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Article

A quantitative assessment of time, frequency, and time-frequency algorithms for automated seizure detection and monitoring

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SUMMARY

Epilepsy is a chronic brain disorder impacting more than 65 million people worldwide (1% of the population). Its primary symptoms, seizures, can occur without warning and can be deadly. Each year, over 100,000 patients die from Sudden Unexpected Death in Epilepsy (SUDEP). A reliable seizure warning system can help patients stay safe. This work presents a comprehensive, comparative analysis of three different signal processing algorithms for automated seizure/ictal detection. The methods perform feature extraction and seizure detection on scalp electroencephalogram (EEG) signals. The first optimized mathematical model, Approximate Entropy, performed statistical time domain analysis using a new sliding window protocol. The second algorithm performed seizure-specific spectral energy binning using the Fast Fourier Transform in the frequency domain. The third method applied signal decomposition to extract ictal features by implementing a time-frequency Discrete Wavelet Transform method. Each epileptic seizure detection algorithm was successfully validated using >75 hours of recordings from the Boston Children's Hospital's CHB-MIT scalp EEG clinical database. Results indicated that the Discrete Wavelet Transform algorithm performed the best, achieving a seizure detection sensitivity of 92% and a specificity of 98%. The experimental results show that the proposed methods can be effective for accurate automated seizure detection and monitoring in clinical care.

INTRODUCTION

Over 65 million people live with various forms of epilepsy (1). Patients in low- and middle-income countries are at double the risk of being diagnosed with epilepsy (1). Over 30% of epilepsy patients do not respond to antiepileptic drugs (2). Seizures, the principal symptom of epilepsy, often occur unpredictably and can lead to convulsions throughout the entire body (2). Loss of consciousness due to an epileptic event may result in physical injuries and fatal falls based on the location where the seizure occurred (e.g., driving, swimming, etc.), this is known as Sudden Unexpected Death in Epilepsy (SUDEP) (2). Seizure alarm systems can help detect these emergency scenarios as they happen, alerting family members and care providers (3). A comparative analysis of the efficiency of seizure detection algorithms can help provide valuable insights for deployment in the next generation of epileptic patient aid devices.

An electroencephalogram (EEG) is a gold-standard test that tracks and records brain electrical patterns (4). An EEG headset contains several surface electrodes to track the brain's electrical activity. The electrodes are placed on the scalp as per the 10/20 international system (**Figure 1A**) (5). Any neuronal synaptic activity in the brain generates a subtle electrical impulse referred to as a postsynaptic potential (4). This small analog voltage fluctuation, measured at the electrodes, is amplified, digitized, and recorded as a continuous flow of voltages vs. time (time series data). An EEG study can show the origin of abnormal activity in the brain and is one of the main diagnostic tests for epilepsy. An EEG can also play a role in diagnosing other brain disorders, such as Alzheimer's disease and narcolepsy (6).

The Children's Hospital in Boston (CHB) and the Massachusetts Institute of Technology (MIT) provide a free-to-use online scalp EEG database (7). The dataset is from 23 pediatric epilepsy patients, each with several seizure recordings. The entire record consists of 686 data sets, with 198 datasets containing seizures, and over 1,000 hours of EEG recordings. The data was recorded at 256 samples per second (Hz) with a 16-bit resolution. A 23-electrode (or 23-channel) EEG, visualized using the EEGLAB tool (8), shows the clinical onset of a patient seizure (ictal) starting at 2162 seconds (**Figure 1B**), which is characterized by the large signal excursion artifacts caused by muscle reflexes in patient 3, from data set 4.

Over the past three decades, much research has been done using time, frequency, and time-frequency analysis methods for the detection of seizure activity in EEGs (9–11). However, a study that cohesively compares these methods using a common framework with validation against publicly available epileptic datasets is necessary. This work presents a thorough examination of three promising seizure detection methods: Approximate Entropy, Fast Fourier Transform, and the Discrete Wavelet Transform.

