

Research on adaptive signal detection and feature extraction method of complex electronic information system

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Abstract: Aiming at the challenge of signal detection and feature extraction in complex electromagnetic environment, this paper proposes an adaptive joint optimization method of signal detection and feature. Faced with the problems of traditional methods relying on prior knowledge, insufficient deep learning generalization ability, and poor adaptability to non-stationary noise, a cascaded framework was constructed that includes variable step size LMS (VSS-LMS) interference suppression, multi head self-attention (MHSA) feature extraction, and dynamic threshold decision-making. VSS-LMS achieves fast convergence and steady-state error balance by improving the tongue line function. MHSA uses multi-scale attention mechanism to focus on the characteristics of target signal adaptively. Adaptive threshold dynamically adjusts the threshold based on local noise power estimation. Experiments show that the detection probability of this method is 96% in the signal-to-noise ratio range of -15 dB to 5 dB, which is more than 15% higher than that of the traditional method. The accuracy of feature classification is over 94.3%, and the false alarm probability is stable below 0.01. The three modules cooperate to improve the detection sensitivity and feature discrimination in dynamic electromagnetic environment, and provide a new scheme for intelligent perception of complex electronic information systems.

Keywords: Complex electronic information system; Signal detection; Feature extraction; VSS-LMS; Multi-head self-attention.

1. Introduction

Complex electronic information system covers radar communication integration platform, electronic warfare system, intelligent Internet of Things network and other forms, and has become an indispensable core infrastructure in modern national defense and civil fields [1]. In this kind of system, it is the fundamental premise to realize reliable situation awareness, signal recognition and intelligent decision-making to accurately detect the target signal and extract the discriminating features from the received data stream in the dynamic electromagnetic environment [2]. However, the current combat and application scenarios are facing severe challenges such as increasingly dense spectrum, diverse signal systems, non-stationary interference and ultra-low signal-to-noise ratio, which puts a great test on traditional signal processing methods.

Traditional signal detection methods, such as matched filtering (MF) and energy detection (ED), highly rely on prior knowledge of target signal parameters and assume that noise follows a stationary Gaussian distribution [3]. However, in the actual complex environment, the prior information of the target signal is often incomplete or even completely unknown, and the noise often presents heavy tail or impulse characteristics, which seriously violates the Gaussian hypothesis and leads to a sharp decline in detection performance. Classic feature extraction methods, including spectral analysis based on fast Fourier transform (FFT) and standard wavelet transform (WT), have limited time-frequency resolution and lack adaptive capability when facing multi-component, fast time-varying signals [4]. In recent years, adaptive filtering technology has been widely used for interference suppression and detection enhancement [5]. However, these methods typically assume that the

interference model is relatively simple and still inadequate in highly nonlinear and non-Gaussian scenarios.

With the rapid development of machine learning and deep learning technologies, convolutional neural networks (CNN), long short-term memory networks (LSTM), and Transformer based architectures have demonstrated excellent performance in automatic modulation recognition and signal classification tasks [6]. Most deep learning detectors need to be trained with large-scale labeled data. When the actual running environment deviates greatly from the training distribution, the generalization ability is obviously insufficient. Signal detection and feature extraction are usually regarded as two independent serial stages, ignoring the inherent coupling relationship between them. The detection quality directly affects the subsequent feature extraction effect, and refined features can in turn improve the detection accuracy by feedback. The existing methods generally lack a unified adaptive mechanism, and it is difficult to cope with the synchronous changes of interference types, signal-to-noise ratio levels and signal characteristics in real time.

Aiming at the above shortcomings, this paper proposes an adaptive signal detection and feature extraction method for complex electromagnetic environment. This article constructs a unified framework that combines an adaptive interference suppression module based on the variable step size LMS (VSS-LMS) algorithm with a deep feature extraction network that integrates multi head self-attention (MHSA) mechanism to achieve joint optimization of detection sensitivity and feature discriminative power; An adaptive threshold decision strategy is designed to dynamically adjust the detection threshold according to the real-time estimated noise power and interference level, and effectively balance the detection probability and false alarm probability under non-stationary conditions.

