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Convolutional Neural Network - Wavelet Transform Fusion for EEG Signal Processing: Explorations and Perspectives

Bo Deng

School of Artificial Intelligence, Neijiang Normal University, Neijiang 641100, Sichuan, China

Abstract: ***This paper systematically explores the research progress and application potential of the integration of Convolutional Neural Networks (CNNs) and Wavelet Transform (WT) techniques in electroencephalogram (EEG) signal processing. By combining the time-frequency localization analysis of wavelet transforms with the deep feature learning capabilities of CNNs, this approach effectively addresses the traditional challenges of EEG signal processing, such as non-stationarity and subtle signal characteristics. The study identifies core challenges, including insufficient real-time performance due to model complexity, variability in cross-subject generalization, and subjective biases in annotated data. Future directions focus on lightweight dynamic fusion architectures, multimodal data collaborative learning, and enhanced clinical interpretability techniques. Through algorithmic innovations and interdisciplinary collaboration between engineering and medicine, breakthroughs in fields such as brain-machine interfaces and precise diagnosis of neurological diseases are expected.***

Keywords: Convolutional Neural Networks; Wavelet Transform; Electroencephalogram Signals; Multimodal Data

1. INTRODUCTION

1.1 Research Background and Significance

Electroencephalographic (EEG) signals serve as a dynamic representation of neural activity in the brain, and their multi-scale characteristics require precise analysis through quantifiable parameters. In the time domain, EEG signals exhibit subtle amplitudes, ranging from 1 to 100 μV, and are susceptible to environmental interference when the signal-to-noise ratio is below 10 dB. The non-stationarity is characterized by the Hurst exponent (0.7-1.3), representing long-range correlations, while non-linear characteristics can be quantified using sample entropy values (1.2-2.0) [1-2]. In the frequency domain, EEG can be divided into δ waves (0.5-4 Hz, with power density >100 $\mu V^2/Hz$ during deep sleep), θ waves (4-8 Hz, showing a 30% increase in power in the prefrontal cortex during memory tasks), α waves (8-13 Hz, with power in the occipital lobe accounting for over 60% during eyes-closed rest), β waves (13-30 Hz, closely related to focus), and γ waves (>30 Hz, involving high-order cognitive 40-80 Hz short-duration oscillations) [3-4].

However, traditional analysis methods face significant limitations. Independent Component Analysis (ICA) often mistakenly eliminates epileptic spike components (70-200 ms, amplitude >150 μV) due to morphological similarities when separating ocular artifacts, leading to a 15%-20% decrease in detection sensitivity. For instance, when epileptic spikes overlap with ocular artifacts (0.5-5 Hz low-frequency oscillations) in the time domain, the ICA algorithm may incorrectly classify them as the same independent component [5-6]. Fourier Transform, due to its fixed time-frequency resolution, struggles to accurately locate the onset of sleep spindles (11-16 Hz, lasting 0.5-1.5 s), with an error range up to ±300 ms. Manual feature engineering relies on empirical thresholds, such as extracting only α-wave asymmetry features in emotion recognition, while neglecting the nonlinear relationship between γ-wave phase synchronization (PLV > 0.6) and valence intensity, which results in feature interpretation explaining less than 40% of the variance [7-8]. These limitations demand breakthroughs through the integration of the hierarchical abstraction capabilities of Convolutional Neural Networks (CNN) and the physical solvability of time-frequency analysis via wavelet transforms, offering a new paradigm for high-precision EEG analysis.

1.2 Research Status

In recent years, both convolutional neural networks (CNNs) and wavelet transform have made significant progress in the field of EEG signal processing, but each individual method still has inherent limitations. CNNs have demonstrated outstanding performance in EEG classification tasks. For example, Yao X et al. proposed a novel model based on Transformer and convolutional neural networks (TCNN) for spatiotemporal feature learning of EEG signals to achieve automatic emotion classification, with the EEG ST-TCNN model achieving an accuracy of 96.67% on the SEED dataset [9]. Tiwari et al. introduced a hybrid method that combines CNNs and long short-term memory networks to predict epilepsy, achieving an accuracy of 98% in predicting epilepsy [10]. However, the fixed scale of the convolution kernels makes it difficult to capture transient features with rapid changes in non-stationary signals. Wavelet transform compensates for this limitation with its multi-scale decomposition capability. For example, Daubechies wavelet (db4) can control the time-frequency localization error of sleep spindles within ±50 ms. However, manually selected wavelet basis functions lack the ability to adaptively represent complex features.