Complexity is an essential characteristic of nonlinear

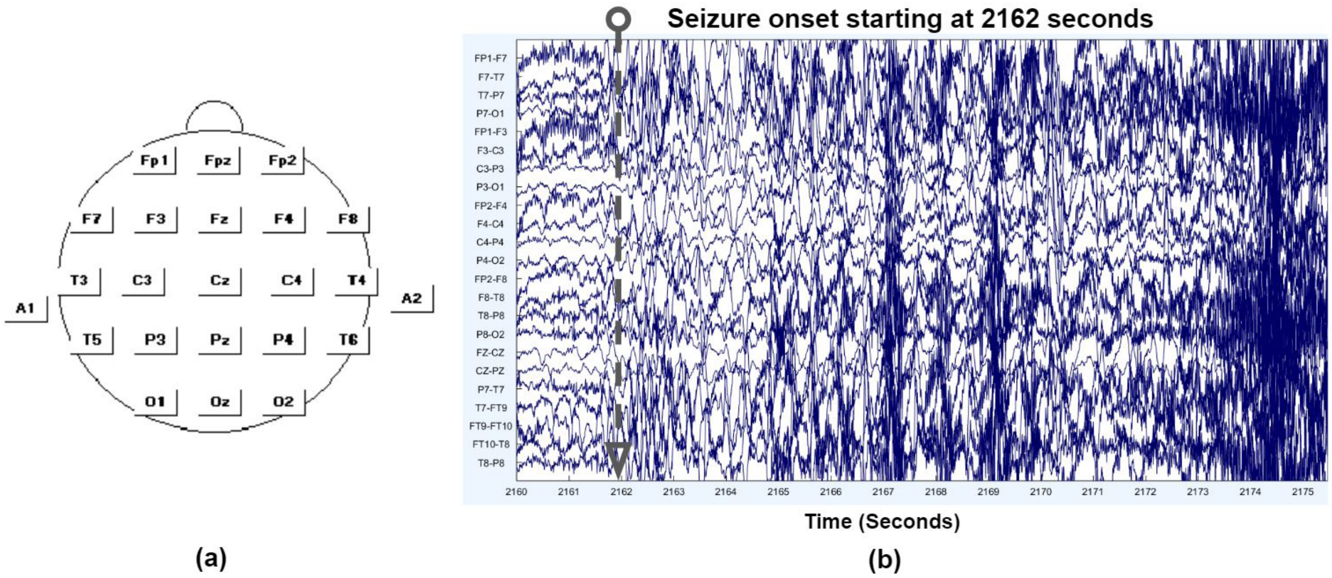

Figure 1. EEG electrode positioning order and EEGLAB examination of an ictal-event. (a) International 10/20 electrode placement system (5) **(b)** A 23-channel scalp EEG showing clinical onset (grey arrow) of patient seizure starting at 2162 seconds, which is characterized by muscle reflexes causing the large signal excursion artifacts (CHB-MIT patient 3, data set 4).

dynamic systems. Approximate entropy (ApEn) is a statistical time domain analysis technique used to quantify waveform regularity and the unpredictability of fluctuations in time series data (12). A time series containing many repetitive patterns has a relatively small approximate entropy, while a less predictable process has a higher ApEn value. The ApEn approach has the following advantages: (1) it requires relatively fewer data points (100 – 5000), and (2) it is robust against noisy data, common in EEG recordings.

The ApEn method has been used to analyze EEG signals of patients under different physiological and cognitive states (13). In this work, an improved ApEn algorithm is proposed to characterize the dynamical properties of the ictal transition in epileptic patients. Based on the observed variations in the ApEn during preictal, interictal and postictal states, the epileptic seizure is detected.

The Fast-Fourier Transform (FFT) converts a signal from the time domain into the frequency domain and has been used for epileptic seizure detection (11). Any time-dependent signal can be broken down into a collection of sinusoids (14). In this way, lengthy and noisy EEG recordings can be rationally plotted in a frequency power-spectrum using the MATLAB discrete *fft()* function (15). Frequency domain FFT analysis was performed on CHB patient data to identify hidden features, applicable for feature extraction.

Wavelets are oscillations with a mean value of zero and can provide adaptive resolution in both time and frequency domains for analysis of non-stationary signals (**Figure 2A**) (16). A coiflet, as an example, is a type of a wavelet with a unique shape that best represents EEG artifacts during a seizure (**Figure 2A**) (17). The wavelet transform has unique higher resolution capabilities in comparison to other restricted, individual time and frequency domain analysis techniques (**Figure 2B**).