2. Methodology

This method adopts the cascade architecture of front-end adaptive filtering, depth feature extraction and adaptive threshold decision (as shown in Figure 1). Firstly, the received signal is subjected to interference suppression and noise cancellation through VSS-LMS adaptive filter, and the purified signal is output. Then, it is sent to the depth feature extraction network which integrates MHSA mechanism to extract the time domain and frequency domain features with discrimination. Finally, the detection threshold is dynamically set according to the real-time estimated noise power to complete the target judgment.

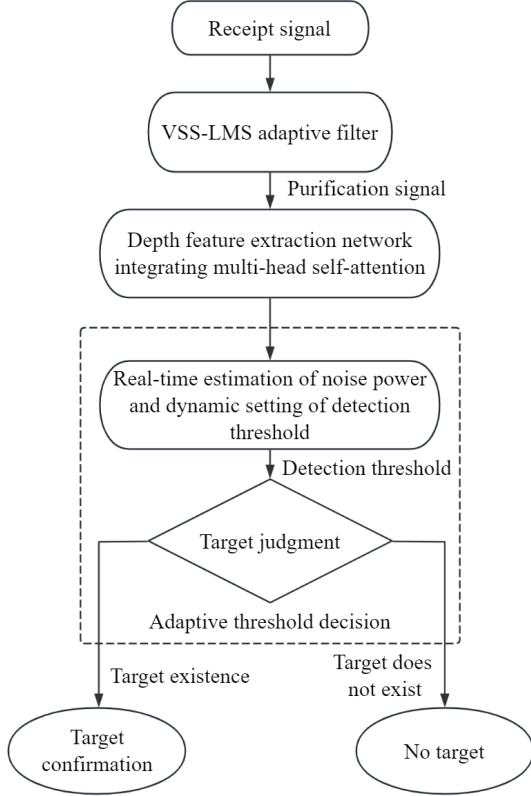


Figure 1. Overall framework of this method

2.1. Adaptive interference suppression based on VSS-LMS

In complex electromagnetic environment, interference signals often have non-stationary characteristics, and fixed step LMS algorithm faces the inherent contradiction between convergence speed and steady-state error. Therefore, this method adopts VSS-LMS algorithm, and its core lies in iterative updating of filter weight vector and adaptive adjustment of step size.

The filter output and error signal are defined as:

$$\begin{cases} y(n)=w^T(n)x(n) \\ e(n)=d(n)-y(n) \end{cases} \quad (1)$$

Where $w(n)$ is the weight coefficient vector of the filter at time n , $x(n)$ is the input signal vector, $d(n)$ is the expected signal, and $e(n)$ is the residual. When the filtering converges, the residual is the purified signal after interference suppression. The weight coefficients are iteratively updated according to the following rules:

$$w(n+1)=w(n)+\mu(n)e(n)x(n) \quad (2)$$

The key to variable step size lies in the design of $\mu(n)$. This method adopts a step size update strategy based on an improved tongue line function, which has an S-shaped curve

characteristic of large errors corresponding to large step sizes and small errors corresponding to small step sizes (as shown in Figure 2), and can balance rapid tracking in the early stage and low steady-state errors in the later stage [7]. A typical form is:

$$\mu(n)=\mu_{\max} \frac{\alpha}{\alpha+\beta e^2(n)} \quad (3)$$

Among them, $\mu_{\max}$ is the upper bound of the step size to ensure the stability of the algorithm; The shape of the $\alpha>0$ control curve, the larger the α , the slower the decay of the step size when the error is small, which is beneficial for fine convergence in the steady-state stage; $\beta>0$ is the error weight factor, which determines the sensitivity of the step size to changes in error. The larger the β , the faster the step size increases with the increase of error, which is suitable for scenarios where interference power changes rapidly. In actual deployment, $\mu(n)$ is constrained within the range of $[\mu_{\min}, \mu_{\max}]$ to prevent numerical anomalies.

