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Real-time Interpretation of EEG Signals for Consciousness State Assessment

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Abstract

Assessing the level of consciousness is critical in clinical practice, especially for patients with traumatic brain injuries or those in a coma or vegetative state. Traditional methods like the Glasgow Coma Scale have limitations, such as inter-observer variability and low sensitivity. In recent years, electroencephalography (EEG) has emerged as a promising approach for assessing consciousness, offering non-invasive, real-time monitoring of brain activity. In this study, we propose a real-time analysis system for assessing consciousness levels using a portable EEG device. Our system analyzes EEG signals and provides valuable insights into consciousness levels, enabling prompt clinical interventions. The real-time nature of our system allows for continuous monitoring and immediate assessment of consciousness levels. Compared to traditional methods, our system offers advantages in terms of real-time functionality, providing a comprehensive evaluation of consciousness. Through extensive experiments using real patient data, our system demonstrates its value as a valuable tool for assessing consciousness levels in clinical practice. It offers healthcare professionals an efficient and reliable method for evaluating consciousness.

Keywords: EEG, TTEMD, ApEn, Brain death diagnosis, Real-time system

I. Introduction

Consciousness encompasses various levels of awareness and cognitive processing, ranging from wakefulness to deep coma. In the spectrum of Disorders of Consciousness (DOC), coma represents the lowest level of consciousness. Assessing consciousness levels is crucial in clinical practice, especially for patients with severe neurological conditions. EEG has emerged as a valuable tool for assessing consciousness due to its non-invasive nature and ability to capture brain dynamics. In recent years, EEG-based consciousness assessment has gained attention, with numerous studies focusing on evaluating consciousness levels using EEG signals (Jennett & Plum, 1972; Laureys et al., 2010; Schiff, 2010). While EEG has shown promise, existing methods have limitations. Traditional approaches often rely on visual inspection or simplistic frequency band analysis, lacking sensitivity to subtle changes in consciousness. Additionally, the complexity of brain activity calls for advanced computational techniques. Accurately assessing consciousness is particularly vital in cases of compromised neurological function, such as brain death. Current methods for determining brain death can be time-consuming and carry risks ("A Definition of Irreversible Coma: Report of the Ad Hoc Committee of the Harvard Medical School to Examine the Definition of Brain Death", 1968; Cao & Chen, 2008; Cui et al., 2017; Marks & Zisfein, 1990; Scott et al., 2013; Szurhaj et al., 2015).

To address these challenges, it is necessary to develop a system that enables the assessment of consciousness levels. In this context, we propose an EEG-based real-time diagnostic system that allows for the continuous observation and analysis of EEG changes (Zhang et al., 2023). Our designed system integrates the methods of Turning Tangent

Empirical Mode Decomposition (TTEMD) (Fleureau et al., 2010) and Approximate Entropy (ApEn) (Pincus, 1991; Shi et al., 2010) for real-time analysis of EEG. TTEMD allows for precise analysis of energy distribution in different frequency bands, while ApEn measures the irregularity of the signal, providing valuable insights into the complexity of EEG signals. However, the limitations of existing systems lie in their heavy reliance on manual assessment, leading to a significant presence of subjective judgments in the evaluation process. This may hinder their practicality in clinical settings. To address these limitations and harness the potential of machine learning, we have developed a new system using a portable EEG device, combining the previously separate calculation algorithms. This integration enables more accurate diagnostics and enhances the system's practicality in clinical environments. Our objective is to compute six sets of values (a total of twelve features) representing the energy and complexity of the EEG signals for each of the six channels using TTEMD and ApEn. Subsequently, we will employ a Support Vector Machine (SVM) classifier to integrate these twelve features together and enhance the diagnostic accuracy. Through extensive experimentation and evaluation, we have demonstrated the effectiveness and reliability of our enhanced system. The integration of the new method, along with the real-time capability of our system, provides a more accurate and efficient tool for assessing consciousness levels.

Our system has been tested on diverse patient data, showcasing an accurate assessment of consciousness levels. The real-time feedback empowers healthcare professionals, facilitating prompt diagnosis, treatment, and management of patients with impaired consciousness. In conclusion, our study presents a novel real-time analysis system that combines TTEMD and ApEn algorithms for evaluating consciousness levels. The integration of these algorithms, along with real-time capability, offers an effective and efficient tool for assessing consciousness in clinical practice. Our system holds great potential for enhancing patient care in cases of impaired consciousness, improving clinical practice, and aiding in brain death diagnosis.

II. METHODOLOGY AND SYSTEM DESIGN

a. The algorithm and principle

Previous studies have shown that Signal decomposition methods based on the features of data, such as empirical mode decomposition (EMD)(Huang et al., 1998; Shi et al., 2011), multivariate empirical mode decomposition (MEMD) (Rehman & Mandic, 2010), and TTEMD (Zheng et al., 2015), can be used to analyze patients' EEG energy. These methods have been shown to be effective in analyzing EEG signals and can provide valuable insights into the level of consciousness of a patient. Previous studies have compared EMD, MEMD, and 2T-EMD, with experiments based on standard artificial signals and patient EEG (Miao & Cao, 2017). In the comparison of algorithm principles, the differences among the three algorithms lie in the channel type and the calculation of local means of the raw signals. Experimental results based on 80 sets of artificial signals with a frequency range of 0 40Hz showed that 2T-EMD has the best overall computational performance in terms of calculation speed and signal representation accuracy.

