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# Electromagnetic Signal Anomaly Detection and Classification Methods Based on Deep Learning

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**ABSTRACT**

With the rapid development of communication technology, the complexity of the electromagnetic environment is increasing, making the detection and classification of electromagnetic signal anomalies a crucial task for ensuring communication quality and security. Deep learning technologies offer new perspectives and methodologies for addressing this issue. However, traditional models often display limited adaptability in complex electromagnetic scenarios, particularly under coherent noise and multi-source interference, and they require extensive labeled data. To overcome these challenges, this paper proposes a novel approach for electromagnetic signal anomaly detection and classification. Initially, an adaptive mechanism for coherent noise suppression is studied to enhance detection performance in complex environments. Subsequently, by integrating deep Q-net (DQN) technology, an intelligent recognition and classification strategy is developed. Through self-learning, this method effectively identifies and classifies abnormal signals, reducing reliance on large volumes of labeled data while improving the system's adaptability to dynamic environments and processing accuracy. This research demonstrates the potential application of deep learning in modern electromagnetic signal processing and holds significant implications for advancing electromagnetic environment monitoring and management technologies.

## 1. INTRODUCTION

In the context of digitalization and networking, electromagnetic signals, as carriers of information transmission and detection, are playing an increasingly important role [1-4]. With the rapid development of wireless communication technology, the electromagnetic environment has become increasingly complex, and the quality and security of electromagnetic signals have faced unprecedented challenges [5, 6]. The detection and classification of abnormal signals, especially in noisy environments, have significant practical significance in the fields of communication security, electromagnetic compatibility testing, and spectrum management [7]. Accurately and effectively identifying and processing abnormalities in electromagnetic signals is a key technology to ensure a clean electromagnetic environment and smooth communication.

With the rapid development of deep learning technology, its application in the field of electromagnetic signal processing has gradually unfolded [8, 9]. Deep learning methods have shown great potential in feature extraction, pattern recognition, and other aspects, providing new solutions for the detection and classification of electromagnetic signal anomalies [10-14]. Through deep learning models, we can more accurately identify the abnormal parts of signals, effectively suppress interference in complex electromagnetic environments, and classify features, thus improving the efficiency and accuracy of electromagnetic signal processing.

However, existing deep learning methods still have certain limitations in the detection and classification of electromagnetic signal anomalies [15-18]. Firstly, traditional deep learning models have insufficient adaptability to dynamically changing electromagnetic environments, and their performance in detection and classification is significantly reduced when facing multi-source interference and non-stationary noise in the electromagnetic field [19, 20]. Secondly, training deep learning models requires a large amount of labeled data, but in practical applications, it is very difficult to obtain a large amount of accurately labeled electromagnetic signal data, which limits the model's generalization ability and practicality [21].

In response to the shortcomings of existing methods, this paper proposes a new method for electromagnetic signal anomaly detection and classification. Firstly, an adaptive coherent noise suppression algorithm is designed, which can effectively improve signal detection performance in complex electromagnetic environments by dynamically adjusting the noise suppression mechanism. Secondly, this paper introduces the DQN technology, which achieves precise identification and classification of electromagnetic signal anomalies through an intelligent decision-making learning process. This method not only improves the accuracy of anomaly detection but also optimizes the classification process, enabling the system to adapt to complex and variable electromagnetic environments without the need for a large amount of labeled data. This research not only expands the application of deep learning in the field of electromagnetic signal processing but also provides new technical means for electromagnetic environment monitoring and management, with significant theoretical value and practical application prospects.

## 2. ELECTROMAGNETIC SIGNAL ANOMALY DETECTION BASED ON ADAPTIVE COHERENT NOISE SUPPRESSION

In the application scenarios of electromagnetic signal anomaly detection and classification, existing problems often include high noise levels caused by complex electromagnetic environments, mutual interference between different signal sources, and the insufficient recognition accuracy of traditional detection methods in multi-signal scenarios. To address these challenges, this paper proposes an electromagnetic signal anomaly detection algorithm based on adaptive coherent noise suppression. This algorithm can more effectively extract and separate target signals from noisy backgrounds, reducing noise interference while preserving signal integrity, thereby improving detection accuracy in multi-signal, dynamically changing environments.

The proposed algorithm first focuses on the electromagnetic signals measured by sensors. These signals typically contain both the target signals and background noise. The target signals are the useful information we wish to detect and analyze, while the background noise may include various interferences, such as natural environmental noise and man-made electronic device interference. The sensor captures the superposition of these two components. Based on this, the first step of the algorithm is to process the captured electromagnetic signals to assess their coherence. The coherence here refers to the phase relationship between different frequency components, indicating whether there is a fixed time delay relationship between signal components. Subsequently, the algorithm infers the background noise transfer function based on the coherence calculated in the previous step. The transfer function is a mathematical model describing the relationship between system input and output, defined by the system's response to different frequency components. In the context of electromagnetic signal detection, the transfer function helps us understand how background noise affects the received signals under specific sensor configurations and environmental conditions. By analyzing the relationship between signal coherence and frequency, the impact of noise on the signal at different frequencies can be estimated, thus constructing a background noise model for the current environment and sensor setup. Finally, the algorithm uses the derived transfer function to specifically filter out the background noise in the electromagnetic signals to be detected. This step essentially implements signal frequency domain filtering through the transfer function. For the detected signals, the algorithm suppresses those frequency components that match the noise characteristics by adjusting the signal's gain at different frequencies, thereby weakening the noise impact and highlighting the target signal. Figure 1 shows the flowchart of the proposed electromagnetic signal anomaly detection method.