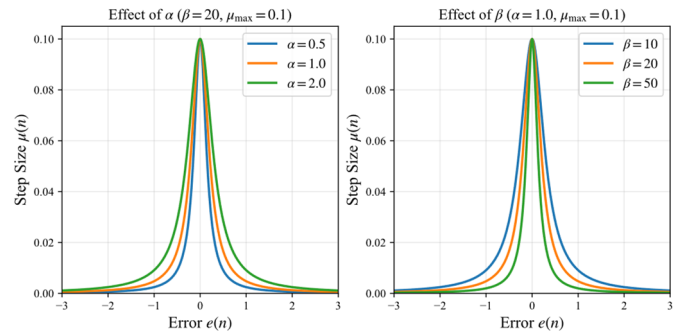


Figure 2. S-shaped curve characteristics of improved tongue line function under different parameters

Figure 2, left image, fixed $\beta=20$, changing α value. It can be seen that the larger the α , the slower the step decay of the curve in the area of smaller error, and the larger the step size in the steady-state stage; The smaller the α , the steeper the curve, and the step size is more sensitive to changes in error. On the right side of Figure 2, fix $\alpha=1.0$ and change β value. It can be seen that the larger the β , the faster the step size increases with the increase of error, making it more sensitive to changes in interference power; The smaller the β , the smoother the curve changes. This design implements an adaptive adjustment mechanism where large errors correspond to large step sizes and small errors correspond to small step sizes, resolving the contradiction between convergence speed and steady-state accuracy of the fixed step size LMS algorithm.

2.2. Deep feature extraction integrating MHSA

The signal purified by VSS-LMS may still contain residual noise and weak target components, so it is necessary to further extract discriminative features. In this method, the purified signal sequence is input into the depth feature extraction network, and its core component is MHSA module.

The basic mechanism of MHSA is to linearly map the input feature sequence to obtain the query matrix Q , the key matrix K and the value matrix V , and calculate the attention weight by scaling the dot product:

$$\text{Attention}(Q,K,V)=\text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (4)$$

Where d_k is the dimension of the bond vector, the purpose of dividing by $\sqrt{d_k}$ is to prevent the softmax gradient from disappearing due to the excessive inner product value [8]. Multiple attention heads are spliced and output after parallel

calculation, so that the network can capture the multi-scale dependence of signals from different subspaces;

$$\text{MultiHead}(Q,K,V)=\text{Concat}(\text{head}_1,\dots,\text{head}_h) W^O \quad (5)$$

Where h is the number of attention heads and W^O is the output projection matrix. The advantage of this mechanism is that the attention weights can adaptively highlight the temporal segments or frequency bands related to the target signal, while suppressing noise dominated regions, thus still being able to extract effective discriminative features under low signal-to-noise ratio conditions.

2.3. Adaptive threshold decision

After feature extraction is completed, it is necessary to determine whether the target exists through threshold judgment. Under the condition of non-stationary noise, the fixed threshold can not maintain a constant false alarm probability, so this method adopts an adaptive threshold strategy based on local noise power estimation.

For each detection unit, take N reference units on both sides of it and estimate the local noise power:

$$\hat{\sigma}^2 = \frac{1}{2N} \sum_{i=1}^{2N} |x_i|^2 \quad (6)$$

The detection threshold is obtained by multiplying the noise estimate by the scale factor:

$$T = \alpha \hat{\sigma}^2 \quad (7)$$

The scale factor α is determined by the expected false alarm probability P_{fa} and the number of reference units N :

$$\alpha = 2N(P_{fa}^{1/(2N)} - 1) \quad (8)$$

This design enables the threshold to automatically adjust with real-time changes in noise power. When interference increases, $\hat{\sigma}^2$ increases, and the threshold is correspondingly raised to avoid a surge in false alarms; When the noise decreases, the threshold is lowered to ensure the detection probability of weak targets [9]. Typical parameters are taken

as $N=8\sim 16$, $P_{fa}=10^{-6}$, and the number of protection units is taken as $2\sim 4$. To enhance the robustness to multi-target scenarios, a sorting and removal strategy is introduced in the selection of reference units. The reference units are first sorted in ascending power order, and suspected interference outliers are removed before calculating the noise estimate, thereby avoiding the degradation of detection performance caused by neighboring target contamination noise estimation.

