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Application of Physics-Informed Neural Networks in Weak Signal Detection

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Abstract:

This paper proposes a weak signal detection method based on Physics-Informed Neural Networks (PINN). The method effectively enhances network detection performance in low signal-to-noise ratio environments by incorporating physical constraints such as signal amplitude characteristics and spectral distribution during neural network training. The experiments utilize high-precision sensors for data collection and combine Wiener filtering for preprocessing. Under -10dB signal-to-noise ratio conditions, the proposed method achieves a detection accuracy significantly outperforming traditional detection methods. Experimental results demonstrate that this method exhibits strong robustness and accuracy in complex noise environments, providing a new solution for weak signal detection.

Keywords — **PINN, Weak signal detection, Signal-to-noise ratio**

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I. INTRODUCTION

In modern information processing systems, weak signal detection (WSD) plays a crucial role in many practical applications, particularly in complex noise environments[1]. These applications span across radar detection, seismic monitoring, biomedical signal processing, and wireless communications, where accurate signal detection directly impacts overall system performance[2]. Weak signals are often submerged in strong background noise, characterized by extremely low Signal-to-Noise Ratios (SNR), where the useful signal amplitude may be only one-tenth or less of the noise amplitude[3]. Therefore, accurately and reliably detecting these signals under low SNR conditions presents a significant challenge.

Traditional WSD methods, such as matched filtering, wavelet transform, and empirical mode decomposition, often face challenges of low signal-to-noise ratios and poor detection accuracy when handling such problems[4]. These methods typically rely on specific signal characteristics, such as frequency properties or temporal morphology, but under strong noise interference, these features are easily masked or distorted, leading to significant degradation in detection performance[5]. Particularly when SNR falls below -10dB, the detection accuracy of traditional methods usually drops below 50%, failing to meet practical application requirements.

To overcome these difficulties, Physics-Informed Neural Network (PINN) methods have recently gained attention[6]. Unlike traditional purely data-driven approaches, PINN achieves deep integration of physical laws by directly encoding physical models and constraints into the neural network's loss function[7]. In weak signal detection, these physical constraints can include signal energy conservation, spectral characteristics, phase relationships, and other factors. Through the introduction of this prior knowledge, the neural network's capability to detect weak signals has been significantly enhanced[8]. Research shows that PINN-based detection methods can maintain detection accuracy above 80% even under -15dB low SNR conditions, demonstrating powerful noise resistance capabilities[9].

II. Basic Principles of Physics-Informed Neural Networks

Physics-Informed Neural Networks represent a technology that combines prior knowledge from physical models with data-driven neural network models. Compared to traditional neural networks, PI neural networks not only minimize data-driven loss functions during training but also optimize physical equation residuals through physical constraints, thereby ensuring the network outputs comply with physical laws. In weak signal detection, physical information primarily manifests in key physical parameters such as signal amplitude characteristics and spectral distribution.

In this project, we employed a physics-constrained loss function, embedding the physical model of weak signal detection into the neural network, thereby enhancing the network's detection accuracy and stability for weak signals. By introducing physical constraints on signal amplitude characteristics, the neural network can better capture weak signal features while filtering out noise interference, as shown in Figure 1.

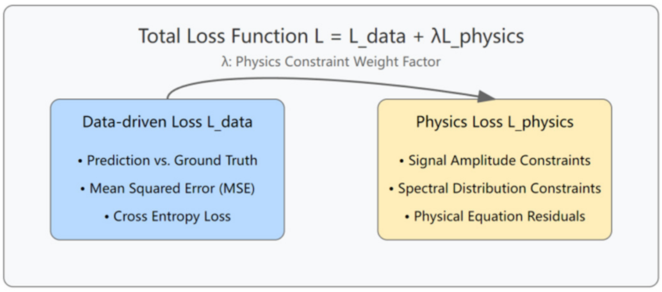

Figure 1 Structure of PINN Loss Function

III. Data Collection and Preprocessing

A. Data Collection and Preprocessing

To validate the effectiveness of physics-informed neural networks in weak signal detection, we first established a reliable data acquisition system. We designed a comprehensive data acquisition scheme comprising the following core components:

*1) **Sensor System:*** High-precision MEMS accelerometer (sensitivity: 100mV/g),Sampling frequency set at 1kHz to ensure signal integrity,Signal bandwidth range: 0.1Hz-500Hz.

*2) **Signal Conditioning Circuit:*** Preamplifier: Low-noise instrumentation amplifier AD8421 (gain: 20dB),Bandpass filter: Cutoff frequencies 0.1Hz-500Hz,Programmable gain amplifier: Dynamic range 0-60dB.