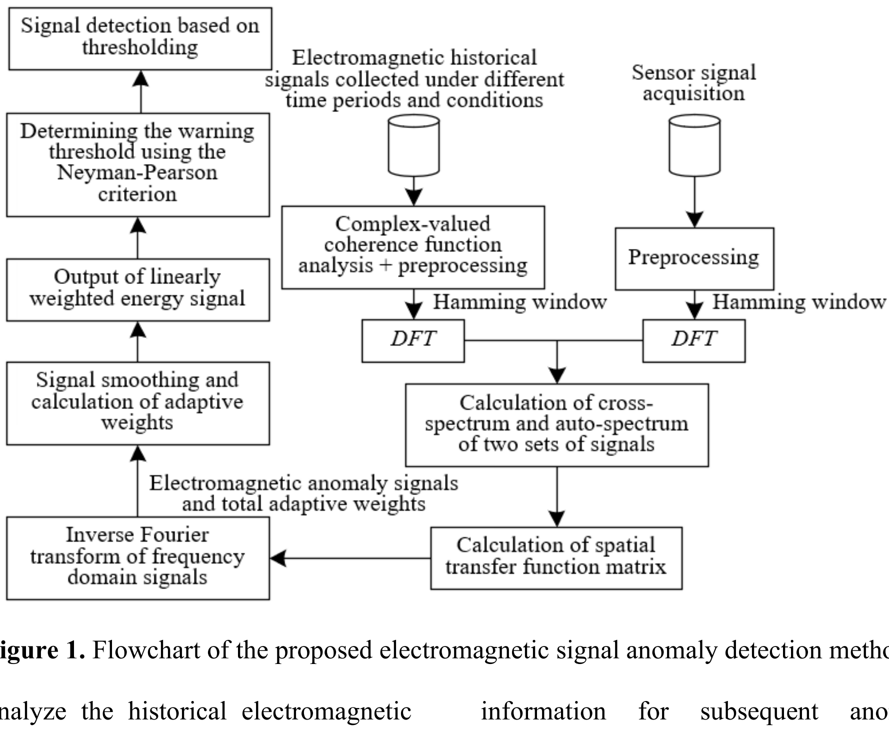


**Figure 1.** Flowchart of the proposed electromagnetic signal anomaly detection method

Specifically, first analyze the historical electromagnetic signal data collected through sensors. This paper uses the complex coherence function to analyze these historical data. The complex coherence function is a complex function that characterizes the frequency domain correlation of signals, providing amplitude and phase information of signal coherence. By analyzing the electromagnetic signal historical data collected under different time periods and conditions through the complex coherence function, researchers can identify changes in signal patterns, providing important prior information for subsequent anomaly detection and classification. This step is the basis for understanding signal behavior and determining subsequent processing strategies. Assuming the auto-power spectral density and cross-power spectral density of two electromagnetic historical signals $b_1(\mu)$ and $b_2(\mu)$ collected at different times and under different conditions are represented by $\theta_{bu,bk}(\mu)$, where $u$, $k$=1,2. Analyzing the collected signal data with the complex coherence function, we have:

$$\Gamma(\mu)=\frac{\theta_{b_1b_2}(\mu)}{\sqrt{\theta_{b_1b_2}(\mu)\theta_{b_1b_2}(\mu)}} \tag{1}$$

Let one segment of electromagnetic historical signal be represented by $b_1$, collecting only normal signals and background noise signals, represented by $r(v)$. Further, set up a sensor, the collected signal represented by $b_2(v)$, including abnormal signals $y(v)$ and the sum of normal signals with background noise signals $r(v)$, represented by $v$ for the number of sampling points, the transfer function between the two signals represented by $g(v)$, the two signals represented as:

$$b_1(v)=r(v) \tag{2}$$

$$b_2(v)=y(v)+g(v)*r(v) \tag{3}$$

After identifying the signal patterns in the historical data, the algorithm will perform Discrete Fourier Transform (DFT) on the reference electromagnetic signal historical data and electromagnetic signal data containing abnormal signals and noise. DFT can convert time-domain signals to frequency-domain, revealing the frequency components of the signal. Performing DFT on both the reference and the signal to be detected, their spectra can be obtained, in preparation for calculating the transfer function and cross-spectral relationship in the next steps, and also providing the basis for the characteristic frequency of the abnormal signal. Assuming the frame index is represented by $j$, $\mu_m=2\pi m/M$, $m=0,1,2,...,M$. If the length of a frame in the sample is represented by $M$, then the discrete form after the DFT is:

