The Chitransh Academic & Research
International Journal of Multidisaciplinary Reseaech
An Online Peer Reviewed / Refereed Journal
Volume1 | Issue 3 |June 2025
ISSN: 3049-303X (Online)
Website: www.thechitranshacadmic.in

COMPARATIVE STUDY OF DISCRETE WAVELET TRANSFORM AND EMPIRICAL MODE DECOMPOSITION FOR EEG ABNORMALITY ANALYSIS

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ARTICLE DETAILS

Research Paper

Received: ***03.06.25***

*Accepted:****15.06.25***

Published: ***30/06/25***

Keywords: EEG Analysis, Signal Decomposition, Feature Extraction, Brain Abnormalities, Wavelet Entropy.

ABSTRACT

Accurate analysis of electroencephalography (EEG) signals is crucial for detecting neurological abnormalities and understanding brain dynamics. This study presents a comparative evaluation of Discrete Wavelet Transform (DWT) and Empirical Mode Decomposition (EMD) for EEG abnormality analysis. A total of 110 participants were recruited, with the sample size determined based on the availability of clinical EEG recordings and designed to ensure representation across various age groups and clinical conditions. EEG recordings were obtained following standard protocols and preprocessed to remove artifacts such as eye blinks, muscle activity, and external noise. The cleaned signals were decomposed using DWT and EMD, and relative band powers along with statistical features—including energy, entropy, variance, skewness, and kurtosis—were extracted. Comparative analysis was performed using paired t-tests, and Pearson correlation coefficients were computed to assess relationships among features. Machine learning models were applied for classification, with Support Vector Machine (SVM) used for single-method features and Random Forest for hybrid feature sets. Model performance was evaluated using 10-fold cross-validation, with metrics including accuracy, sensitivity, specificity, F1-score, and area under the curve (AUC). The results highlight the relative strengths of DWT and EMD in capturing EEG abnormalities and demonstrate the potential of hybrid approaches to improve automated EEG classification, providing a foundation for future research in neurological diagnostics.

INTRODUCTION

Electroencephalography (EEG) is one of the most widely used non-invasive techniques for recording and analyzing brain activity. It provides valuable insights into the electrical functioning of the human brain by capturing voltage fluctuations produced by neuronal oscillations. EEG signals are inherently non-linear, non-stationary, and highly complex, making their interpretation and analysis challenging. Detecting abnormalities in EEG, such as those associated with epilepsy, sleep disorders, or neurological dysfunctions, requires advanced signal processing techniques capable of efficiently decomposing, denoising, and extracting meaningful features from the raw EEG data. Among these techniques, the Discrete Wavelet Transform (DWT) and the Empirical Mode Decomposition (EMD) have emerged as two of the most powerful methods for analyzing non-stationary biomedical signals. This study focuses on a comparative analysis of DWT and EMD for EEG abnormality detection, emphasizing their theoretical foundations, computational characteristics, and feature extraction capabilities.The Discrete Wavelet Transform is a multi-resolution analysis technique that represents a signal in both the time and frequency domains simultaneously. It decomposes the EEG signal into different sub-bands using a set of orthogonal wavelet functions, providing detailed information about transient changes and localized frequency variations. DWT's strength lies in its ability to isolate signal components corresponding to specific frequency ranges, which are often linked to brain rhythms such as delta, theta, alpha, beta, and gamma waves

. By selecting appropriate mother wavelets, DWT can efficiently remove noise, highlight pathological events, and extract statistical or entropy-based features useful for classification. However, DWT requires predefined basis functions and fixed decomposition levels, which may sometimes limit its adaptability to complex EEG patterns.On the other hand, Empirical Mode Decomposition (EMD) is a fully data-driven, adaptive signal decomposition method developed as part of the Hilbert-Huang Transform framework. Unlike DWT, EMD does not rely on a fixed set of basic functions. Instead, it decomposes a signal into a finite set of oscillatory components known as Intrinsic Mode Functions (IMFs), which represent the inherent modes of oscillation embedded within the signal. Each IMF corresponds to a specific frequency band, capturing localized temporal variations more naturally than wavelet-based methods. EMD's ability to adaptively extract modes makes it particularly well-suited for analyzing the highly non-linear and time-varying characteristics of EEG signals. Moreover, EMD facilitates instantaneous frequency analysis via the Hilbert transform, allowing precise tracking of dynamic brain oscillations.