The main advantage of using a discrete wavelet transform (DWT) method is that the resolution of time and frequency can be adapted to the frequency content of the examined patterns (18). The DWT filters signals using low-pass and high-pass filters to yield approximate and detailed sub-bands, respectively (**Figure 2C**). With each increasing level (1–7), the signal segment is further decomposed into a lower frequency range. As EEG data is noisy in nature, the DWT approach can help denoise the waveform and enunciate the key features at each level. The MATLAB *wavedec(x, n, wname)* function (19) returns the wavelet decomposition of the 1-D signal *x* at level *n* using the wavelet *wname* (*coif3* in this case).

The effort has the following key goals: develop mathematical models for ictal-event classification and automated seizure detection of scalp EEG data; ensure >80% detection accuracy and minimal false alarm occurrence; and quantitatively assess multiple seizure detection approaches that enable highest overall accuracy. The final ApEn, FFT, and Wavelet algorithms had accuracies of 90%, 92%, and 95% respectively.

RESULTS

A continuous EEG monitoring and automatic seizure detection algorithm framework was proposed and employed throughout this work (**Figure 3**). In step (*i*) the CHB-MIT Scalp EEG database (publicly available at PhysioNet (7)) was converted from a binary EDF format to a readable ASCII format in step (*ii*). The third step (*iii*) was to pre-process the raw EEG signals to separate noise from the signal of