$$B_1(\mu_m,j)=R(\mu_m,j) \tag{4}$$

$$B_2(\mu_m,j)=Y(\mu_m,j)+G(\mu_m,j)\bullet R(\mu_m,j) \tag{5}$$

After obtaining the signal's spectrum, the algorithm will use the data of the reference signal and the abnormal noise-containing signal to generate the transfer function. The generation of the transfer function relies on the cross-spectral relationship between the data of two signals, which is the correlation in the frequency domain of the two signals, combining power spectral density and phase information, and can characterize the linear relationship between signals. Through the cross-spectral relationship, the algorithm can construct a mathematical model describing how the signal is transferred from input to output. Assuming the auto-spectrum and cross-spectrum of $b_1(\mu)$ and $b_2(\mu)$ are represented by $T_{BuBk}$, $u,k=1,2$, and the auto-spectrum of $r(\mu)$ by $T_{RR}(\mu,j)$. Specifically, using the cross-spectral relationship between $b_1(v)$ and $b_2(\mu)$, the transfer function can be obtained:

$$T_{B_1B_2}(\mu,j)=T_{YR}(\mu,j)+G(\mu,j)T_{RR}(\mu,j) \tag{6}$$

Because the abnormal signal is incoherent with the background signal, $T_{RR}(\mu,j)=0$, thus a simplified form is:

$$T_{B_1B_2}(\mu,j)=G(\mu,j)T_{RR}(\mu,j) \tag{7}$$

In order to more accurately filter out background noise and abnormal signals, the algorithm needs to adaptively adjust the transfer function. This adjustment is based on the estimation of the auto-spectrum and cross-spectrum of the signals, which can reflect changes in noise and abnormal signals. The auto-spectrum provides the strength information of a single signal at various frequencies, while the cross-spectrum provides the correlation information between two signals. Combining this information, the algorithm can automatically adjust the transfer function to adapt to changes in the signal, ensuring that while filtering out noise, the target signal is preserved to the greatest extent. Let the transfer function be represented by $G(\mu)$, then we have:

$$G(\mu,j)=\frac{T_{B_1B_2}(\mu,j)}{T_{RR}(\mu,j)}=\frac{T_{B_1B_2}(\mu,j)}{R_{B_1B_1}(\mu,j)} \tag{8}$$

After completing the processing in the frequency domain, the algorithm will perform an inverse Fourier transform on the processed frequency domain signal, converting it back into a time-domain signal. This step is to re-obtain a signal that can be analyzed on a time series. Since the signal may be processed in segments in the frequency domain, at this time, the overlap-add method is used to reconstruct the complete time-domain signal. Overlap-add is a technique of overlapping and adding, used to seamlessly splice segmented signals that have been filtered in the frequency domain, thereby restoring a continuous time-domain signal. Thus, the final output is the purified target signal, providing accurate basic data for the subsequent anomaly detection and classification stage. The following formula gives the expression for reconstructing the time-domain target signal $y(v)$:

$$y(v)=D^{-1}\left(B_2(\mu)-G(\mu)B_1(\mu)\right) \tag{9}$$

In the context of electromagnetic signal anomaly detection and classification, even after the preliminary processing of electromagnetic signals using an adaptive coherence noise suppression method, signals often still contain residual noise and interference. These unstable factors can lead to a decrease in the performance of the detection algorithms, manifested as indistinct signal features, decreased classification accuracy, and insufficient sensitivity to weak signal variations. To address these issues, it is necessary to smooth the processed signals. In order not to interfere with the learning process of deep learning models and to improve the accuracy and reliability of signal classification, this paper chooses to use the Savitzky-Golay filter for signal smoothing. The Savitzky-Golay filter smooths the signal by fitting a polynomial to the data within a moving window of the signal, and using the evaluation result of this polynomial as the smoothed signal. This method can effectively preserve the characteristics of the signal, such as peaks, width, and height, and compared to other smoothing techniques, it can maintain important structural features of the signal while reducing noise, thereby improving the performance of deep learning models in the detection and classification of electromagnetic signal anomalies.

The Savitzky-Golay filter smooths a signal by fitting a polynomial to the data in a local window of the signal and replacing the value at the center point of the window with the value of the polynomial. Specifically, taking the 5-point quadratic construction method as an example, where the five points are $a[-2]$, $a[-1]$, $a[0]$, $a[1]$, $a[2]$, the following equation provides the quadratic parabolic expression constructed based on these five points:

$$d(u) = x_0 + x_1 \times u + x_2 \times u^2 \tag{10}$$

The objective of the method is to find the optimal coefficients $x_0$ that satisfy the least squares fit, which can be expressed as:

$$R = \sum \big(d(u) - a(u)\big)^2, u = -2, -1, 0, 1, 2 \tag{11}$$

If the value of the above equation is minimized, equivalent to the minimization of $R$'s partial derivatives, then:

$$\frac{\partial R}{\partial x_o} = 0 \tag{12}$$

The three coefficients can be determined based on the equations of partial derivatives. After smoothing, further calculations of the square of the signal are weighted, and adaptive weights are computed. Squared weighting is to amplify potential features in the signal, making the abnormal part more prominent for easier identification. Adaptive weights are dynamically adjusted based on the local characteristics of the signal, enhancing the model's sensitivity to important features in the signal while reducing the impact of less important parts. Subsequently, normalization is performed to ensure the numerical stability of the feature signals. Finally, the Neyman-Pearson criterion is used to determine the alert threshold, based on which the final judgment result of the signal is obtained. The Neyman-Pearson criterion is a decision-making criterion that maximizes the detection probability by choosing a threshold. In the task goal of electromagnetic signal anomaly detection, this means that the system can detect as many real anomalies as possible while maintaining a low false alarm rate. Through this step, the system can convert the smoothed feature signal into the final judgment result based on the set threshold, thereby completing the task of signal anomaly detection and classification.