3. Experimental analysis

The simulation platform is MATLAB 2023a and Python 3.10, the sampling rate is 10 MHz, the signal system includes BPSK, QPSK and LFM, the interference types include broadband noise suppression, narrowband interference and swept frequency interference, the interference-to-signal ratio JSR is 0~20 dB, and the noise is AWGN superimposed non-stationary color noise. The data set is divided into training set and test set according to 7:3, and the SNR range is -15~10 dB. The comparison methods include fixed step size LMS, NLMS, CNN, LSTM, traditional CA-CFAR, fixed threshold and the method in this paper. VSS-LMS filter order 32, $\mu_{\max}=0.05$, $\mu_{\min}=10^{-4}$, $\alpha=1.5$, $\beta=10$; MHSA has 4 heads, $d_k=64$, Layer 2; CFAR reference unit 16, protection unit 2, $P_{fa}=10^{-6}$.

As shown in Table 1, VSS-LMS in this paper has the lowest MSE under all SNR conditions, with a convergence iteration reduction of about 56.7% compared to fixed LMS, and a steady-state MSE reduction of over 35%. Figure 3 shows the MSE convergence curve. In this paper, the method converges to -25 dB in about 500 iterations, and the fixed LMS converges to -18 dB in about 1200 iterations, which shows that the variable step size strategy can give consideration to both fast tracking and low steady-state error.

Table 1. Performance comparison of different interference suppression algorithms

Algorithm	MSE $\times 10^{-3}$ @-10dB	MSE $\times 10^{-3}$ @-5dB	MSE $\times 10^{-3}$ @0dB	MSE $\times 10^{-3}$ @5dB	Convergence iteration number
Fixed LMS	8.2	5.6	3.1	1.8	1200
NLMS	6.9	4.3	2.5	1.4	900
VSS-LMS	5.1	3.0	1.6	0.9	520

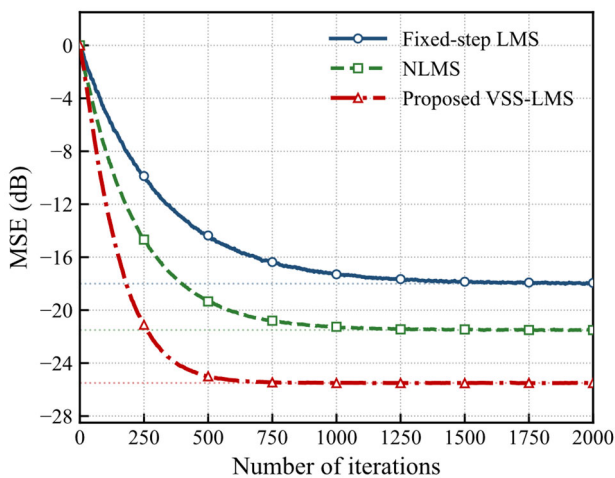


Figure 3. MSE convergence curves of different algorithms

Table 2 shows that the feature extraction network fused with MHSA still achieves 94.3% accuracy at low SNR, which is 9.1 percentage points higher than CNN. Figure 4 is a

visualization of t-SNE features. In this paper, the clustering within classes is tighter, the distance between classes is longer, and CNN features obviously overlap. Figure 5 is a heat map of attention weight. The weight of this method in the time-frequency region where the target signal appears is significantly enhanced, and the noise region is effectively suppressed, which shows that MHSA can adaptively focus on the discriminant features.

Table 2. Performance comparison of feature extraction network

Method	Accuracy/%	F1	AUC
CNN	85.2	0.84	0.88
LSTM	87.6	0.86	0.90
Transformer	90.1	0.89	0.93
MHSA	94.3	0.93	0.96

The false alarm probability fluctuates between $10^{-3}\sim 10^{-5}$ under non-stationary noise with a fixed threshold, while the traditional CFAR remains stable at around 10^{-6} . In this paper, the adaptive threshold stabilizes around 10^{-6} and P_d is higher (see Table 3). Figure 6 shows the adaptive threshold tracking curve.