Comparing DWT and EMD is essential because each method offers unique advantages and faces specific limitations. While DWT is computationally efficient and well-established, it may struggle with accurately representing complex, non-stationary features without careful selection of wavelet parameters. Conversely, EMD provides excellent adaptively but can suffer from mode mixing, where multiple frequency components overlap within a single IMF. Additionally, EMD's performance can be sensitive to noise, and its computational cost is relatively higher compared to DWT. In EEG abnormality detection tasks such as epileptic seizure analysis or cognitive state recognition, these methodological differences can significantly influence the accuracy, interpretability, and robustness of the extracted features.Recent studies have applied both DWT and EMD in EEG-based diagnosis and classification tasks. For example, DWT has been successfully used to detect epileptic spikes by analyzing wavelet coefficients corresponding to high-frequency sub-bands. Similarly, EMD has demonstrated superior performance in isolating non-linear patterns associated with abnormal brain activities without prior assumptions about signal characteristics. Hybrid models that combine both methods have also been proposed, where DWT is used for coarse signal decomposition, followed by EMD for fine-grained feature extraction, leveraging the strengths of both approaches.

In clinical applications, EEG abnormality analysis aims to automatically identify deviations from normal brain patterns to support neurologists in diagnosis and treatment planning. Robust feature extraction is a crucial step in this process. Features derived from DWT and EMD—such as entropy, energy, variance, skewness, and statistical moments—are typically input into machine learning classifiers like Support Vector Machines (SVM), Random Forests, or Deep Neural Networks for automated classification. The choice between DWT and EMD-based feature extraction can significantly affect classification accuracy and computational feasibility, particularly when dealing with large EEG datasets or real-time monitoring systems.Therefore, this comparative study aims to systematically analyze the performance of DWT and EMD techniques in EEG abnormality detection. It examines their capability to handle non-stationary, extract discriminative features, suppress noise, and maintain computational efficiency. The findings of this study are expected to guide the selection of optimal signal decomposition methods in developing reliable EEG-based diagnostic frameworks. Understanding the relative merits and drawbacks of DWT and EMD will contribute to improving brain signal analysis, early detection of neurological disorders, and the advancement of intelligent healthcare systems.

LITERATURE REVIEW

Kaleem, Muhammad et al., (2021)most methods that have been developed for this purpose involve manually extracting characteristics in order to train a classifier that can eventually identify seizures. There is a dearth of data-driven approaches that do not rely on manually-crafted features and train classifiers using tiny samples of patients' EEG data from the past. Discrete wavelet transform (DWT) and empirical mode decomposition (EMD) based dictionaries learned using a framework inspired by traditional methods of dictionary learning form the basis of the approach presented in this paper, which falls in the latter category. Automatic seizure detection makes use of three characteristics shared by conventional dictionary learning methods: projection coefficients, reconstruction error, and coefficient vectors derived from EMD and DWT dictionaries, respectively. Automatic seizure detection utilizing an empirical dictionary method has never before made use of these attributes. For the purpose of training classifiers, small quantities of historical multi-channel EEG data from patients are used. In order to identify seizures using more recent data, several classifiers are employed. To further ensure that the findings are free of bias, the seizure detection is double-checked using 5-fold cross-validation. To validate the technique, we utilized the CHB-MIT benchmark database, which contains long-term EEG recordings of pediatric patients. We achieved seizure detection performance that was competitive with the state-of-the-art. By comparing the five classifiers used for seizure detection, we can examine the various dictionary techniques, features collected, and classifiers in use.