## 3. ELECTROMAGNETIC SIGNAL ANOMALY DETECTION AND CLASSIFICATION BASED ON DQN

The existing problems in the classification and identification of electromagnetic signal anomalies primarily include the traditional methods' tendency to confuse modulation modes in noisy environments, difficulty adapting to dynamic changes, and the high cost of obtaining labeled data. To adapt to the complexity and variability of the electromagnetic signal environment, while avoiding the limitations of existing supervised learning methods when facing unknown or interfering signals, this paper chooses to implement electromagnetic signal anomaly detection and classification based on DQN. The DQN algorithm, which integrates the feature extraction capability of deep learning and the decision-making learning capability of reinforcement learning, can learn effective strategies through interaction with the environment under partially supervised conditions. The advantage of DQN lies in its ability to effectively classify various modulation methods through self-exploration and learning, without relying on a large amount of labeled data, and to continuously optimize the identification strategy through cumulative rewards, especially for finely distinguishing easily confused signals. Therefore, the method based on DQN is expected to solve these problems present in traditional algorithms, improving the accuracy and robustness of electromagnetic signal anomaly detection and classification, and meeting the demand for intelligent analysis of electromagnetic signals in practical applications.

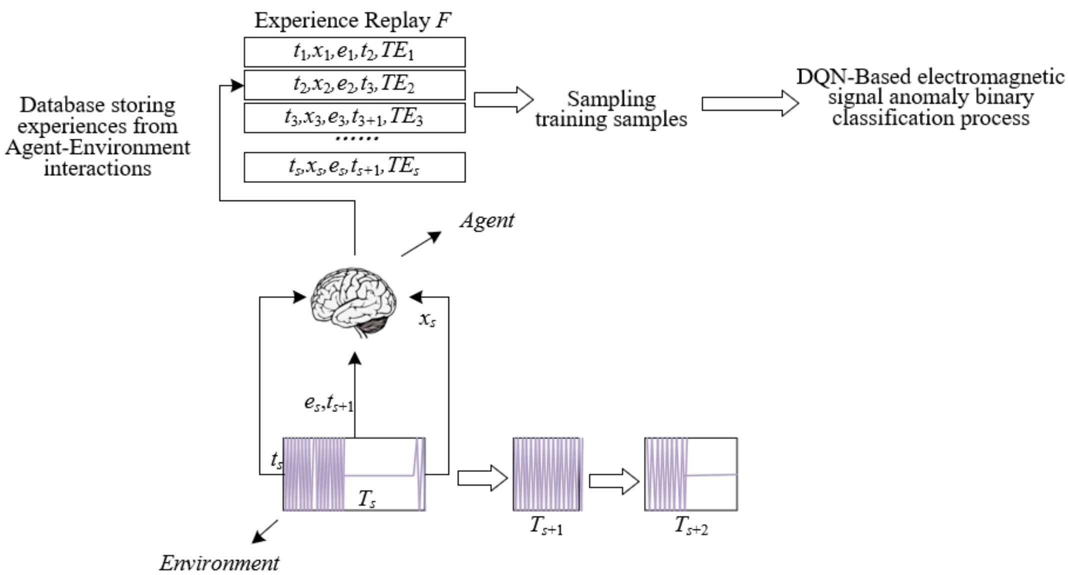


**Figure 2.** Design of electromagnetic signal anomaly detection and classification system based on DQN

In the application scenario of electromagnetic signal anomaly detection and classification, the misidentification of certain signals may have more severe consequences than others. For example, in the field of communication security, unrecognized abnormal signals may lead to security vulnerabilities, while in the medical field, the misjudgment of certain key signals may affect the diagnosis of diseases. Therefore, for those signals that are easily confused and of high criticality, the DQN needs to increase their identification accuracy through imbalanced classification. If an imbalanced classification mode is not set, meaning the agent adopts a balanced recognition strategy for all types of signals, the system may not provide sufficient attention to those more important signals, leading to a low overall system recognition accuracy, especially in situations where tolerance for errors is extremely low. By adjusting the reward mechanism, providing higher rewards for the correct identification of those key signals, and possibly setting greater penalties for incorrect identifications, the DQN can be motivated to focus more on these signals, improving their recognition accuracy, thereby enhancing the overall system performance and reliability. Figure 2 shows the design principle of the electromagnetic signal anomaly detection and classification system based on DQN.

The electromagnetic signal anomaly detection and classification system based on DQN can be likened to a strategy game where the agent's goal is to identify non-standard or anomalous signals in the electromagnetic spectrum by learning, focusing particularly on signals that appear infrequently, are unknown, or may indicate interference and threats. In this game, the agent analyzes electromagnetic signal samples to predict whether they belong to an anomalous category. When the agent's prediction matches the actual label, i.e., successfully detecting an anomalous signal, it receives positive points; conversely, if it fails to correctly identify an anomaly, or incorrectly classifies a normal signal as anomalous, it is penalized by score deduction. To reinforce the identification of high-risk signals, the system sets higher rewards and penalties for types of anomalous signals that are usually harder to detect. Through this incentive mechanism, the DQN model is trained to focus on accurately identifying and classifying anomalous patterns in electromagnetic signals.