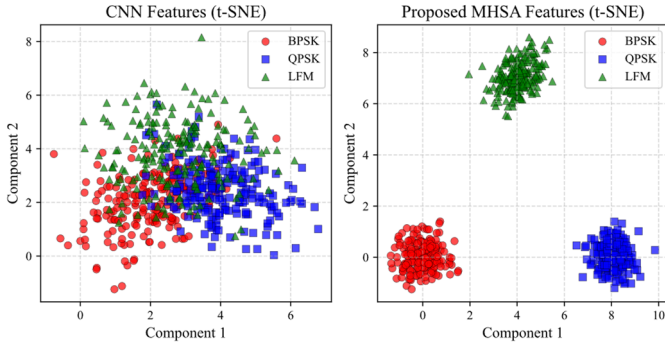


Figure 4. Feature t-SNE scatter plot

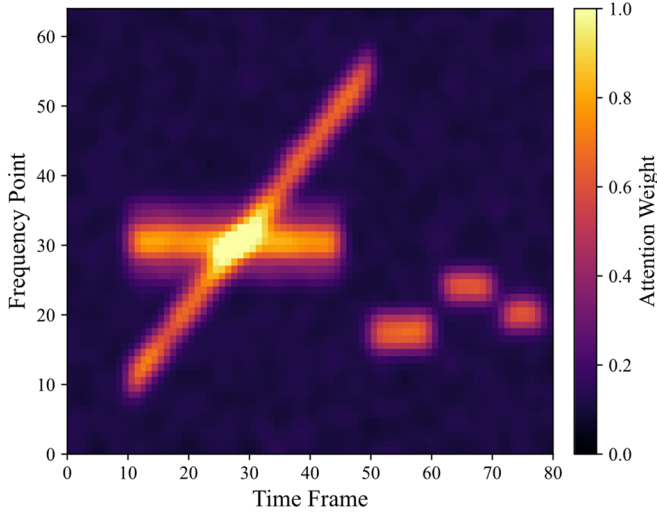


Figure 5. MHSA weighted heatmap

When the noise power suddenly changes, the threshold in this article quickly follows, and a fixed threshold produces obvious false alarm spikes, indicating that the adaptive threshold strategy can effectively balance the detection probability and false alarm probability.

Table 3. Comparison of detection probabilities P_d of different detection methods

SNR/dB	Fixed threshold	Traditional CFAR	Our
-15	0.21	0.35	0.48
-10	0.38	0.56	0.71
-5	0.62	0.78	0.89
0	0.81	0.91	0.96
5	0.93	0.97	0.99

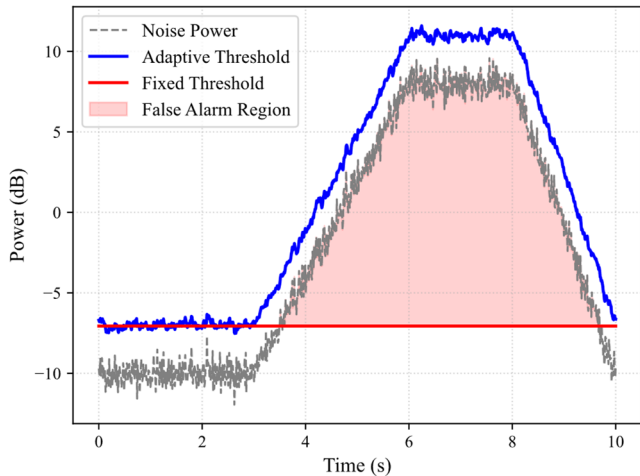


Figure 6. Adaptive threshold tracking curve

Table 4. Ablation experiment (SNR=-5 dB)