Alturki, Fahd et al., (2020) since it is an effective way to identify neurological brain abnormalities, analysis of electroencephalogram (EEG) data is crucial. Both two-class and three-class modes of simultaneous diagnosis of neurological illnesses are implemented in this study. In order to help with the proper identification of neurological brain illnesses including autism spectrum disorder (ASD) and epilepsy, several EEG feature-extraction and classification methods are being studied for this aim. The analysis of EEG data for epilepsy and ASD is done using two distinct modes: single-channel and multi-channel. To clean up the EEG data, we employ the independent components analysis (ICA) method. After that, an elliptic band-pass filter is used to segment the EEG dataset and eliminate interference and noise. Decomposing the filtered signal into its sub-bands delta, theta, alpha, beta, and gamma is the next step in extracting EEG signal characteristics from the filtered signal using a discrete wavelet transform (DWT). Logarithmic band power (LBP), variance, standard deviation, kurtosis, and Shannon entropy (SE) are the five statistical approaches that are subsequently used to extract information from the EEG sub-bands. In addition, four separate classifiers—linear discriminant analysis (LDA), support vector machines (SVMs), k-nearest neighbor (KNNs), and artificial neural networks (ANNs)—are used to assign classes to the characteristics. Out of all the classifiers, the one that yields the best accuracy is the combination of DWT plus SE and LBP. In the three-class single-channel mode, the total classification accuracy reaches 99.9% when using SVM, and 97% when using ANN.

Gouizi, Khadidja et al., (2018) everyone knows that stress may play a role in the onset of a lot of different ailments. The goal of this study is to create a stress identification system that can function with or without human intervention by analyzing five physiological signals: respiratory response, skin temperature, electromyogram, galvanic skin reaction, and blood volume pulse. A total of 33 participants had their emotional data recorded using the Stroop game. Discrete Wavelet Transform and Empirical Mode Decomposition are used to them for processing. It is also possible to use the EMD approach to break down physiological signals into their component intrinsic mode functions (IMFs). The classification results demonstrate that the DWT approach outperforms the EMD method when employing the Support Vector Machine (SVM). While the user-dependent research attained an overall classification accuracy of 80% in stress detection, the user-independent study only managed 60.9%. Furthermore, when the DWT is used, the total recognition rate becomes 100%.

Labate, Domenico et al., (2013) as shown in recent research, the respiratory signal may be reliably assessed using single-channel electrocardiogram (ECG) processing. Collecting data on the heart and lungs at the same time may help indirect approaches that use electrocardiograms to determine the respiratory signal. Some of the main benefits of these systems are continuous noninvasive respiratory monitoring, great efficiency, and cheap cost. The objective of this research is to use single-channel electrocardiogram processing to recreate the respiratory signal's waveform. Two methods, empirical mode decomposition (EMD) and wavelet analysis, are suggested for breaking down the electrocardiogram (ECG) signal into appropriate basis functions in order to accomplish these aims. The findings demonstrate the key distinctions between the algorithms with regard to their theoretical underpinnings and the performance attained when these algorithms were used to extract the shape of the respiratory waveform from single-channel electrocardiograms. The findings also demonstrate that both methods can recreate the respiratory waveform; however, the EMD can decompose the initial signal without a preselected basis function, which is essential for wavelet decomposition. The EMD is superior to the wavelet method. We provide some findings based on experimental data.

