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TIME–FREQUENCY ANALYSIS AND MACHINE LEARNING FOR DETECTING BRAIN OSCILLATIONS IN EEG DATA

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ABSTRACT

High-frequency oscillations (HFOs) in electroencephalography (EEG) signals serve as vital biomarkers for identifying epileptogenic zones. However, their transient nature and low amplitude make reliable detection challenging. This paper reviews and compares major time–frequency (TF) analysis methods—Short-Time Fourier Transform (STFT), Continuous Wavelet Transform (CWT), and Hilbert–Huang Transform (HHT)—highlighting their role in enhancing temporal and spectral resolution for HFO detection. The study also explores the integration of machine learning (ML) techniques, including Support Vector Machines (SVMs), Convolutional Neural Networks (CNNs), and hybrid deep learning models, to achieve automated and accurate detection. By combining TF analysis with ML frameworks, recent approaches demonstrate significant improvements in sensitivity, specificity, and clinical applicability. This review emphasizes how the fusion of advanced signal processing and data-driven algorithms can optimize EEG analysis workflows, supporting more reliable diagnosis and decision-making in epilepsy management.

Keywords: High-Frequency Oscillations, Time–Frequency Analysis, EEG Signal Processing, Machine Learning, Epilepsy.

1. INTRODUCTION

High-frequency oscillations (HFOs), encompassing ripples (80–250 Hz) and fast ripples (250–500 Hz), have emerged as significant biomarkers in electroencephalography (EEG) for identifying epileptogenic zones. Accurate detection of these oscillations is crucial for surgical planning and patient management. However, the transient nature and low amplitude of HFOs pose challenges for reliable identification. High-frequency oscillations (HFOs), including ripples (80–250 Hz) and fast ripples (250–500 Hz), have been recognized as important biomarkers in electroencephalography (EEG) for identifying epileptogenic zones. Accurate detection of these oscillations is crucial for surgical planning and effective patient management. However, due to their transient nature and low amplitude, detecting HFOs reliably remains challenging.

Traditional time-frequency (TF) analysis methods, such as Short-Time Fourier Transform (STFT) and Continuous Wavelet Transform (CWT), improve temporal and spectral resolution in EEG analysis but can struggle with brief HFO events. The Hilbert-Huang Transform (HHT), combining Empirical Mode Decomposition with Hilbert spectral analysis, has shown superior performance in detecting subtle oscillations in nonstationary EEG signals.

Machine learning (ML) approaches have been increasingly integrated with TF analysis to improve HFO detection. Supervised methods, particularly Support Vector Machines (SVMs), have been successfully applied to classify EEG signals and HFO patterns, providing robust performance in medical data classification [1]. Unsupervised learning techniques, such as clustering, have also been explored for detecting HFO patterns without labeled datasets [2].

Deep learning methods, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), automatically extract features from TF representations of EEG signals and have demonstrated superior detection rates for HFOs [3]. Advanced architectures, such as spiking neural networks (SNNs), have been proposed for real-time detection, enabling efficient clinical applications.

Moreover, the development of open-source frameworks and standardized pipelines for HFO detection facilitates reproducibility and cross-study validation [4]. These resources enhance the comparability of methods and accelerate research into HFOs for epilepsy treatment.

In summary, the integration of TF analysis methods with ML and deep learning approaches has significantly advanced HFO detection. Combining these techniques provides higher accuracy, better temporal resolution, and automated processing capabilities, ultimately supporting improved clinical decision-making in epilepsy management [5]. The overall workflow for EEG-based high-frequency oscillation (HFO) detection, integrating preprocessing, time–frequency analysis, and machine learning classification, is illustrated in Figure 1.

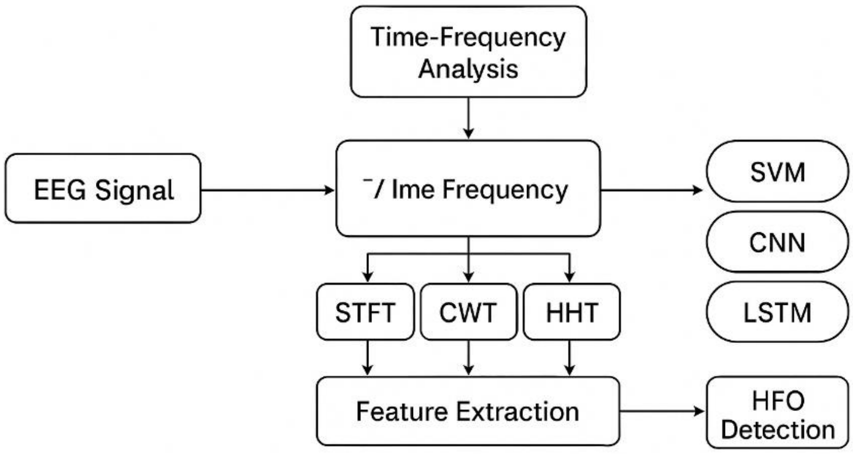

Figure 1: EEG signal processing pipeline.

