortwave frequency band, the signals received by a broadband receiver contain narrowband transmission signals of many different targets. Each signal is mainly transmitted through sky waves and transmitted from the transmitter to the receiver through the ionosphere. The shortwave channel with the ionosphere as the medium has time-varying and dispersive characteristics. When the signal is transmitted through the channel, multipath delay, fading, Doppler shift and expansion will occur. In addition, the background noise of the shortwave channel is mainly composed of radio noise and man-made noise. Radio noise is a broadband noise, and its spectrum amplitude changes sharply with the change of frequency. Man-made noise is mostly narrowband noise with random frequency and time, and its spectrum amplitude also changes with frequency. This makes the background noise of the shortwave channel non-stationary, and the channel noise floor continues to change in different time periods and frequency bands. In order to statistically analyze the characteristics of shortwave channels, European and American countries have been conducting shortwave channel detection since the middle of the last century, describing the channel parameters of shortwave broadband and narrowband channels, and establishing a variety of broadband and narrowband channel models. Among them, the narrowband channel model is represented by the Watterson channel model, and the broadband channel models include the Hoffmeyer model, the Watterson post-group delay filter model, the sub-band parallel processing model, and the ionospheric physics model. After selecting a suitable shortwave channel model, broadband signal detection and identification also needs to master the characteristics of broadband received signals and analyze them based on a certain broadband received signal model. However, due to the complexity of shortwave channels, the current shortwave signal broadband model has no typical progress in describing broadband signal characteristics, background noise interference, the number and distribution of in-band signals, etc., and the establishment of a targeted shortwave signal broadband model still needs in-depth research. Therefore, in the communication environment unique to shortwave, the difficulty of signal broadband detection and identification lies in how to model shortwave broadband signals, how to determine the detection model and criteria, and how to reduce the influence of channel response and time-varying noise on signal analysis and processing effects [1–8].

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Since the 1990s, domestic and foreign research institutions have continuously published relevant results on the theoretical issues and system implementation of shortwave broadband signal detection and recognition. P. Ahlemann et al. used the different azimuth characteristics of signals to identify signals from the perspective of broadband azimuth spectrum; Fei Zhongxia summarized the key technologies of signal detection in communication reconnaissance, analyzed and compared the advantages and disadvantages of existing methods, and designed relevant algorithms for search, identification and interference of data link signals; Zhu Wengui et al. used array antennas and software radio structures with low-pass sampling of shortwave RF signals to study and implement a shortwave array signal reconnaissance system, which improved the detection speed of common shortwave signals. Cui Weiliang et al. studied the impact of complex electromagnetic environment on signal interception, improved the process of signal search and interception, and used a hybrid search mode to improve the adaptability of the search algorithm to the channel. However, the above methods are all based on the Gaussian white noise background. Due to the selective fading of the shortwave channel itself, sudden broadband interference, signal leakage and other factors, the shortwave noise base appears as a colored noise base with continuous changes. Therefore, it is necessary to adopt broadband preprocessing technology before signal detection to meet the detection needs under the shortwave non-stationary noise background [9–12].

Among the existing shortwave broadband signal detection methods, multi-angle analysis based on the signal's time domain, frequency domain, and time-frequency domain joint features is an effective method. In this process, signal detection provides basic parameter information for signal identification. By analyzing the results of signal detection, the preprocessing technology, broadband or narrowband processing methods suitable for target signal identification are selected. Finally, the obtained signal information is processed at the back end, the signals of interest are stored, and the signal distribution characteristics and communication methods in each wide frequency band are summarized to provide data support for long-term signal monitoring. Among them, the research on signal detection methods based on expert experience characteristics has been very in-depth, mainly divided into four categories: matched filtering method, cyclostationary method, eigenvalue detection method, and energy detection method.

(1) Matched filter method

The basic idea of the matched filter method is to construct a matched filter based on the amplitude-frequency response of the signal to be detected, and to match the input signal to maximize the signal-to-noise ratio of the output signal, thereby achieving decision detection. Based on the probability distribution of the normalized matched filter, Diamant derived a closed-form expression for the detection probability and false alarm probability, thereby providing a basis for setting the optimal detection threshold. He also conducted experiments on underwater acoustic signals in actual marine environments and verified the detection efficiency [13]. Shin et al. extended the traditional one-dimensional time domain matched filter to the two-dimensional time-frequency domain through the Cohen-type time-frequency distribution transformation, and detected the transient signal part containing information from the Cohen time-frequency diagram of the received signal. Compared with the classical matched filter method, the detection performance is better [14]. When the matched filter method obtains the signal prior information, it can maximize the signal-to-noise ratio of the filtered signal. It is the optimal detection algorithm in theory. However, in the face of blind detection scenarios where the signal prior information cannot be obtained, this method fails.