Existing fusion methods primarily present three technical approaches: 1) Serial fusion (e.g., wavelet denoising followed by CNN classification), where Chen J X et al. improved the classification accuracy of the DEAP dataset in emotion recognition tasks to 86.7% [11]; 2) Parallel feature fusion, based on synchronized squeezing transform and deep convolutional neural networks, which uses Fourier synchronized squeezing transform and wavelet synchronized squeezing transform to evaluate the time-frequency matrix of EEG signals. This method achieves over 99% accuracy, sensitivity, and specificity for both local and non-local EEG signal classification [12]; 3) Embedded fusion (e.g., wavelet convolutional layer), where wavelet convolutional neural networks based on attention mechanisms are used for epilepsy EEG classification, increasing the AUC value for epilepsy prediction to 98.89% [13]. However, current research still faces the following bottlenecks:

1) Low feature interaction efficiency: In parallel fusion, the dimensional differences between time-domain features (such as sample entropy) and frequency-domain features (such as wavelet energy) result in difficulties in feature space alignment, requiring dimensionality reduction via principal component analysis (PCA).

2) Insufficient dynamic adaptability: Existing fusion strategies often use fixed weight allocation (e.g., time-frequency features are fused in a 6:4 ratio), which fails to adapt to the dynamic characteristics of EEG signals.

3) Weak cross-subject generalization: Current models show significant performance degradation in cross-subject testing. For instance, on the BCI Competition IV 2a dataset, the accuracy of the same model was 89.1% for the training subjects but only 72.3% on new subject data, highlighting the challenge posed by individual physiological differences on model robustness [14].

These limitations indicate that existing fusion methods have not fully explored the synergistic potential of CNNs and wavelet transform. There is an urgent need for breakthroughs in feature coupling mechanisms, dynamic adaptive modeling, and cross-domain generalization.

2. FUNDAMENTALS OF CONVOLUTIONAL NEURAL NETWORKS AND WAVELET TRANSFORM

2.1 Principles of Convolutional Neural Networks

Convolutional Neural Networks (CNNs) achieve automatic feature extraction through a hierarchical structure consisting of convolutional layers, pooling layers, and fully connected layers. The convolutional layer uses a one-dimensional kernel that slides along the time axis, exploiting the local weight sharing property to extract the temporal features of EEG signals. The ReLU activation function enhances the nonlinear modeling capability. The pooling layer compresses the feature dimensions through max pooling, suppressing high-frequency noise interference while preserving key temporal patterns. The fully connected layer integrates global features to perform classification, such as outputting four types of movement intentions through Softmax in motor imagery tasks [15-16]. The hierarchical abstraction mechanism of CNNs allows shallow layers to capture δ/θ wave rhythms (0.5-8 Hz), while deeper layers capture cross-frequency correlations (e.g., phase-amplitude coupling between β and γ bands), providing an efficient framework for end-to-end analysis of EEG signals.

2.2 Principles of Wavelet Transform

Wavelet transform provides a multi-scale analysis framework for the interpretation of non-stationary features in EEG signals by dynamically adjusting the time-frequency window. Its core lies in the use of scalable and shiftable wavelet basis functions, overcoming the global frequency domain limitation of Fourier transform and enabling precise capture of the local time-frequency characteristics of signals. Discrete wavelet transform decomposes the raw EEG into physiological frequency bands such as δ, θ, α, β, and γ through cascaded high-pass and low-pass filters. Combined with adaptive threshold denoising techniques, it improves the signal-to-noise ratio by 12-18 dB after suppressing electromyographic artifacts, while retaining the sharp rising-edge features of epileptic spikes. The choice of wavelet basis directly affects the analysis performance: the Morlet wavelet, due to its excellent time-frequency focusing property, is commonly used for extracting the instantaneous energy of γ waves (40-80 Hz) in emotion recognition. However, fixed wavelet basis functions are insufficient to accommodate individual differences in EEG signals, necessitating integration with convolutional neural networks to dynamically optimize the parameters of the basis functions, thereby enhancing adaptability across subjects [17].

3. EXPLORATION OF CNN-WAVELET TRANSFORM FUSION METHODS

3.1 CNN Method Based on Wavelet Transform Preprocessing

Wavelet Transform-Based Preprocessing enhances feature extraction and multi-scale signal reconstruction, providing high signal-to-noise ratio EEG input data for CNNs. The raw EEG is decomposed into five layers using discrete wavelet transform, with the sym5 wavelet basis function employed to separate the δ-γ frequency band components. The high-frequency detail coefficients are processed with soft thresholding using the SURE thresholding method. The reconstructed signal is further decomposed into five subbands corresponding to physiological frequency bands: δ, θ (4-8 Hz), α (8-13 Hz), β (13-30 Hz), and γ (30-80 Hz). Two-dimensional time-frequency maps are generated through time-frequency energy calculation and encoded as RGB three-channel images for input into a lightweight CNN model.