TTEMD is a modified version of EMD, TTEMD overcomes the mode mixing problem of EMD by using a turning tangent criterion to guide the sifting process, resulting in better decomposition performance. Given the advantages and limitations of the various signal processing algorithms available for EEG analysis, the present system has opted for the TTEMD as the primary method. The TTEMD algorithm provides a way to decompose signals that have multiple channels without the need for projections. This is achieved through the computation of the signal mean envelope and the re-definition of the signal mean trend, which is calculated by interpolating between the barycenter of elementary oscillations (Fleureau et al., 2011). By using this approach, TTEMD can effectively identify local features of the signal and decompose it into a finite set of components, making it a powerful tool for time-frequency analysis of nonlinear and non-stationary signals. The TTEMD algorithm can be summarized as follows:

Let's consider a function s belonging to the class C^1, implying its differentiability and possession of a continuous first derivative. The tangent vector to function s is denoted as T_s. For any given point t in the real numbers $\mathbb{R}$, the value $a_s(t)$ can be understood as the Euclidean inner product of $\mathbb{R}^{D+1}$, represented by $\langle ., . \rangle$, between the tangents to s just before and after the point t. Here, D represents the dimension. Notably, α_s reaches its maximum at a specific point t when both vectors $T_s(t-h)$ and $T_s(t+h)$ are collinear, indicating a consistent direction and smooth transition of the tangents. Moreover, the continuity of the inner product operation ensures the preservation of this property.

For all $t \in \mathbb{R}$, we have

$$a_s(t) = \left\langle \lim_{h \to 0} T_s(t-h), \lim_{h \to 0} T_s(t+h) \right\rangle \tag{1}$$

An oscillation extremum of the function s is defined as a local minimum of the function α_s. According to Equation (1), it also corresponds to a local minimum of the following function:

$$\beta_s : t \mapsto \beta(t) = \left\| \frac{ds}{dt}(t) \right\|^2 \tag{2}$$

Consider two consecutive oscillation extrema represented by points $P_1 = [t_1, s(t_1)]^T$ and $P_2 = [t_2, s(t_2)]^T$. The barycentre, denoted as $M_{p_1} \to M_{p_2}$, of the corresponding elementary oscillation can be calculated as follows:

$$M_{p_1} \to M_{p_2} = \left[\frac{t_1 + t_2}{2}, \frac{1}{t_2 - t_1} \int_{t_1}^{t_2} s(t)\, dt \right]^T \tag{3}$$

After obtaining the IMFs, the frequency domain of the IMFs is obtained using the Fast Fourier Transform (FFT). The energy of each IMF is then calculated by summing the squared magnitudes of its frequency components. The EEG energy of each frequency band was obtained by summing the energies of the IMFs within that band. The specific calculation process is shown in Figure 1 below.

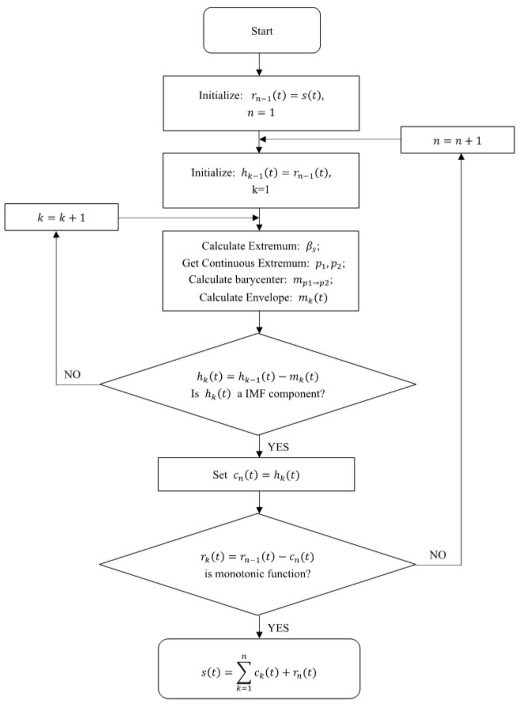

Figure 1. TTEMD computation flowchart.

The ApEn algorithm measures the irregularity or complexity of a time series. It calculates the logarithmic likelihood that subseries that are close in amplitude will remain close on the next incremental comparison. A smaller ApEn value indicates a more regular and predictable time series, while a larger ApEn value indicates a more irregular and unpredictable time series.

The basic idea of ApEn is to quantify the predictability of a time series by comparing the similarity between patterns of data within the series. It is calculated by counting the number of times that a pattern repeats itself within a given tolerance window. The ApEn algorithm can be expressed using the following simplified mathematical formula:

$$A_m(r, N) = -\ln\left(\frac{C_m(r, N)}{C_{m+1}(r, N)}\right) \tag{4}$$

where $A_m(r, N)$ is the ApEn value for a given time series with length N, tolerance level r, and pattern length m; $C_m(r, N)$ and $C_{m+1}(r, N)$ are the number of pattern matches of length m and $m + 1$ that are similar within the tolerance level r.