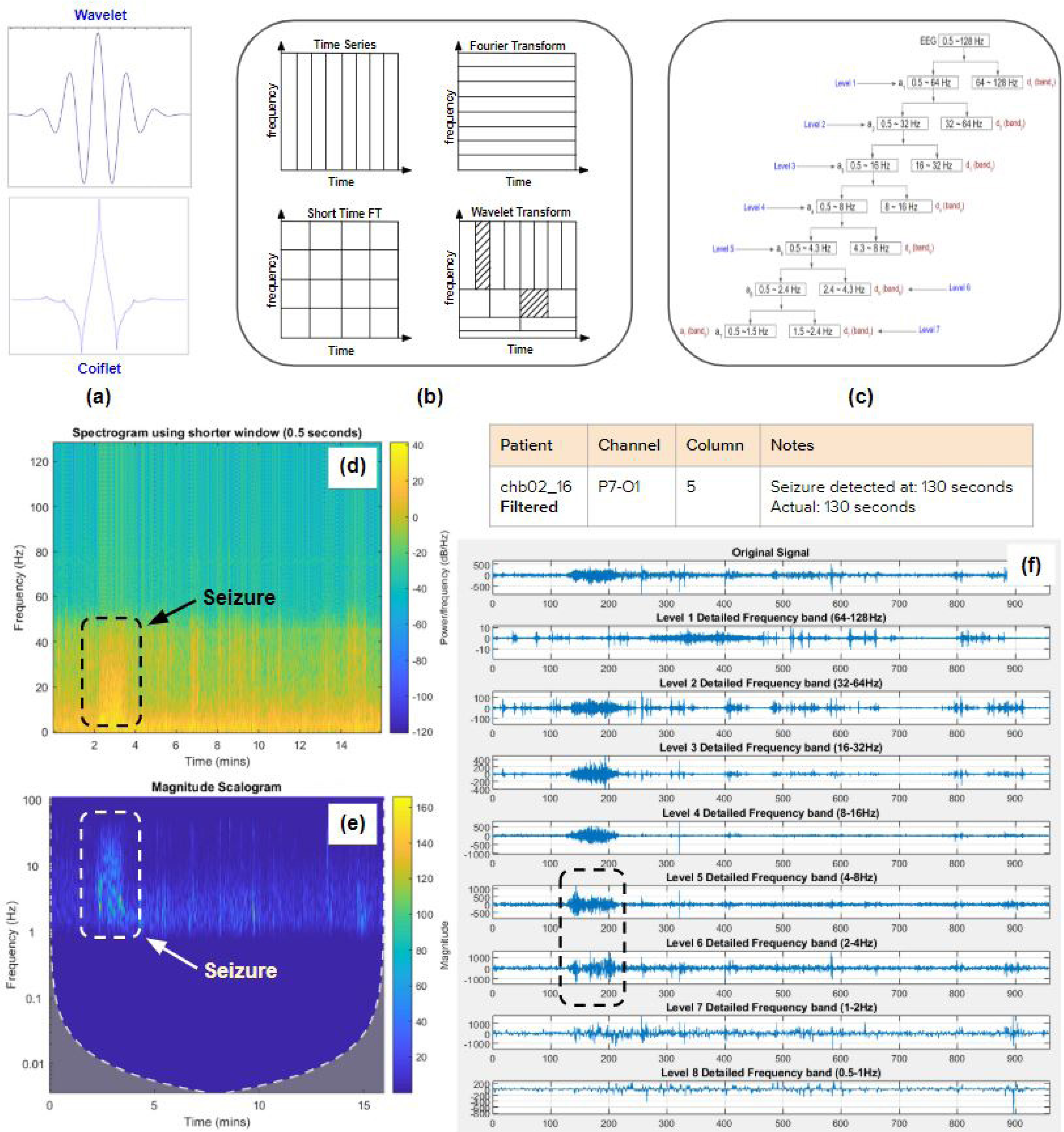

Figure 2. Time-frequency based wavelet analysis accurately identifies ictal events. (a) The coiflet wavelet used for DWT analysis **(b)** Time and frequency resolutions for various transforms **(c)** DWT Frequency band decomposition of an EEG signal **(d)** FFT-based spectrogram clearly reveals the seizure event starting at 130 seconds **(e)** CWT analysis proves to be an effective tool for seizure detection with coefficient values peaking at 130 seconds **(f)** Results from an eight-level DWT show that ictal events are most clearly represented and have the highest magnitude in the 2–8 Hz range at levels 5, 6.

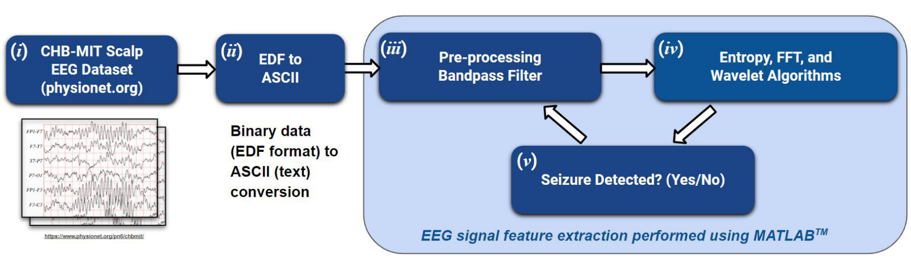

Figure 3. Proposed seizure detection algorithm flow using MATLAB™ numerical computing software.

interest. A digital bandpass filter with a frequency ranging from 0.35 to 45 Hz was used to alleviate the influence of low- and high-frequency noise. Feature extraction is performed on the filtered EEG data using multiple EEG classification methods (step *iv*) and the classifier results are analyzed with appropriate thresholds to reliably detect seizures in step (*v*).

To account for continuous EEG signal acquisition of time series data, steps (*iii*)-(*v*) are repeated in a loop. The entire analysis was coded and simulated using MATLAB (15).

Time Domain EEG Feature Extraction Algorithm

Multiple hours of raw and filtered versions of EEG time series data were first visually inspected using MATLAB to carefully identify the features critical to distinguish normal, interictal (between seizures), and ictal events in EEG signals from other types of brain activity. A single channel 24-minute CHB-MIT raw EEG signal trace for patient 24, data set 1 (**Figure 4A**). Clinically, the ictal event occurs between 480–505 seconds, as observed by a sudden spike in brain activity. Two key observations are made from studying the expanded and closer view of the EEG waveform during a seizure (**Figure 4B**): a substantial increase in signal amplitudes (exceeding 1 mV) due to abnormal discharges in a large number of neurons in the brain and the periodic and synchronous nature of the EEG, resembling a sinusoid. These two fundamental attributes are insightful and crucial for automated ictal event feature extraction. On the other hand, a closer EEG signal view during a non-ictal phase (**Figure 4C**) exhibits a complex signal with a much lower magnitude (typically in the tens of μV) with a high degree of randomness. These discernable characteristics in signal behavior separate ictal and non-ictal intervals (i.e. seizure and ‘normal’ electrical activity) and can be used to identify transitions between epileptic states.