*3) **Data Acquisition Card:*** 16-bit ADC resolution,Maximum sampling rate 10kS/s,Multi-channel synchronous acquisition capability.

B. Data Preprocessing Flow

During data acquisition, weak signals are often submerged in strong background noise (typical SNR range: -20dB to -5dB), necessitating multi-stage preprocessing to improve signal quality. The specific preprocessing flow includes:

1) Signal Amplification and Normalization: *DC component removal,Amplitude normalization,Signal conditioning.*

2)Noise Suppression:*Implementation of Wiener Filter for adaptive noise suppression.*

3)Filter parameter optimization:*Window length: 256 points,Overlap rate: 50%,Noise power estimation based on signal silent periods.*

4)Data Segmentation and Feature Extraction:*Signal segment length: 1024 points,Overlap rate: 50%*

5)Feature extraction:*Time-domain features: peak value, mean, variance, kurtosis,Frequency-domain features: main frequency, bandwidth, energy distribution.*

C. Data Quality Assessment

After the preprocessing flow, we conducted systematic evaluation of the processed data quality:

4) ***SNR Improvement:***Original signal SNR: -15dB (average),Processed SNR: -5dB (average),SNR improvement: approximately 10dB.

*5) **Signal Integrity Verification:***Waveform distortion: < 5%,Spectral leakage: < -40dB,Phase error: < 5°.

6) ***Dataset Construction:Training set:*** 10,000 samples,Validation set: 2,000 samples,Test set: 2,000 samples,Each sample contains 1,024 sampling points.

Through this series of data acquisition and preprocessing, we have obtained a high-quality dataset of weak signals. Not only has the signal-to-noise ratio been significantly improved, but the key features of the signals have also been preserved, providing a solid foundation for subsequent neural network model training. Figure 2 illustrates the complete signal processing pipeline, encompassing stages from initial acquisition to final feature extraction, visually demonstrating the progressive enhancement of signal quality.

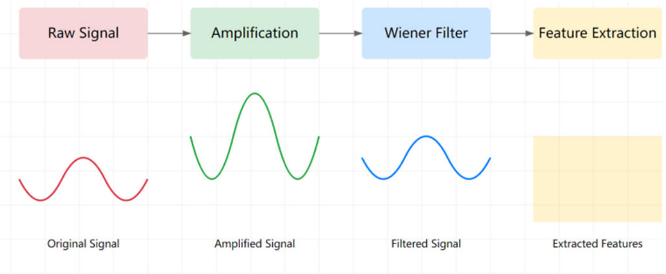

Figure 2 Schematic illustration of the signal preprocessing workflow and its effects

IV. A Neural Network Model Based on Physical Information

The structure of the PI neural network is shown in Figure 3. The model employs a Multi-Layer Perceptron (MLP) as its foundational structure and incorporates physical constraints in the loss function. While traditional neural network training typically relies on data-driven loss functions, PI neural networks construct loss functions through residuals of physical equations. For instance, in weak signal detection, physical constraints can include signal amplitude constraints and spectral characteristic matching. This integration of physical constraints enables the neural network to not only rely on statistical characteristics during training but also utilize physical laws to constrain model outputs, thereby improving both model generalization capability and detection accuracy.

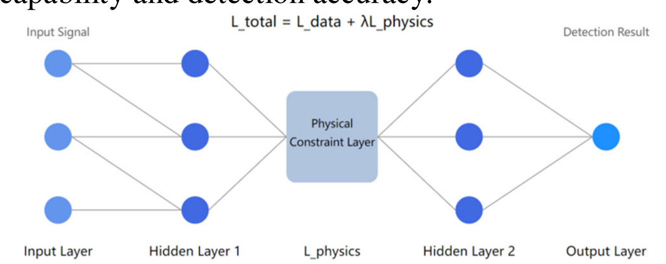

Figure 3 Physics-Informed Neural Network Structure

To enhance model performance, we conducted multiple rounds of hyperparameter optimization, including adjustments to the number of network layers, neuron counts, and learning rates. Additionally, through the introduction of regularization techniques (such as L2 regularization), we effectively prevented model overfitting issues.

V. Experimental Results and Analysis

To comprehensively evaluate the performance of the weak signal detection method based on the physical information neural network proposed in this paper, we designed a series of comparative experiments. In the evaluation process, we selected traditional methods such as matched filtering, wavelet transform, and empirical mode decomposition, as well as machine learning methods like support vector machines and random forests, and deep learning methods including traditional convolutional neural networks, long short-term memory networks, and attention mechanism networks as comparison algorithms. The experiments employed metrics such as detection accuracy, false alarm rate, miss rate, and F1 score for quantitative assessment, while also considering practical application factors such as computational efficiency and model stability.