This paper formulates the task of anomaly signal detection and classification as a series of sequential decision problems and uses a DQN-based approach to solve these problems. The design steps are as follows:

(1) Constructing the DQN environment. In this environment, the state space $T$ consists of a collection of signal samples captured from the electromagnetic environment, which can be represented as $Q=\{<q_u,a_u>|u=1,2,3,...\}$, where $q_u$ represents a signal sample, and $a_u$ represents the features of the sample. Each signal sample $q_u$ corresponds to a label indicating whether the signal is anomalous. At any given moment $s$, the current state $T_s$ reflects a signal sample from a new dataset and its corresponding features. The agent's task is to accurately determine whether these samples are anomalous signals. This process involves a continuous decision-making framework, where the agent must use limited historical information to continually optimize its strategy for detecting anomalous signals. This is achieved by processing feedback signals from the environment to improve recognition and response to potential threats in the electromagnetic environment.

(2) The task at hand involves processing a shuffled dataset, which randomly provides a signal sample at each time step. Unlike other traditional signal detection and classification systems, the agent's goal here is to determine whether a signal is anomalous, rather than identifying its signal processing type. Suppose at time $s$, the current state $T_s$ presented by the environment corresponds to the signal sample $q_s$, which comes with a label $a_s$ indicating whether the sample is anomalous. The agent observes this signal sample $q_s$ and generates a classification action $b_s$ based on its learned strategy, aiming to categorize the signal as normal or anomalous. If the agent's classification action $b_s$ matches the actual label $a_s$ (i.e., correctly identifies the signal's anomaly status), the agent receives a positive reward; if it does not match, the agent is penalized, receiving a negative return. Through such feedback, the agent is motivated to accumulate a higher total score, thereby enhancing its accuracy in discriminating anomalous signals. The agent stores the data from each interaction with the environment in an experience pool $F$, and when taking actions, it selects an action randomly with a certain probability based on a linear annealing $\varepsilon$-greedy strategy, or chooses the action estimated to be optimal with probability 1-$\varepsilon$, i.e., the action that maximizes the state-action value function. This process continues, with the agent continually learning through interactions with the environment, not only accumulating experience of individual signals but also enhancing its recognition capability of the entire electromagnetic signal environment's anomalous states.