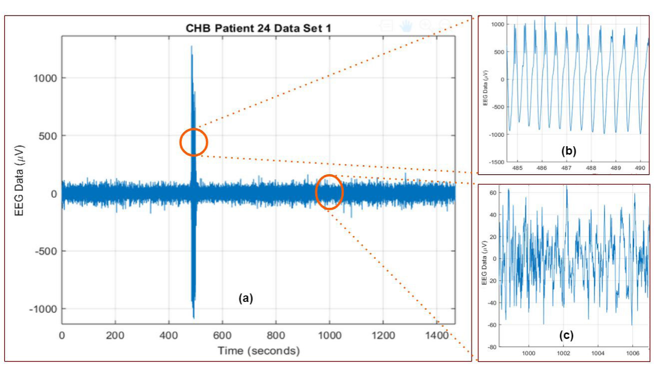

Figure 4. Analysis of CHB-MIT patient 24 reveals the synchronous nature of epileptic seizures. (a) A 24-minute raw EEG signal trace with an ictal-event (seizure) between 480–505 seconds (patient 24 data set 1) **(b)** Expanded EEG (~1mV) and a periodic signal **(c)** Expanded EEG waveform during non-seizure. Note lower signal amplitude (μV) and high randomness.

ApEn algorithm

Given *N* points of a time series data and the similarity criterion *r*, the ApEn is approximately equal to the average natural logarithm of the conditional probability that vectors similar for *m* points remain comparable at the next point. The similarity is validated using a vector distance calculation (12-13) as shown in Step 1 (**Figure 5A**), with the conditional probabilities for each window computed in Step 2. The similarity of two vectors is judged in the final step as a subtraction operation, resulting in a final ApEn value. Intuitively, for a predictable signal (such as a seizure), the conditional probabilities across two adjacent vectors would be similar, producing a small value for ApEn when subtracted. However, a noisy random EEG signal would have diverse conditional probabilities, resulting in high entropy.

The ApEn algorithm was implemented in MATLAB using the CHB-MIT scalp EEG dataset and the framework previously outlined (**Figure 3**). The raw EEG signals are pre-processed to remove high frequency noise. A Butterworth digital bandpass filter of order 5 with a cutoff frequency from 0.35 to 45 Hz (20) was applied. Within this range of frequencies, the complete information about the signals of interest is still retained. Early ApEn analysis showed that obtaining ApEn parameters - vector dimension (*m*), the filtering threshold (*r*) and the ideal window size (*N*) - were critical for reliable feature extraction of seizures. A multi-variable sweep was performed using MATLAB to arrive at the optimal values used in this study (**Figure 5B**).

The frequency response of the bandpass filter displayed

Step 1: Vector Distance Calculation

$$C_i^m(r) = \frac{(number\ of\ x(j)\ such\ that\ d[x(i),x(j)] \le r)}{(N-m+1)}$$

Where

$$d[x,x^*] = max_a|u(a) - u^*(a)|$$

Step 2: For each m value compute

$$\phi^m(r) = \frac{\sum_{i=1}^{N-m+1} ln(C_i^m(r))}{(N-m+1)}$$

Final Step: ApEn for $u(i)$ is given as

$$ApEn = \phi^m(r)-\phi^{m+1}(r)$$

(a)

ApEn Parameter	Meaning	Values used (in MATLAB)
m	Vector dimension	*m=2 and m=3*
r	Filtering threshold	1 μV
N	Data points per EEG window	512 (2 seconds)

(b)

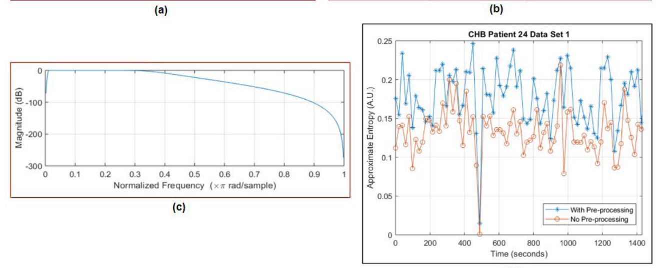

Figure 5. The epileptic EEG signal is preprocessed via a fifth-order Butterworth bandpass filter prior to ApEn analysis. (a) ApEn algorithm (12) with three key steps resulting in a quantified value of waveform regularity. **(b)** Optimal values used for m, r, and N parameters in the ApEn calculation. **(c)** Frequency response of the fifth-order digital Bandpass filter. **(d)** The graph shows the seizure onset at 480 seconds as marked by a sharp drop in ApEn value towards zero. Signal preprocessing improves signal-to-noise ratio by 32%.