3.2 CNN and Wavelet Transform Parallel Processing Method

The parallel processing of CNN and Wavelet Transform achieves multidimensional feature fusion of EEG signals through a dual-pathway feature collaboration mechanism. In the dual-stream parallel architecture, the CNN pathway employs one-dimensional convolution kernels to directly process the raw EEG, extracting deep temporal domain features such as long-range rhythmic associations during epileptic seizures. The wavelet pathway decomposes the δ, θ, α, β, and γ frequency band sub-signals using discrete wavelet transform, with each subband input into a lightweight CNN for extracting frequency-domain local features (e.g., transient oscillations of γ waves in the 40-80 Hz range). The feature fusion strategy includes early and late fusion approaches: Early fusion concatenates the temporal features (128 dimensions) and frequency-domain features (5×32 dimensions) after the convolutional layers, followed by joint classification through a fully connected layer, improving the AUC of epileptic seizure detection to 0.96. Late fusion uses a weighted voting mechanism, achieving an accuracy of 88.2% on the DEAP emotion dataset, a 4.7% improvement over the single model. Attention-guided dynamic fusion further optimizes feature interaction efficiency—spatial attention mechanism dynamically assigns weights based on the physiological significance of EEG channels, while time-frequency attention uses wavelet time-frequency energy maps to locate key time windows, reducing the false positive rate of epileptic prediction by 42%.

3.3 Improved CNN Method Based on Wavelet Convolution

The improved method based on wavelet convolution constructs a feature extraction layer with physical interpretability by embedding the multiscale characteristics of wavelet transform into the design of CNN convolution kernels. The wavelet convolutional layer replaces traditional fixed convolution kernels with learnable wavelet basis functions, dynamically adjusting the time-frequency receptive field through parameterized scale and shift factors.

4. APPLICATION OF CNN-WAVELET TRANSFORM FUSION IN EEG SIGNAL PROCESSING

4.1 Epileptic EEG Signal Detection and Prediction

The CNN-wavelet transform fusion technique significantly enhances the detection sensitivity and pre-ictal warning capability of epileptic EEG signals through multiscale feature joint modeling and dynamic prediction mechanisms. Research based on the CHB-MIT dataset demonstrates that after decomposing EEG into δ-γ frequency band sub-signals using wavelet transform, CNN extracts time-domain features of each frequency band through cascaded convolution layers. During seizure onset, the γ-band in the temporal lobe shows an energy surge of 80%-120%, while the θ-band continuously rises by 25%-40% in the frontal lobe 5-15 minutes before a seizure. The fusion model achieves a detection sensitivity of 98.3% through a cross-frequency attention mechanism. Pre-ictal prediction locates precursor features by using the time-frequency energy matrix generated by continuous wavelet transform: transient high-frequency oscillations and a 40%-60% decrease in the δ-α phase-amplitude coupling (PAC) index 10-30 minutes before a seizure. A bidirectional LSTM model, accelerated on FPGA hardware, achieves 30-minute-level prediction (AUC=0.94, false alarm rate <0.2 events/day) [18].

4.2 Emotion Recognition Based on EEG Signals

The CNN-wavelet transform fusion technique significantly enhances the ability to analyze the nonlinear dynamic characteristics of EEG signals in emotion recognition tasks through multimodal feature co-modeling. Research based on the DEAP emotion dataset demonstrates that wavelet transform, particularly through time-frequency energy analysis of the Gamma frequency band, can precisely capture transient features of emotional valence and arousal. In high arousal states, Gamma wave energy surges by 60%-90% in the frontal lobe channels (F3/F4), while negative valence emotions induce phase synchronization (PLV > 0.65) between Theta waves (4-8 Hz) and Gamma waves in the right temporal lobe (T8). The fusion model employs a dual-stream architecture: the wavelet pathway extracts time-frequency energy maps, while the CNN pathway uses 3D convolution kernels to extract spatiotemporal features across channels. An attention mechanism is introduced to dynamically weight the contribution of frontal Gamma energy and occipital Alpha wave asymmetry features.

5. ISSUES AND CHALLENGES

The complex structure of the CNN-wavelet transform fusion model leads to a significant increase in computational resource requirements, limiting its deployment in real-time scenarios and on edge devices. The parallel architecture of wavelet multi-scale decomposition and CNN significantly increases the number of parameters, with a single inference requiring 15-25G floating point operations. On GPU servers, the processing latency for a single sample reaches 80-120 ms, far exceeding the real-time requirements of wearable devices (<50 ms).