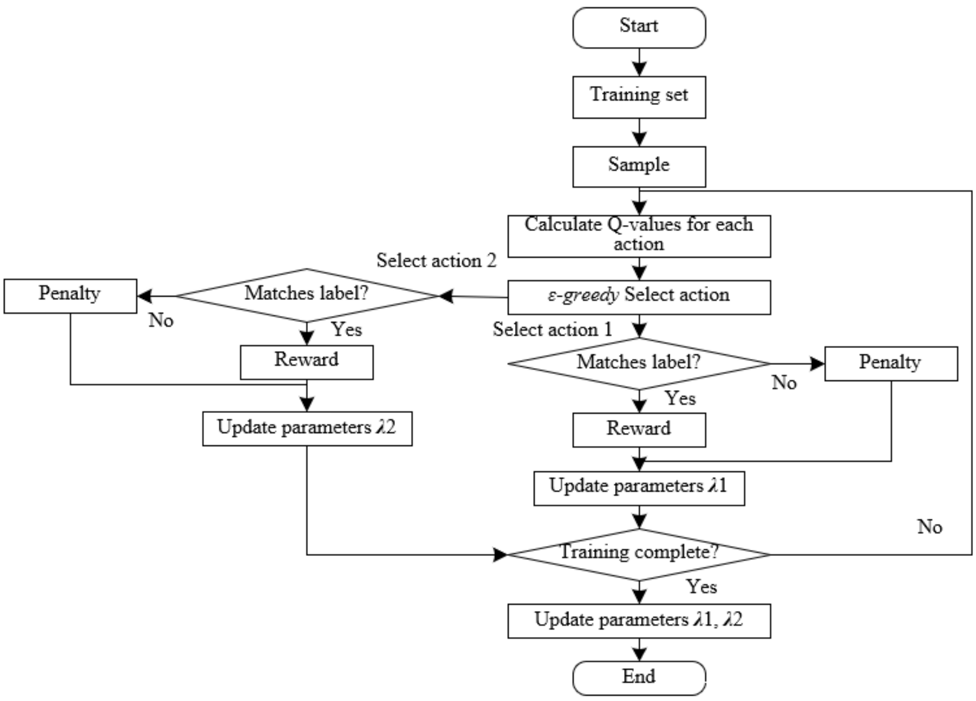


**Figure 3.** Flowchart of electromagnetic signal anomaly binary classification based on DQN

(3) Setting of the reward function. The setting of the reward function directly influences the behavior guidance during the agent's learning process. This paper focuses on whether signals are anomalous, thus all signals can be divided into two major categories: normal signals ($Q_1$) and anomalous signals ($Q_2$). Anomalous signals may include some subclasses with similar features, which are more prone to misjudgment in practical applications, thus requiring more precise recognition by the agent. In this context, when the agent correctly identifies a normal signal, it is given a base positive reward; when it correctly identifies an anomalous signal, considering the importance and difficulty of anomaly signal detection, it is given a higher positive reward. Conversely, if the agent incorrectly classifies a normal signal as anomalous, or an anomalous signal as normal, a negative reward should be assigned. Figure 3 provides a flowchart for the binary classification of electromagnetic signal anomalies based on DQN. To drive the learning process more effectively, this negative reward can be differentiated based on the specific type and importance of the signal, for example, incorrectly judging a high-risk anomalous signal as normal should incur a more severe penalty. In this way, the reward function not only promotes the agent's learning to distinguish between normal and anomalous signals but also encourages the agent to discriminate between different categories of anomalous signals more finely, making the agent tend towards improving accuracy throughout the training process, especially when classifying those more difficult-to-identify anomalous signals.

The definition formula for the reward function is as follows:

$$e_s = \begin{cases} +1, e_s = a_s, q_s \in Q_1 \\ +x, e_s = a_s, q_s \in Q_2 \\ -1, e_s \neq a_s, q_s \in Q_1 \\ -x, e_s \neq a_s, q_s \in Q_2 \end{cases} \tag{13}$$

Through efforts to accumulate a higher total score $RW$, the system will undergo continuous training and learning.

$$RW = \sum_{s=1} e_s \tag{14}$$

## 4. EXPERIMENTAL RESULTS AND ANALYSIS

As shown in Figure 4, it can be observed that the performance trend of Support Vector Machine (SVM), Principal Component Analysis (PCA), and the adaptive coherent noise suppression algorithm proposed in this paper under different Signal-to-Noise Ratio (SNR) conditions. In extremely low SNR environments (-20dB to -2dB), the accuracy of all three methods is low, due to the high level of noise making it difficult to distinguish signal features. However, as the SNR increases, the accuracy of all methods increases. The proposed method surpasses SVM and PCA in accuracy starting from -10dB, and in the high SNR environment of 0dB to 30dB, the proposed method shows a more stable and higher accuracy. Especially in the range of 10dB to 18dB, the accuracy of the proposed method reaches the peak value of 0.64, while in this range, the accuracy of SVM and PCA is maintained between 0.51 to 0.52 and 0.57 to 0.61, respectively. Analyzing the above experimental data, it can be concluded that the adaptive coherent noise suppression algorithm proposed in this paper has significant performance advantages for signal detection in complex electromagnetic environments. Especially in the medium to high SNR range, the proposed method not only has high accuracy but also shows higher robustness and stability compared to SVM and PCA. This result indicates that by dynamically adjusting the noise suppression mechanism, the proposed method can more effectively adapt to changes in different SNRs, improve the accuracy of signal detection, especially in better SNR conditions, it can effectively overcome the interference of coherent noise, and provide more reliable detection performance.