expected patterns, ultimately removing high frequency EEG signal noise (**Figure 5C**). The resulting MATLAB plot after ApEn application precisely detects the seizure onset of patient 24, data set 1 at 480 seconds (**Figure 5D**), marked by a conspicuous drop in the ApEn value. The graph also shows the signal preprocessing benefit with an improvement of 32% in ApEn due to enrichment in the average signal-to-noise ratio (SNR).

Implementation of the Sliding Window Protocol on EEG signals

The incoming EEG time series data is often segmented into smaller processing windows, typically in smaller non-overlapping 1–2 second slices (**Figure 6A**). Real-time data computation requires the ApEn calculation in the first window to be completed by the time the next window frame arrives. A sliding window approach was implemented that overlaps the EEG time series slices and ApEn computation (**Figure 6A**), with a 50% (0.5 second) overlap. ApEn results with and without overlapping windows were evaluated for CHB patient 15, data set 6 (**Figure 6B**). The increased number of intermediate ApEn points helps emphasize the ictal features better, allowing for improved seizure detection.

The efficacy of the enhanced ApEn algorithm with the sliding-window approach in MATLAB for CHB patients was evaluated for two patients (**Figures 6C-D**). In each case, the raw EEG data is displayed with the corresponding ApEn results. The proposed approach articulately identified the ictal event that is indicated by a pronounced drop in the computed ApEn values, falling toward zero. The proposed method, even in the presence of noisy EEG input streams, can efficiently identify seizures automatically.

Frequency Domain EEG Feature Extraction Algorithm

A 7 second raw EEG signal trace for patient 24, data set 1, highlighting the periodic seizure signature, is shown (**Figure 7A**). A 128-point FFT was performed to generate the corresponding frequency spectrum (**Figure 7B**). The frequency spectrum shows the dominant peaks in the 2–6 Hz range. Repeating the study on other patient data confirmed that the principal peaks occur in the 2–6 Hz spectrum during an ictal event. This primary observation is used for seizure-specific feature extraction. The spectrum binning to identify seizures was implemented in the core section of the MATLAB code and followed the algorithmic flow previously outlined (**Figure 3**). The raw EEG data in time domain and the dominant spectral components obtained from binning in the frequency domain were collated from FFT analysis on 0.5 second EEG slices for two patients (**Figures 7C-D**). In each case, the spectral peaks during seizures are conspicuous, marked by a clear presence of an assertive slow wave "ictal" component in the 2–6 Hz range.

Time-Frequency Seizure Classification Based on a Wavelet Decomposition Method

Epileptic EEG signal analysis using ApEn and FFT methods revealed that seizures can be accurately identified

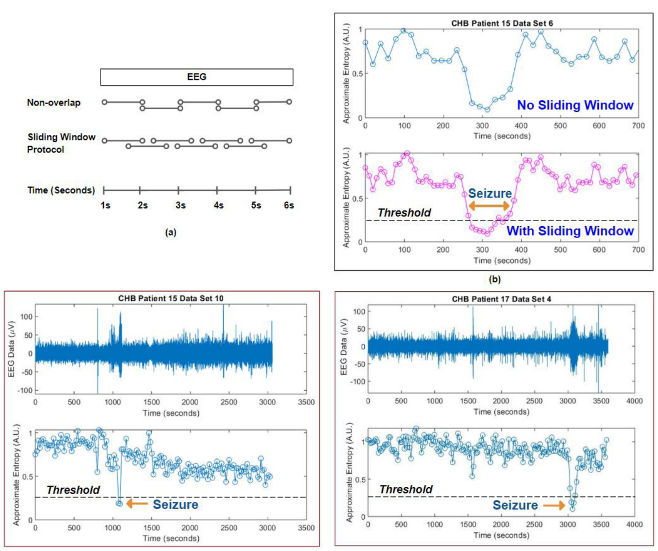

Figure 6. Sliding window protocol benefit and ApEn analysis of two CHB-MIT patients. (a) Sliding window concept by overlapping time series EEG data. **(b)** The benefit of the sliding window approach with a 0.5 second overlap can be observed in the lower subplot. The increased number of points help bring out additional features within the data **(c, d)** show drops in the ApEn values during a seizure onset between 272-390 seconds. These features are used to classify the ictal event as a seizure, if the ApEn values drops below a specified threshold.