Electroencephalogram signal analysis faces significant challenges from noise interference and label reliability. Traditional preprocessing methods often lead to the loss of high-frequency features while suppressing eye movement and electromyography artifacts. Furthermore, subjective differences in expert annotations and individual physiological variations result in millisecond-level deviations in seizure period labels, and the emotional labels exhibit a high degree of dispersion, with a variability of up to 1.5 points. Current technological advancements focus on three areas: 1) Adaptive noise suppression techniques based on dynamic filtering, which improve the signal-to-noise ratio (SNR) to 18 dB using recursive least squares methods while preserving key gamma wave features; 2) A semi-supervised learning framework that generates high-confidence pseudo-labels from 10% of annotated data, driving an F1-score breakthrough of 0.78 in emotion recognition; and 3) Multimodal cross-validation that integrates eye tracking and facial expression analysis, boosting the Kappa coefficient of label consistency to 0.85. However, in mobile scenarios, a 40% increase in electromyography interference exposes the scenario generalization flaws of noise suppression models, and the lack of standardized labeling protocols hinders cross-institutional data collaboration. Future work must integrate domain adaptation techniques to develop noise-robust models, optimize distributed label quality via federated learning frameworks, and simultaneously establish multi-center annotation protocols to reduce subjective bias, ultimately forming an EEG analysis system that balances signal fidelity and label reliability.

The CNN-wavelet fusion model faces dual challenges of individual physiological differences and experimental condition fluctuations in cross-individual and cross-scenario generalization, such as signal attenuation fluctuations caused by differences in skull thickness and baseline drift of signals due to electrode impedance changes. Existing optimization strategies focus on domain adaptation techniques, dynamic model architecture adjustment, and data augmentation methods, significantly enhancing cross-individual classification performance through adversarial feature distribution alignment, network depth adaptive switching based on signal complexity, and cross-subject signal synthesis. To address the bottleneck in cross-device and cross-task generalization, wavelet-convolution joint feature decoupling techniques effectively reduce cross-device classification errors by separating physiological common features from device-specific noise, though with a significant increase in model complexity. Current research needs further optimization of network architecture design to reduce computational redundancy while maintaining noise suppression capability, and achieve low-loss transfer across tasks by constructing task-independent feature spaces. Experiments show that these methods can improve cross-task transfer performance, but further efforts are needed to seek a better balance between model lightweighting and generalization ability, exploring collaborative optimization paths for efficient feature decoupling mechanisms and distributed training frameworks.

The existing CNN-wavelet fusion strategy is constrained by rigid feature interaction mechanisms and insufficient parameter adaptability, making it difficult to accommodate the dynamic characteristics of EEG signals. Static fusion methods struggle to balance the collaborative differences between high-frequency transient features and low-frequency slowly varying features due to fixed weight allocation, resulting in significant fluctuations in classification accuracy across task scenarios. Dynamic fusion techniques achieve feature self-adaptive weighting through a spatiotemporal-frequency dual-path attention mechanism, effectively enhancing the contribution weight of high-frequency transient features and reducing false alarm rates. However, the additional computational load introduced by extra parameters limits its deployment efficiency. Adaptive wavelet basis learning enhances the matching degree between the wavelet basis and task frequency bands by jointly optimizing wavelet scale factors and convolution kernel parameters, significantly improving classification performance. Nevertheless, the non-differentiability of wavelet transforms leads to insufficient end-to-end training stability, requiring the use of surrogate gradients or frequency-domain relaxation methods, such as complex wavelet networks, to balance convergence speed and generalization error. Future directions focus on the integration of neural architecture search and meta-learning to automatically construct task-driven dynamic fusion topologies. Preliminary experiments suggest that this approach can reduce cross-subject classification accuracy fluctuations, but high computational costs limit its application. There is an urgent need for lightweight search strategies to overcome efficiency bottlenecks while exploring differentiable wavelet operators and dynamic parameter sharing mechanisms to reduce complexity while ensuring model generalization capability, thus advancing EEG analysis across scenarios towards efficient adaptation.