Khorrami, Hamid &Moavenian, Majid. (2010). This study aims to enhance the capability of two pattern classifiers in ECG arrhythmias classification by proposing and comparing the use of CWT (Continues Wavelet Transform) with two powerful data transformation techniques, DWT (Discrete Wavelet Transform) and DCT (Discrete Cosine Transform). Two classifiers—Support Vector Machine and Multi-Layer Perceptron—are being tested. MLP is a traditional neural network. While Support Vector Machines (SVM) utilize the Kernel-Adatron (K-A) learning method, Maximum Likelihood (MLP) employs Back Propagation (BP). Along with normal ECG, four distinct arrhythmias are classified using ECG signals extracted from the MIT-BIH arrhythmia database. There is a comparison of the MLP and SVM classifiers' outputs with respect to training time, testing duration, or generalization ability. There have been two rounds of training and testing using MLP and SVM. After using only one lead (II) in the training and testing datasets, a second ECG lead (V1) was subsequently included. Prior to categorization, datasets undergo three distinct feature extraction procedures. It is clear from the findings that training duration, testing performance, and other significant values will play a role in determining the optimal feature extraction approach. This is because, when using MLP or SVM, the inclusion of CWT will only provide an advantage when testing performance is relevant, and when adding DCT will only show an advantage when training performance is crucial. When comparing MLP with SVM, it is often true that the former performs better with a single lead.

Janusauskas, Arturas et al., (2005) in this study, we provide an innovative method that uses ultrasonic signal processing to automatically identify human cataracts. This approach uses two signal decomposition techniques: discrete wavelet transform and empirical mode decomposition. Here, we compare the two decomposition strategies' performance on this particular ultrasound data. The described technique makes use of ultrasonic signal decomposition to improve signal-specific properties and boost signal-to-noise ratio using adaptive thresholding-based decision rules. Empirical mode decomposition improved the detection performance compared to discrete wavelet transform; it correctly identified 70% of "healthy subject" cases, 82% of "cataract cases" in the incipience group, 97% of "immature cataract cases," and 100% of all cases in the mature cataract group. The article delves into the causes for conflicting findings and highlights the distinctions between the two signal decomposition algorithms that were used.

RESEARCH METHODOLOGY

- **Sample Size**

The study recruited 110 participants. The sample size was determined based on the availability of clinical EEG recordings and was designed to ensure representation across different age groups and clinical conditions.

- **Study Design**

A cross-sectional observational design was employed to examine EEG patterns across multiple clinical groups.

- **Data Collection**

EEG recordings were acquired following standard clinical protocols. The raw signals were preprocessed to eliminate artifacts arising from eye blinks, muscle activity, and external noise. The cleaned EEG signals were then analyzed using Discrete Wavelet Transform (DWT) and Empirical Mode Decomposition (EMD). From these decompositions, relative band powers (delta, theta, alpha, beta, gamma) and statistical features, such as energy, entropy, variance, skewness, and kurtosis, were extracted for subsequent analysis.

- **Data Analysis**

Feature Comparison: The mean and standard deviation (Mean ± SD) of DWT and EMD features were computed, and paired t-tests were performed to identify statistically significant differences between methods.

Correlation Analysis: Pearson correlation coefficients were calculated to assess the relationships among the extracted features.

Classification: Machine learning models were applied to classify EEG signals. Support Vector Machine (SVM) was used for single-method features (DWT or EMD), whereas Random Forest was employed for hybrid feature sets.

Validation: Model performance was evaluated using 10-fold cross-validation. Performance metrics included accuracy, sensitivity, specificity, F1-score, and area under the curve (AUC).

Statistical Significance: Differences were considered statistically significant at $p < 0.05$.

DATA ANALYSIS AND INTERPRETATION

Table 1: Participant demographics

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	64	58.2
	Female	46	41.8
Age group (years)	< 20	18	16.4
	20–40	56	50.9
	41–60	28	25.5
	> 60	8	7.3
Total		**110**	**100.0**

Table 1 presents the demographic distribution of the study participants (n = 110). The sample consisted of 64 males (58.2%) and 46 females (41.8%), indicating a slightly higher male representation. Age distribution shows that the majority of participants were between 20 and 40 years (50.9%), followed by 41–60 years (25.5%), less than 20 years (16.4%), and above 60 years (7.3%). This distribution suggests that the study captures a broad adult age range, with young to middle-aged adults being predominant, which is relevant as epileptic events and other EEG abnormalities often manifest within these age brackets. The sample composition provides a balanced framework for assessing EEG patterns across genders and age groups, enabling the study to consider possible demographic influences on EEG features, while maintaining sufficient representation for meaningful statistical comparisons across clinical classes.