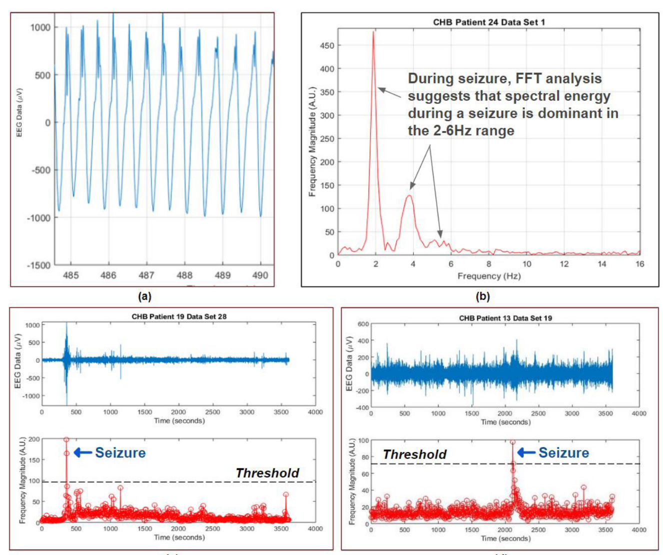

Figure 7. Frequency decomposition of seizure data reveals dominant spectral energy components from FFT analysis of two CHB-MIT patients. (a) Expanded EEG waveform during a seizure, note large signal amplitude (mV) and its periodic nature. **(b)** Frequency spectrum during a seizure (2–6Hz) obtained using MATLAB. **(c, d)** show articulate increases in spectral energy at 300 seconds (patient 19) and 2100 seconds (patient 13) during epileptic events. The spectral peaks are used to classify the ictal event as a seizure, if the spectral magnitude crosses a specified threshold.

in the time domain or in the frequency domain, with both approaches providing good resolution in their respective domains. However, EEG signals are non-stationary in nature, and are best represented using wavelet-based time-frequency interpretations (9).

Wavelet analysis was performed on patient 2 dataset 16 (**Figures 2D**–**F**). A short (0.5 second) window spectrogram derived from an FFT calculation clearly reveals the seizure between 2–4 minutes (**Figure 2D**). A Continuous Wavelet Transform (CWT, MATLAB *cwt()* function), as the name suggests, allows for simultaneous analysis of EEG waveforms rather than discretizing the data into frequency bands as with the DWT method (18). The coefficients from CWT analysis on patient 2 were plotted in a scalogram (**Figure 2E**). The time-frequency scalogram clearly shows the seizure starting at 130 seconds. Frequency decomposition using DWT clearly identifies the seizure in the low-frequency (2–8 Hz) range at levels 5 and 6 (**Figure 2F**).

The results from validating time, frequency, and time-frequency domain analysis for scalp EEG ictal feature extraction against 50 datasets from the CHB-MIT database (7) is next presented. An improved ApEn statistical approach provided a seizure detection accuracy of 90%. FFT and spectral energy analysis enabled an accuracy of 92%. A combined time-frequency based Discrete Wavelet Transform (DWT) utilizing "coiflets" resulted in a 95% accurate algorithm (**Table 1**). Algorithmic performance results in terms of sensitivity and specificity for the three methods were also computed. The sensitivity ranges from 84–92% and the specificity ranges from 96–98%. Every automated ictal classification result was authenticated against actual seizure labels specified in the CHB-MIT dataset, as marked by a medical professional.

Table 1. Seizure detection accuracy from validating all three signal processing techniques against the CHB-MIT scalp EEG dataset.