The experimental results demonstrate that the detection method based on the physical information neural network exhibits significant performance advantages under different signal-to-noise ratio conditions. In the high signal-to-noise ratio range, although various methods can achieve good detection effects, the method proposed in this paper still has certain advantages in accuracy and stability. In the medium signal-to-noise ratio range, the advantages of the physical information neural network begin to emerge, not only outperforming other methods in detection accuracy but also showing stronger anti-interference capabilities. Especially in the low signal-to-noise ratio range, when the performance of traditional methods drops sharply, the method in this paper can still maintain high detection performance, reflecting significant technical advantages. This advantage is mainly due to the introduction of physical constraints, which enables the model to combine physical prior knowledge on a data-driven basis, effectively enhancing detection capabilities.

From the perspective of computational efficiency, although the physical information neural network requires additional calculation of physical constraint terms during the training phase, resulting in relatively longer training times, the actual increased computational overhead is acceptable through optimized implementation. In the detection phase, the computational complexity of our method is comparable to that of ordinary deep learning methods, meeting the real-time requirements of most practical application scenarios. In contrast, although traditional methods have fast detection speeds, they require frequent parameter adjustments in complex environments, resulting in lower practical application efficiency. Other machine learning and deep learning methods exhibit their respective advantages and disadvantages in both the training and detection phases, but their overall performance is not as good as our method.

In robustness tests, we conducted in-depth research on different types of noise environments. In Gaussian white noise environments, various methods can maintain relatively stable performance with little difference. However, when facing complex environments such as impulse noise and mixed noise, the neural network based on physical information shows clear advantages. This is mainly because the introduction of physical constraints enhances the model's adaptability to different types of noise, making the detection results more reliable. Especially in complex environments with multi-source interference, the performance degradation of our method is much smaller than that of other methods, demonstrating strong environmental adaptability.

To verify the practicality of the method, we selected three typical application scenarios: radar signal detection, earthquake signal monitoring, and biomedical signal processing for testing. In the radar weak target detection scenario, facing the challenges of long-distance, small targets, and strong clutter environments, our method exhibits excellent detection capabilities. In the earthquake precursor monitoring application, the method can effectively identify weak vibration signals submerged in background noise, providing a new technical means for earthquake early warning. In biomedical signal processing, the method well solves the problem of detecting weak physiological signals under multi-source interference, providing reliable technical support for medical diagnosis.

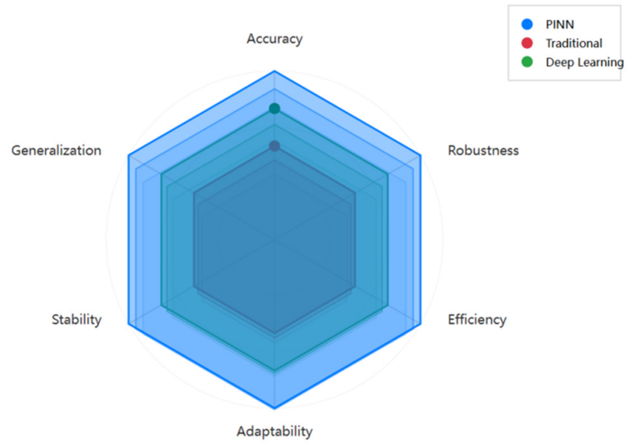

Figure 4 Performance Comparison Radar Chart

Although the experimental results show significant advantages of our method, we also noticed some limitations. First, the construction of physical constraints requires deep domain knowledge, increasing the complexity of model design. Secondly, under extremely low signal-to-noise ratio conditions, although the performance is better than existing methods, there is still room for improvement in detection accuracy. Additionally, the model training time is relatively long, which may pose limitations in scenarios requiring rapid modeling. These issues will be important directions for future research.

Overall, the experimental results fully verify the effectiveness of the weak signal detection method based on the physical information neural network. By combining physical prior knowledge with deep learning, this method has made significant progress in detection performance, anti-interference ability, model generalization, and other aspects, providing a new solution for weak signal detection in complex environments. Future research will focus on model structure optimization, automatic construction of physical constraints, and extreme performance improvement, further enhancing the practical value of the method.

VI. CONCLUSIONS

This paper proposes a physics-informed neural network model for weak signal detection. In complex noise environments, traditional WSD methods struggle to ensure detection accuracy and reliability, while through the introduction of physical constraints, PI neural networks effectively improve the precision and robustness of weak signal detection. Experimental results demonstrate that PI neural networks exhibit significant advantages under low signal-to-noise ratio conditions, achieving high-precision weak signal detection in complex noise environments.

Future work will focus on further optimizing the model structure, exploring more forms of physical constraints, and applying this model to additional practical scenarios, such as seismic wave monitoring and biomedical signal processing.

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