Configuration	P_d	P_{fa}	Classification accuracy/%
VSS-LMS only	0.62	About 10^{-5}	82.1
Only MHSA	0.68	About 10^{-6}	90.5
VSS-LMS+MHSA, Fixed threshold	0.79	About 10^{-5}	93.8
Complete Method	0.89	About 10^{-6}	94.3

The ablation results in Table 4 indicate that the combination of VSS-LMS and MHSA can significantly improve detection and classification performance, and the adaptive threshold further stabilizes P_{fa} around 10^{-6} . In terms of real-time performance, the method proposed in this article has a single frame inference time of approximately 12.5 ms, slightly higher than the fixed LMS's 8.2 ms, but lower than the Transformer's 18.3 ms, which can meet the real-time processing requirements of most complex electronic information systems.

4. Conclusion

Experiments have shown that VSS-LMS outperforms fixed LMS and NLMS in terms of convergence speed and steady-state error; MHSA feature extraction has stronger discriminative power at low signal-to-noise ratios; Adaptive threshold can stably control false alarms and improve detection probability in non-stationary noise. After the three modules are linked, the detection sensitivity and feature discrimination of the system in the dynamic electromagnetic environment are jointly optimized.

References

- [1] Le, S., & Cheng, X. (2026). Research on the evaluation method of complex electronic information system: The evolution from traditional method to intelligent paradigm. *Journal of International Education and Science Studies*, 3(5), 44-47. <https://doi.org/10.62639/SSPJIESS08.20260305>
- [2] Xu, Z., Mei, W., Yu, J., Wang, H., & Li, Y. (2019). Research on the lightning disaster risk assessment of electronic information system with intuitionistic fuzzy information. *Journal of Intelligent and Fuzzy Systems*, 37(2), 2043-2050. <https://doi.org/10.3233/JIFS-179267>
- [3] Zhao, Y., Liu, Y., Liu, S., Chen, H., & Wang, L. (2025). Detecting and suppressing dolphin clicks in whistle signals using adaptive matched filtering and interpolation algorithm. *The Journal of the Acoustical Society of America*, 157(6), 4057-4068. <https://doi.org/10.1121/10.0036828>
- [4] Jaskólski, K., Czaplinski, W., & Tomczak, A. (2024). Spectral analysis of compass errors based on fast Fourier transform and reduction absolute errors using a pass-band finite impulse response filter. *Polish Maritime Research*, 31(2), 109-120. <https://doi.org/10.2478/POMR-2024-0027>
- [5] Poonguzhali, D. S., Prabakar, N. T., & Elamaram, V. (2025). FPGA-based design and implementation of cascaded digital filters for enhanced auscultation in digital stethoscopes. *Circuits, Systems, and Signal Processing*, 45(6), 1-30. <https://doi.org/10.1007/S00034-025-03416-Y>
- [6] Zhang, W., Zhou, Y., & An, Y. (2026). Research on automatic signal modulation recognition methods based on deep learning. *Computer Informatization and Mechanical System*, 9(1), 66-74. <https://doi.org/10.12250/JPCIAM2026090213>
- [7] Zhao, B., Xiao, Y., Shen, H., Liu, J., & Zhang, Q. (2025). Variable step-size LMS algorithm based on variational Versoria function and variational Gaussian function.

- International Journal of Adaptive Control and Signal Processing, 39(4), 709-723. <https://doi.org/10.1002/ACS.3970>
- [8] Liu, X., Jia, Z., Xun, M., Wang, H., & Chen, Y. (2025). MSFHNet: A hybrid deep learning network for multi-scale spatiotemporal feature extraction of spatial cognitive EEG signals in BCI-VR systems. *Medical & Biological Engineering & Computing*, 63(11), 1-18. <https://doi.org/10.1007/S11517-025-03386-Y>
- [9] Huang, S., Tang, X., & Chen, Z. (2025). Study on noise analysis and frequency estimation in aircraft laser speed measurement technology. *Journal of Engineering Innovations & Technology*, 7(2), 14-24. <https://doi.org/10.69610/J.IEM.20250415>