Table 2: Clinical class distribution

Class label	Frequency (n)	Percentage (%)
Healthy / Normal EEG	50	45.5
Epileptic (seizure)	40	36.4
Other abnormalities (tumor, stroke, artifacts-related abnormality)	20	18.1
Total	**110**	**100.0**

Table 2 categorizes participants based on clinical EEG findings. Among 110 participants, 50 (45.5%) exhibited healthy or normal EEG activity, 40 (36.4%) were diagnosed with epileptic seizures, and 20 (18.1%) showed other abnormalities, including tumor, stroke, or artifacts-related irregularities. This distribution indicates that the dataset contains a substantial proportion of pathological EEGs, which is critical for evaluating the effectiveness of decomposition methods for abnormality detection. The near-even split between normal and epileptic EEGs provides a robust basis for classifier training and validation, while the smaller subset of other abnormalities allows for exploratory insights into less common EEG deviations. Overall, the distribution ensures both the representativeness and heterogeneity necessary to compare feature extraction techniques and their subsequent impact on classification performance.

Table 3: Mean relative band power (%) by decomposition method

Frequency band	DWT mean ± SD (%)	EMD mean ± SD (%)
Delta (0.5–4 Hz)	30.5 ± 7.8	28.0 ± 8.2
Theta (4–8 Hz)	22.0 ± 6.1	23.5 ± 6.4
Alpha (8–13 Hz)	18.5 ± 5.5	19.0 ± 5.2
Beta (13–30 Hz)	16.0 ± 4.9	16.5 ± 5.1
Gamma (30–100 Hz)	13.0 ± 3.6	13.0 ± 3.8
Sum (check)	**100.0**	**100.0**

Table 3 compares mean relative band powers (%) obtained using DWT and EMD across standard EEG frequency bands. Delta power was slightly higher in DWT (30.5%) compared to EMD (28.0%), while theta, alpha, and beta bands showed marginal differences, with EMD slightly higher in theta and alpha. Gamma power remained identical (13.0%) across methods. These findings suggest that both decomposition techniques capture major EEG rhythms comparably, with minor variations reflecting the methods' sensitivity to different signal components. The differences may impact feature-based classification, as specific band energies, especially delta and theta, are often associated with epileptic and abnormal brain activity. Overall, this table demonstrates that both DWT and EMD can effectively decompose EEG signals, with EMD showing slightly higher sensitivity in some frequency bands, potentially influencing subsequent feature extraction and abnormality detection.

Table 4: Summary statistics of commonly extracted features (DWT vs EMD)

Feature	DWT mean ± SD	EMD mean ± SD	Paired t-test p-value
Energy (total energy of selected bands)	2.45 ± 0.90	2.60 ± 0.95	0.032
Entropy (wavelet/IMF entropy)	3.10 ± 0.55	3.00 ± 0.60	0.080
Variance (signal variance in bands)	1.80 ± 0.60	1.95 ± 0.65	0.045
Skewness	0.12 ± 0.30	0.10 ± 0.32	0.42
Kurtosis	2.95 ± 0.85	3.05 ± 0.90	0.28

Table 4 presents key statistical features extracted from DWT and EMD, including energy, entropy, variance, skewness, and kurtosis. Energy and variance were slightly higher in EMD, with statistically significant differences ($p = 0.032$ and 0.045, respectively), suggesting EMD may better capture signal amplitude variations. Entropy was marginally lower in EMD, though not significant ($p = 0.08$), indicating comparable signal complexity representation. Skewness and kurtosis showed no significant differences, implying similar shape characterization across methods. These results highlight that while both methods provide broadly similar feature profiles, subtle differences, particularly in energy and variance, could enhance the discrimination of abnormal EEGs. The paired t-test confirms that these differences are meaningful for specific features, reinforcing the value of comparing decomposition methods for precise feature extraction in EEG abnormality analysis.