2. TIME-FREQUENCY ANALYSIS METHODS

Time-frequency (TF) analysis provides a framework for examining EEG signals simultaneously in both the temporal and spectral domains. This is especially important for high-frequency oscillations (HFOs), which are transient and often low in amplitude, making them difficult to detect using conventional time-domain or frequency-domain methods alone [1].

2.1 Short-Time Fourier Transform (STFT)

The Short-Time Fourier Transform (STFT) divides the EEG signal into short segments and computes the Fourier transform of each segment. STFT provides a fixed time-frequency resolution, which allows the detection of relatively stable HFO patterns but can be limited in capturing very brief events [5]. Despite this limitation, STFT remains widely used due to its simplicity and computational efficiency [5, 6].

2.2 Continuous Wavelet Transform (CWT)

Continuous Wavelet Transform (CWT) offers variable time-frequency resolution by decomposing the EEG signal into wavelets of different scales. CWT is highly effective for detecting transient oscillatory events, such as ripples and fast ripples, because it provides better temporal localization for high-frequency components [3], [7]. Integration with machine learning classifiers can further improve automated HFO detection and EEG sleep stage classification [10].

2.3 Hilbert-Huang Transform (HHT)

The Hilbert-Huang Transform (HHT) combines Empirical Mode Decomposition (EMD) with Hilbert spectral analysis, providing adaptive decomposition of nonstationary and nonlinear EEG signals. HHT captures intrinsic mode functions (IMFs) and their instantaneous frequencies, highlighting subtle HFOs that may be obscured in standard TF representations [4], [6]. HHT has shown high sensitivity for detecting both physiological and pathological HFOs and can complement other TF techniques like STFT and CWT [5].

2.4 Hybrid TF-ML Approaches

Recent studies have demonstrated that integrating TF features with machine learning models, including CNNs and deep learning frameworks, significantly enhances HFO detection accuracy [7, 9]. These hybrid approaches leverage the strengths of both TF analysis and automated feature extraction, providing robust performance for complex EEG datasets. Such methods have enabled more reliable classification of pathological versus physiological HFOs and sleep stage identification [8, 10].

In summary, TF analysis methods—STFT, CWT, and HHT—offer complementary advantages for HFO detection. While STFT is computationally simple, CWT and HHT provide superior temporal resolution and sensitivity for transient events. Integration with machine learning and deep learning techniques further enhances performance, enabling automated, high-accuracy detection in clinical EEG data. A visual comparison of the time–frequency characteristics obtained from the three major methods—STFT, CWT, and HHT—is presented in Figure 2, illustrating the differences in temporal and spectral resolution among them.

3. MACHINE LEARNING IN HFO DETECTION

Machine learning (ML) techniques have become increasingly important in the automated detection and classification of high-frequency oscillations (HFOs) in EEG signals. Traditional TF analysis methods such as STFT, CWT, and HHT provide rich feature representations; however, manual detection and analysis remain time-consuming and prone to variability. Integrating ML models with TF features enables more accurate and reproducible identification of HFOs [1, 2, 3].

The integration of artificial intelligence (AI) and machine learning (ML) in medical diagnostics has significantly improved accuracy and early detection across various medical fields, including radiology, cardiology, and neurology. These advances demonstrate the growing impact of data-driven algorithms on clinical decision-making, as discussed by Hofer and Lechner [11].

3.1 Supervised Learning Approaches

Supervised learning algorithms, particularly Support Vector Machines (SVMs), have been widely applied to classify EEG signals containing HFOs. These methods rely on labeled training datasets to learn decision boundaries that separate pathological and physiological HFO events [1]. Recent works have shown that combining SVMs with TF-derived features, such as wavelet coefficients or Hilbert spectra, significantly improves classification performance [5].

Random Forests (RF) and Gradient Boosting methods have also been applied to HFO detection, providing advantages such as resistance to overfitting and interpretability of feature importance [12]. These models have been used to analyze large EEG datasets for both clinical and research purposes.

3.2 Deep Learning Approaches

Deep learning approaches, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), allow automatic feature extraction from time-frequency representations. CNNs have demonstrated exceptional performance in HFO classification, learning spatial and temporal patterns from spectrograms or scalograms [3, 7]. RNNs and Long Short-Term Memory (LSTM) networks exploit temporal dependencies in EEG signals, capturing dynamic oscillatory behaviors that are indicative of HFOs [12].

Advanced hybrid models combining CNNs and LSTMs have been proposed to leverage both spatial and temporal features simultaneously. These models achieve higher detection accuracy and can classify physiological versus pathological HFOs more reliably [8].

3.3 Unsupervised and Semi-Supervised Methods

Unsupervised learning algorithms, such as k-means clustering or density-based clustering, have been explored to detect HFO patterns without requiring labeled data [1]. Semi-supervised learning methods, which combine limited labeled data with large unlabeled datasets, have also shown promise in improving detection performance while reducing labeling effort [12].

3.4 Practical Implications

The integration of ML models with TF analysis facilitates automated HFO detection in clinical EEG recordings. This integration reduces inter-rater variability, accelerates data processing, and supports decision-making for epilepsy diagnosis and surgical planning [4, 6, 3]. The continuous improvement of deep learning architectures and availability of large annotated datasets are expected to further enhance the accuracy and reliability of automated HFO detection [13].