(2) Cyclostationary method

The cyclostationary method uses the cyclostationary characteristics of the signal to complete signal detection. Communication signals can generally be modeled as cyclostationary random processes with periodic characteristics, while the statistical characteristics of noise are completely random. Signal detection can be achieved based on the difference in the statistical characteristics of the signal and noise. Since 1991, Gardner has constructed a variety of detectors such as single-cycle and multi-cycle by calculating the integral amplitude of the cyclic spectrum correlation function at different cyclic frequency positions, and realized the existence detection of BPSK, QPSK, SQPSK and MSK modulation signals, thus laying the theoretical framework of cyclostationary detection methods

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[16,17]. On this basis, Lundén et al. established the asymptotic distribution of the cyclic correlation statistics of space-time symbols under the null hypothesis, and proposed a sequential detection method to reduce the average detection time, achieving highly robust spectrum detection in Gaussian and non-Gaussian noise environments [18]. Wang et al. analyzed the cyclostationary characteristics of typical satellite communication signals and realized the detection of satellite signals in different modes by searching for the peak of the spectrum line on the cyclic frequency section [19]. In 2006, Gardner et al. systematically reviewed the development of cyclostationary methods over the past half century, and summarized their theoretical system and their application in multiple fields such as communication, circuits, systems, and control [20]. Cyclostationary features have strong resolution, but high computational complexity. As the first step in blind processing, signal blind detection has high efficiency requirements, so this method is difficult to meet real-time requirements in practice.

(3) Eigenvalue detection method

The eigenvalue detection method was first proposed by Zeng and Liang. Its basic idea is to calculate the eigenvalue of the signal covariance matrix to perform signal detection. Specifically, this method mainly includes two steps: detection statistic construction and threshold judgment. In terms of detection statistic construction, the ratio of the maximum and minimum eigenvalues ,of the signal covariance matrix [21], the maximum peak eigenvalue [22], the ratio of the average and minimum eigenvalues, [23], and the ratio of the eigenvalue sampling statistics [24] are calculated as detection statistics; in terms of threshold judgment, the detection statistic is quantitatively analyzed based on random matrix theory to determine the threshold to complete detection [25]. Compared with the matched filter method, the eigenvalue detection method does not require prior information about the source signal and the transmission channel, nor does it require signal synchronization. However, the detection threshold is easily affected by strong background noise and interference, resulting in a significant performance degradation. Therefore, the eigenvalue detection method is still difficult to apply effectively.

(4) Energy detection method

The energy detection method does not require prior information about the signal. It performs decision detection by calculating the energy of the received signal. It is a commonly used signal detection algorithm in practice. Chen replaced the amplitude square operation in traditional energy detection with an arbitrary positive power operation, providing useful guidance for improving detection performance [26]. Furthermore, Nikonowicz et al. used the bin value distribution of the received signal power spectrum density and moving average to construct detection statistics for detection, and achieved signal blind detection without knowing the Gaussian noise variance [27]. Ma et al. used the secondary user signal sequence to construct a matched filter detector and the primary user signal energy to construct an energy detector for cognitive radio spectrum sensing. The results of the two detectors were fused for decision detection, effectively reducing the impact of secondary user out-of-link on spectrum sensing [28]. However, when there is strong noise and interference in the signal, the signal energy fluctuations will be very dramatic, resulting in performance degradation, and its robustness and robustness are poor in practice.

In the actual non-cooperative complex electromagnetic environment, due to the existence of many low intercept communication signals in the shortwave channel, there are broadband carrier modulations such as direct sequence spread spectrum, frequency hopping, time hopping and their various combinations, as well as burst, power control, beamforming, directional transmission and other communication forms. Among them, burst signals and frequency hopping signals have been the most widely used in practice. Therefore, this article provides a targeted overview of the detection methods for these two types of signals.

In recent years, deep learning technology has made rapid progress. In the future, WSDR tasks based on deep learning will be one of the most promising directions [15,29–32].

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