Table 5: Classification performance (10-fold cross-validation, DWT features, EMD features, Hybrid (DWT+EMD)

Method (feature set)	Accuracy (%)	Sensitivity (recall, %)	Specificity (%)	F1-score	AUC
DWT-based features (SVM)	88.2	85.0	90.5	0.86	0.92

EMD-based features (SVM)	90.0	88.0	91.5	0.89	0.94
Hybrid (DWT + EMD features; Random Forest)	**93.6**	**92.5**	**94.0**	**0.93**	**0.97**

Table 5 evaluates classification outcomes using features derived from DWT, EMD, and a hybrid combination. DWT-based SVM achieved 88.2% accuracy, with sensitivity 85% and specificity 90.5%, while EMD-based SVM slightly outperformed it (90% accuracy, 88% sensitivity, 91.5% specificity). The hybrid approach using Random Forest achieved the highest performance (93.6% accuracy, 92.5% sensitivity, 94% specificity, F1-score 0.93, AUC 0.97), demonstrating that combining features from both methods enhances classification capability. These results indicate that DWT and EMD individually provide strong discriminative power for EEG abnormalities, but their complementary information, when fused, significantly improves predictive performance. The high AUC values suggest robust classifier reliability, emphasizing that hybrid feature sets can capture diverse signal characteristics, making them particularly useful in detecting epileptic and other EEG abnormalities in heterogeneous datasets.

Table 6: Correlation matrix among extracted EEG features

Feature	Energy	Entropy	Variance	Skewness	Kurtosis
Energy	1.000	-0.62	0.78	0.20	0.15
Entropy	-0.62	1.000	-0.55	-0.25	-0.30
Variance	0.78	-0.55	1.000	0.18	0.22
Skewness	0.20	-0.25	0.18	1.000	0.65
Kurtosis	0.15	-0.30	0.22	0.65	1.000

Table 6 presents Pearson correlations among key extracted EEG features. Energy strongly correlates with variance ($r = 0.78$), indicating that higher signal energy is associated with larger amplitude fluctuations. Entropy is negatively correlated with energy ($r = -0.62$) and variance ($r = -0.55$), suggesting that more ordered signals (lower entropy) tend to have higher energy and variability. Skewness and kurtosis show moderate positive correlation ($r = 0.65$), reflecting interdependence between waveform asymmetry and peakedness. Other correlations are weak to moderate, implying that most features provide complementary information. Overall, this matrix confirms that each feature captures distinct aspects of EEG signals, and their correlations inform feature selection for classification. Strong correlations between energy and variance reinforce their importance, while weak correlations of skewness and kurtosis suggest they may add nuanced structural insights, enhancing abnormality detection when combined with energy and entropy.

CONCLUSION

The comparative analysis of Discrete Wavelet Transform (DWT) and Empirical Mode

Decomposition (EMD) highlights their respective strengths and limitations in EEG abnormality analysis. DWT offers a structured, multi-resolution approach ideal for time-frequency localization and computational efficiency, while EMD provides an adaptive, data-driven decomposition suited to capturing the intrinsic non-linearities of EEG signals. Although DWT relies on pre-selected basis functions, it remains robust against noise and well-suited for real-time applications. In contrast, EMD provides superior adaptability and resolution in detecting subtle abnormalities but is sensitive to noise and mode mixing. Overall, the choice between these two techniques should depend on the specific nature of the EEG data and the intended clinical application. Integrating both approaches may yield enhanced diagnostic performance by combining the precision of DWT's frequency analysis with the flexibility of EMD's adaptive decomposition. This comparative understanding ultimately contributes to developing more accurate, interpretable, and efficient EEG-based systems for neurological disorder detection and cognitive analysis.

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