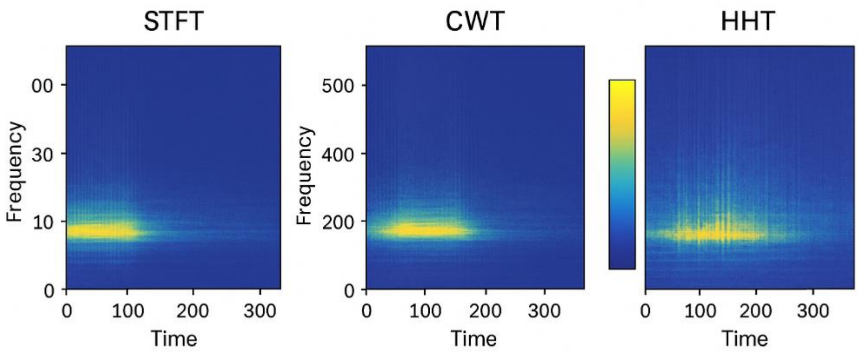

Figure 2: Comparison of time–frequency representations of a sample EEG signal using STFT, CWT and HHT

4. COMPARATIVE ANALYSIS OF TF METHODS

Time-frequency (TF) analysis methods are widely used to detect high-frequency oscillations (HFOs) in EEG data. The main approaches—Short-Time Fourier Transform (STFT), Continuous Wavelet Transform (CWT), and Hilbert-Huang Transform (HHT)—each offer distinct advantages and limitations. A comparative analysis highlights their suitability for different applications and clinical requirements [5, 6, 7].

4.1 Method Comparison

- STFT provides uniform time-frequency resolution, making it computationally efficient and easy to implement. However, its fixed resolution may not capture brief, high-frequency events accurately [5, 6].
- CWT offers variable time-frequency resolution, enabling better temporal localization of transient oscillations such as HFOs. It is particularly effective when combined with machine learning for automated detection [3, 7].
- HHT is adaptive and well-suited for nonstationary and nonlinear signals. By decomposing EEG signals into intrinsic mode functions (IMFs), HHT can highlight subtle HFO events that may be missed by other methods [4, 6].

4.2 Quantitative Comparison

The table 1 summarizes the key characteristics of each TF method regarding temporal resolution, frequency resolution, computational complexity, and sensitivity for HFO detection.

Table 1: Comparison of Time-Frequency Methods for HFO Detection

Method	Temporal Resolution	Frequency Resolution	Computational Complexity	HFO Detection Sensitivity
STFT	Medium	Medium	Low	Medium
CWT	High (variable)	High (variable)	Medium	High
HHT	Very High	High	High	Very High

4.3 Integration with Machine Learning

Integrating TF methods with machine learning further enhances HFO detection. CWT and HHT, in particular, provide features suitable for supervised and deep learning classifiers, such as SVMs, CNNs, and LSTMs [3, 7, 8]. Recent studies have demonstrated that combining TF features with hybrid ML models improves classification accuracy, reduces false positives, and allows automated sleep stage and HFO classification [14].

4.4 Summary

STFT, CWT, and HHT each provide valuable insights into EEG signals for HFO detection. While STFT is simple and efficient, CWT and HHT offer superior resolution and sensitivity. Integrating these TF methods with machine learning enables high-accuracy automated detection and supports clinical decision-making [5, 15].

5. CONCLUSION

High-frequency oscillations (HFOs) in EEG signals serve as critical biomarkers for identifying epileptogenic regions and understanding complex neural dynamics. Accurate detection and classification of HFOs are essential for both clinical decision-making and research applications, yet remain challenging due to their transient nature and low amplitude.

This study has reviewed and comparatively analyzed the major time-frequency (TF) analysis methods—STFT, CWT, and HHT—and their integration with machine learning techniques for automated HFO detection. Each method offers distinct advantages: STFT provides computational efficiency with moderate resolution, CWT enables adaptive temporal and spectral localization suitable for transient oscillations, and HHT excels at capturing subtle nonstationary signals.

Combining TF analysis with machine learning frameworks, including supervised and deep learning approaches, allows for automated, high-accuracy detection of HFOs. Hybrid methods that leverage both temporal and spectral features improve classification performance, reduce the need for manual annotation, and facilitate scalable EEG analysis.

The comparative assessment highlights trade-offs between temporal and frequency resolution, computational complexity, and sensitivity to HFO events. These insights support the design of robust, clinically relevant pipelines for EEG analysis, emphasizing the importance of method selection based on the specific application and dataset characteristics.

In conclusion, the integration of advanced TF techniques with machine learning represents a promising and practical approach for automated HFO detection. Future research should focus on developing patient-specific models, improving real-time detection capabilities, and enhancing the interpretability of automated systems to support clinical adoption. This direction promises to improve diagnostic accuracy, reduce workload, and ultimately enhance patient outcomes in epilepsy management.

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