6. OUTLOOK

6.1 Model Performance

Future improvements in the performance of CNN-wavelet fusion models can be achieved from multiple dimensions of innovation: Firstly, optimizing the model structure by incorporating cross-attention mechanisms to capture long-range dependencies across frequency bands in EEG signals, thereby enhancing the ability to model temporal features. Secondly, developing a differentiable wavelet learning framework to adaptively optimize the time-frequency focusing properties of the wavelet basis through end-to-end training, enabling precise extraction of dynamic frequency band features. Simultaneously, designing frequency-domain sensitive dynamic convolution kernels that adjust the weight of kernel functions based on the spectral characteristics of the input signal to improve cross-subject generalization ability. On the training strategy side, integrating meta-learning with wavelet-domain data augmentation techniques can enhance model adaptability in few-shot learning scenarios. From an interdisciplinary perspective, theories from neuroscience can be leveraged to construct biologically interpretable hybrid architectures based on spiking neural networks, optimizing the detection sensitivity to specific neural oscillatory patterns. Performance validation requires the establishment of a standardized EEG test set covering multiple pathological and physiological states, with cross-center cross-validation to assess model robustness. The core challenge lies in balancing the computational efficiency of dynamic parameter optimization with model generalization performance, necessitating the exploration of lightweight architecture search strategies and the collaborative optimization of differentiable wavelet operators, advancing the reliable application of fusion models in clinical settings.

6.2 Multimodal Data Fusion

CNN-wavelet transform fusion technology can enhance the robustness of brain state decoding by integrating EEG signals with multimodal physiological data. The multimodal fusion adopts a tensor fusion strategy combined with cross-modal attention mechanisms, dynamically allocating the association weights of different modality features, significantly improving classification accuracy in emotion recognition tasks. For spatiotemporally heterogeneous data, a spatiotemporal alignment network captures the synergistic effects between neural activity and physiological behavior through joint time-frequency analysis and motion feature extraction techniques. Current challenges focus on issues such as temporal misalignment due to differences in sampling rates across heterogeneous data and cross-modal noise coupling. It is necessary to develop adaptive resampling algorithms and disentangled representation learning techniques to suppress spurious correlations and enhance cross-subject generalization ability. In the future, hybrid architectures of spiking neural networks and wavelet transforms can be explored to achieve deep fusion of multimodal data in a biologically inspired feature space, while simultaneously optimizing dynamic feature alignment mechanisms and noise decoupling strategies. This will facilitate the development of a fusion framework that balances temporal synchronization and modality complementarity, advancing the practical application of cross-modal brain-machine interfaces in complex scenarios.

6.3 Clinical Translation

The clinical translation of CNN-wavelet transform fusion technology requires overcoming the bottlenecks of data standardization and model interpretability. Existing systems demonstrate high accuracy in epilepsy focus localization and seizure prediction; however, the "black-box" nature of the algorithms and poor cross-device compatibility limit their clinical adoption. Accelerating the technology's implementation requires multidimensional collaboration: developing interpretable modules that align with medical standards to enhance physician trust, utilizing feature contribution visualization to improve diagnostic accuracy; promoting cross-vendor data standardization protocols to reduce feature drift caused by device differences; and constructing a cloud-edge collaborative architecture to optimize screening efficiency in primary healthcare settings. In the future, continuous model iteration based on real-world data, combined with dynamic feature calibration techniques, will address the issue of inter-center data heterogeneity and promote the technology's penetration into grassroots healthcare. The core challenge lies in balancing model complexity and interpretability, necessitating the establishment of interdisciplinary collaboration mechanisms between medicine and engineering to optimize the entire chain—from algorithm design and data governance to clinical application—ultimately bridging the gap from laboratory effectiveness to clinical utility.

7. CONCLUSION

The CNN-wavelet transform fusion technology significantly enhances the accuracy and efficiency of electroencephalogram signal processing through multi-scale feature collaboration and dynamic optimization mechanisms. It has demonstrated clinical potential in tasks such as epilepsy detection, emotion recognition, and sleep monitoring. This technology overcomes the limitations of traditional methods in analyzing non-stationary signals by combining the advantages of wavelet time-frequency localization analysis and CNN hierarchical abstraction, enabling the precise capture of subtle EEG features and cross-band association modeling. However, issues such as high model complexity, weak generalization across individuals, and subjective labeling still limit its large-scale application, requiring further exploration of lightweight dynamic fusion architectures and multimodal data joint learning to enhance robustness. Future research should focus on: 1) interpretability enhancement techniques, improving clinical trust through feature contribution visualization; 2) edge computing optimization, enabling real-time processing on wearable devices (latency < 30 ms); 3) the construction of multi-center standardized data platforms to promote algorithm generalization and clinical translation. With the development of brain-machine interfaces and neurostimulation technologies, this fusion approach holds promise for breakthrough applications in the diagnosis and treatment of neurological diseases and intelligent human-machine interaction.

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