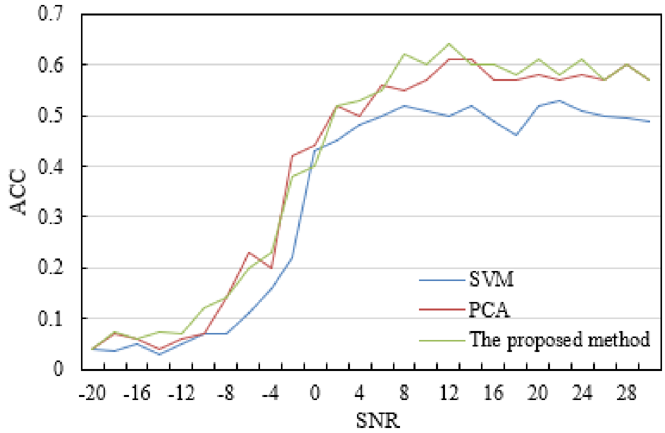


**Figure 4.** Comparison of accuracy of electromagnetic signal anomaly detection methods under different SNR conditions

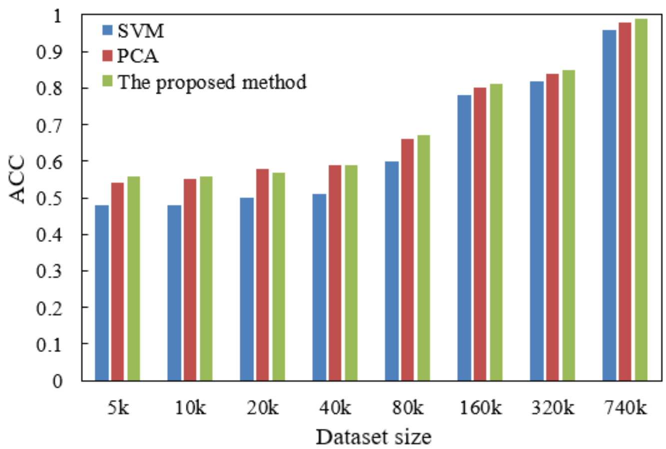


**Figure 5.** Comparison of accuracy of electromagnetic signal anomaly detection methods under different dataset sizes

Figure 5 shows the impact of different sizes of datasets on the accuracy of SVM, PCA, and the adaptive coherent noise suppression algorithm proposed in this paper. Initially, on a 5k dataset, the accuracy of the proposed method is 0.56, slightly higher than SVM's 0.48 and PCA's 0.54. As the size of the dataset increases, the accuracy of all methods gradually increases, indicating that more data have a positive impact on model performance. Especially when the dataset size reaches 160k, the accuracy of the proposed method reaches 0.81, surpassing SVM's 0.78 and PCA's 0.8. When the dataset size further increases to 740k, the accuracy of the proposed method reaches 0.99, while SVM and PCA reach 0.96 and 0.98, respectively. These results show that as the amount of data increases, the proposed method can better learn and adapt to signal features, achieving higher detection accuracy. The above experimental results clearly show that the adaptive coherent noise suppression algorithm proposed in this paper can effectively handle large-scale datasets and show significant performance improvement as the dataset size increases. In all tested dataset sizes, the proposed method always maintains performance equal to or better than SVM and PCA, especially in large datasets, the accuracy of the proposed method is nearly perfect. This highlights the efficiency and accuracy of the adaptive algorithm in learning signal features in complex electromagnetic environments.

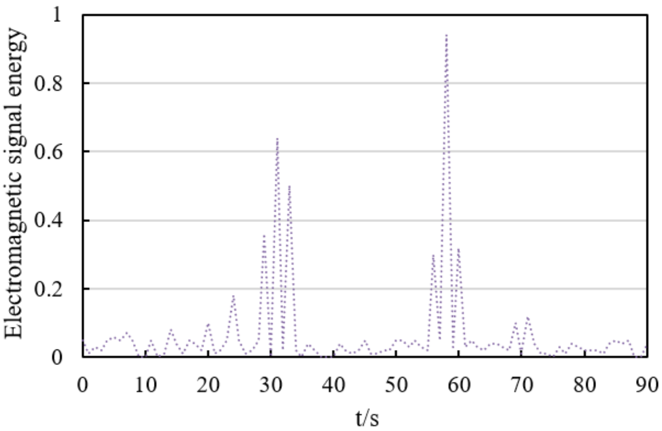


**Figure 6.** Electromagnetic signal anomaly detection results using traditional coherent noise suppression algorithm

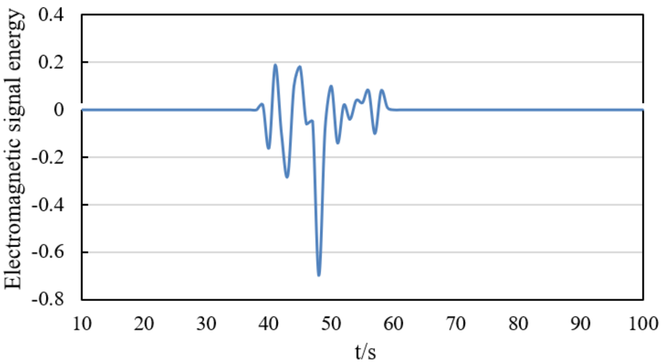


**Figure 7.** Electromagnetic signal anomaly detection results using adaptive coherent noise suppression algorithm

In simulated complex electromagnetic environments, the adaptive coherent noise suppression algorithm proposed in this paper was compared with traditional algorithms, and the experimental results are shown in Figures 6 and 7. In the experiments, the background signal was simulated through direct superposition, causing the normal signal and electromagnetic anomaly signal to have extremely high coherence in the frequency domain, almost close to 1, except at specific moments (at 50 seconds). When processing such data, the traditional coherent noise suppression algorithm, affected by non-Gaussian white noise, failed to effectively detect the weak electromagnetic anomaly signals. However, when the same set of data was processed using the adaptive algorithm designed in this paper, the results showed significant fluctuations at the moments when the target appeared, indicating that the electromagnetic anomaly signals were well preserved and the SNR was improved. This marks the superior detection capability of the adaptive algorithm over traditional methods. It can be concluded that although the adaptive coherent noise suppression algorithm demonstrated an advantage in detecting weak electromagnetic anomaly signals in the experiments, it also has some limitations. Especially near the appearance of the target signal, the algorithm produced significant fluctuations, which may lead to the risk of false positives. Also, small spikes were observed in non-target signal areas, which might be the result of over-adjustment in the algorithm's adaptive process. These issues reveal that while the adaptive algorithm is superior to traditional algorithms, there is still room for improvement in accuracy and stability. Therefore, future research should focus on reducing false positives and spikes, further refining and optimizing the adaptive mechanism to achieve more accurate and robust anomaly detection in various complex electromagnetic environments.

**Table 1.** Performance comparison of different electromagnetic signal anomaly identification classification methods

| Model | | *Acc* | *Sp* | *Sc* | *MAcc* |
|---|---|---|---|---|---|
| *Stacked Autoencoders* | | 0.9325 | 0.9451 | 0.8451 | 0.9154 |
| *DenseNet* | | 0.8895 | 0.8562 | 0.8956 | 0.8754 |
| *GRU* | | 0.8745 | 0.9231 | 0.8874 | 0.9126 |
| *BiLSTM* | | 0.8623 | - | 0.9236 | - |
| *TRPO* | | 0.9125 | 0.74 | 0.9362 | 0.8326 |
| *DDPG* | | 0.9784 | 0.925 | 0.9415 | 0.9354 |
| *CVAE* | | - | 0.911 | 0.825 | 0.865 |
| *GAN* | *CGAN* | 0.9315 | 0.9451 | 0.9362 | 0.9356 |
| | *RGAN* | 0.9316 | 0.9532 | 0.9356 | 0.9451 |
| | *WGAN* | 0.9235 | 0.9236 | 0.9254 | 0.9123 |
| | *CycleGAN* | 0.9254 | 0.9125 | 0.9215 | 0.9235 |
| The proposed method | | 0.9653 | 0.9654 | 0.9635 | 0.9658 |