Time Domain Entropy Analysis		Target: Positive	Target: Negative
Model	Positive	42	2
Model	Negative	8	48
Accuracy = 90%		Sensitivity 84%	Specificity 96%
Frequency Domain FFT Method		**Target: Positive**	**Target: Negative**
Model	Positive	43	1
Model	Negative	7	49
Accuracy = 92%		Sensitivity 86%	Specificity 98%
Time-Frequency Wavelet Analysis		**Target: Positive**	**Target: Negative**
Model	Positive	46	1
Model	Negative	4	49
Accuracy = 95%		Sensitivity 92%	Specificity 98%

Sensitivity and specificity values are provided in each case. The DWT wavelet analysis approach provides the highest overall seizure detection success rate of 95%.

DISCUSSION

Epilepsy has a great impact on the everyday life of patients. Several wearable devices have been proposed in the literature to detect seizures via patient monitoring (21-22). Such seizure alarms and aids for epilepsy patients would serve three main purposes: 1) Seizure detection, 2) seizure alarming and 3) recording of 30–60 seconds of pre-ictal and ictal EEG signals for precise diagnosis. A smart headband for epileptic seizure detection is presented in (23), but is expensive. There is a need to develop and implement real-time, high-speed, and accurate algorithms on various low-cost hardware devices for seizure detection and pervasive global use. Specifically, these medical devices demand precise seizure classification algorithms with reduced computational overheads.

In this paper, three seizure detection techniques are evaluated and classified as time, frequency, and wavelet (time–frequency) techniques. The time domain method analyzes signals based only on the time and magnitude components of time series data, and there is no visibility into the frequency components of the signal. The frequency domain approach provides a more articulate frequency spectrum of the signal. The advantage of the signal transformation from one domain to another is that it provides valuable insights and points out the important properties of the signals, which cannot be seen by visual inspection of the original signal alone, thus helping distinguish different states in seizure EEG signals. A wavelet transform as a time–frequency analyzing tool provides improved time and frequency localization capability. It uses long time windows for low-frequency components and short time intervals for high-frequency components of the signals.

Among the three methods evaluated, the DWT classification approach on epileptic EEG signals shows excellent promise for seizure classification and monitoring, with the analysis successfully detecting a seizure on 46 of 50 epileptic datasets, with an improved accuracy of 95%. The elastic principle of the wavelet enables short time signal components to be better detected and more precisely localized by the DWT approach when compared to results obtained by FFT and time domain methods.

In each algorithm, appropriate thresholding of the extracted features is critical for robust and reliable automated seizure detection. A combination of hard and soft threshold criteria was employed. When applying the ApEn algorithm on EEG signals, the resulting entropy values rapidly dropped towards zero during ictal events. Experimenting with the limits showed that a hard ApEn threshold of 0.25 was optimal. In the case of FFT and DWT algorithms, a variable thresholding approach was applied. A seizure was identified as "true" only when current feature extracted vector values (e.g., integrated spectral energy in the FFT 2–6 Hz band or the DWT coefficients in levels 5/6) exceeded five times the magnitude of a rolling average over time. The seizure detection algorithms provide high values for sensitivity and specificity for EEG data sets in the CHB-MIT database without any additional assumptions of seizure patterns. The algorithms can be a valuable tool for fast and effective monitoring of long-term scalp EEG recordings. As future work, implementing patient-specific screening using adaptive thresholds may allow for improved seizure detection accuracy.

METHODS

The programming and analysis were performed using MATLAB numerical computing software. The work was carried out in phases — starting with time domain, followed by frequency domain, and finally a combined time-frequency analysis. The first algorithm, approximate entropy, was developed following observations of EEG signal patterns during seizures. Next, the work transitioned from the time domain into the frequency domain using FFT functions. Spectral energy binning using the short-term Fourier transform revealed that the seizure signals contained slow waves with large magnitudes. The FFT results led to the development of the second seizure classifier. The final method implemented a "best-of-both-worlds" strategy by analyzing signals in the time-frequency domain. The DWT approach using coiflets enables optimal time-frequency resolution across all frequency ranges by consistently extracting key seizure features in EEG data. The models were optimized using signal pre-processing and a sliding window protocol, increasing the accuracy of each algorithm. In the MATLAB code, a 50% (0.5 second) overlap is used in the computation loop. After all model parameters were finalized, they were tested using >75 hours of data from the CHB-MIT database (**Table 1**). To further validate the algorithms' effectiveness, a robustness check was performed using alternate *non-seizure* EEG databases (sleep database (24), motor movement/imagery database (25)). All algorithms passed the robustness trials successfully, with no additional false alarms reported.

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