The performance comparison of different electromagnetic signal anomaly identification classification methods presented in Table 1 shows that the method based on DQN significantly outperforms other models. Specifically, the method achieved an accuracy (*Acc*) of 0.9653, specificity (*Sp*) and sensitivity (*Sc*) of 0.9654 and 0.9635 respectively, and a mean accuracy (*MAcc*) of 0.9658. Compared to traditional models such as Stacked Autoencoders, DenseNet, GRU, BiLSTM, and other reinforcement learning-based models like TRPO and DDPG, our method demonstrated higher overall classification performance. Moreover, even in comparison with various Generative Adversarial Network (GAN) variants, including CGAN, RGAN, WGAN, and CycleGAN, our method still showed superior identification and classification capability. It can be concluded that the electromagnetic signal anomaly identification classification method proposed in this paper based on DQN, stands out among all compared methods with its high accuracy and balanced specificity and sensitivity performance. This result proves that the proposed method is not only capable of effectively identifying and classifying electromagnetic signal anomalies but also demonstrates significant robustness and adaptability in dealing with uncertainties and dynamic changes in electromagnetic environments. Compared to traditional models, the application of DQN reduces the dependency on large volumes of labeled data, enhancing the model's generalization ability in detecting unknown signals.

Table 2 presents a performance comparison of different DQN frameworks in the task of electromagnetic signal anomaly recognition and classification. The DQN method proposed in this paper achieved the best performance in terms of accuracy (*Acc*), specificity (*Sp*), sensitivity (*Sc*), and mean accuracy (*MAcc*), with an accuracy rate of 0.9689, specificity and sensitivity both at 0.9687, and mean accuracy reaching 0.9765, significantly higher than other DQN variants such as Double DQN, Multi-step DQN, and Distributed DQN. These data fully demonstrate the superior performance of the proposed method in the detection and recognition of electromagnetic signal anomalies, setting a new benchmark for adaptability and accuracy in electromagnetic environments. The reason why the proposed method outperforms other DQN frameworks in multiple performance metrics is attributed to its innovative algorithmic design, including but not limited to more refined state space design, efficient reward function construction, and optimized network structure. These optimizations allow the DQN algorithm to better understand the characteristics of complex electromagnetic signals, thereby achieving more precise identification and classification. Moreover, the high performance of this method indicates that it can effectively process a large amount of unlabeled data, which is of great significance for the frequently encountered problem of scarce labeled samples in practical applications. In summary, the DQN method proposed in this study has demonstrated excellent performance in the task of electromagnetic signal anomaly recognition, proving its potential as an effective electromagnetic signal processing tool.

**Table 2.** Performance comparison of different DQN frameworks in electromagnetic signal anomaly recognition and classification task

| Model | *Acc* | *Sp* | *Sc* | *MAcc* |
|---|---|---|---|---|
| Double DQN | 0.9362 | 0.9354 | 0.9351 | 0.9365 |
| Multi-step DQN | 0.9584 | 0.9562 | 0.9548 | 0.9512 |
| Distributed DQN | 0.9362 | 0.9361 | 0.9368 | 0.9368 |
| The proposed method | 0.9689 | 0.9687 | 0.9687 | 0.9765 |

## 5. CONCLUSION

This study proposes a novel method for electromagnetic signal anomaly detection and classification, effectively addressing the deficiencies of existing methods in complex electromagnetic environments. The unique adaptive coherent noise suppression algorithm significantly improves signal detection performance, capable of dynamically adjusting the noise suppression level according to the real-time SNR, thus adapting to the variable electromagnetic environment. Furthermore, the application of DQN technology further enhances the system's ability to precisely identify and classify electromagnetic signal anomalies, maintaining high accuracy even in situations with limited data labeling resources. Experimental results show that the proposed method exhibits outstanding detection and classification performance under different SNR conditions and dataset sizes, and performs better than traditional methods under various DQN frameworks.

The approach not only improves the accuracy and robustness of anomaly detection but also provides an efficient way to handle unlabeled electromagnetic data, offering significant practical application value. However, the limitations of the study include the potential need to adjust the adaptive noise suppression algorithm and reinforcement learning model for specific scenarios to ensure optimal performance. Additionally, the high computational complexity of deep learning models may limit their deployment in real-time or resource-constrained scenarios. Future work could explore optimizing computational efficiency and reducing model complexity to accommodate a wider range of application demands. Integration of more types of signal processing techniques and advanced machine learning algorithms to further enhance the system's detection and classification capabilities can also be considered. Exploring the generalizability of the adaptive algorithm in different electromagnetic environments and how to quickly adapt to new signal types or interference patterns are also important future directions. Furthermore, research on the security and interpretability of data-driven methods is a critical future direction to ensure the reliability of electromagnetic signal processing systems.

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