To calculate $C_m(r, N)$, first, a vector of the data points with length m is created by selecting sequential data points from the time series. The Euclidean distance between each pair of vectors is then calculated, and if the distance is less than or equal to the tolerance level r, the vectors are considered similar. The number of similar vectors is then counted and divided by the total number of vectors, resulting in the probability $C_m(r, N)$. The same procedure is repeated for pattern length $m + 1$ to calculate $C_{m+1}(r, N)$.

The ApEn value ranges from 0 to infinity, with lower values indicating higher regularity or predictability in the time series. A commonly used threshold value for distinguishing between regular and irregular time series is 0.2.

b. System Composition

The system composition for the proposed experiment consists of an OpenBCI Cyton board and a personal computer (PC) equipped with a Python programming environment. Python was selected as the programming language due to its versatility, ease of use, and availability of various open-source libraries for signal processing and data analysis. The OpenBCI Cyton board is a versatile and affordable biosensing device that can record multiple channels of EEG signals with high accuracy and low noise. It consists of eight channels that can be connected to different electrode configurations. The equipment used is shown in Figure 2 below.

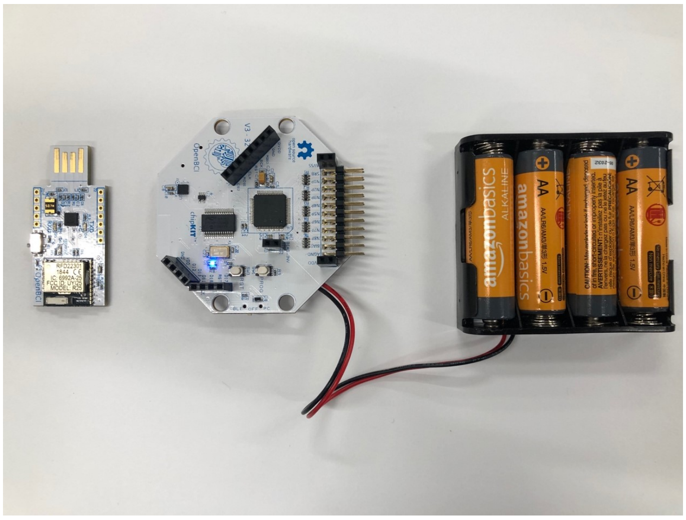

Figure 2. Experimental USB Dongle and an OpenBCI Cyton board with 4 dry batteries.

The OpenBCI Cyton board was used to collect EEG signals from six electrodes: F7, F8, F3, F4, Fp1, and Fp2, as well as one ground electrode (GND) and one reference electrode (A2) that were placed on the forehead and earlobe, respectively.

The recorded EEG signals were transmitted from the OpenBCI Cyton board to the PC via a dongle. The PC was used to receive and process the EEG signals in real time using Python scripts. The Python environment was configured to include necessary libraries for signal processing, such as NumPy, SciPy, and Matplotlib. The TTEMD and ApEn algorithms were implemented in Python scripts to extract relevant features from the EEG signals. The extracted features were then used to classify the consciousness level of the subject in real time. The system architecture is shown in Figure 3.

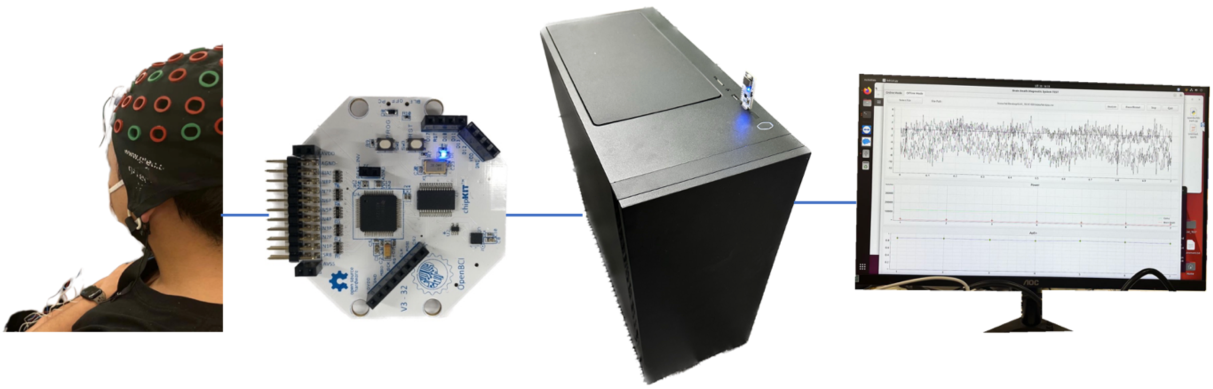

Figure 3. System structure diagram.

In the specific geographical region where the study was conducted (Saitama Prefecture in this case), a common source of interference in the EEG signals is the 50Hz power line frequency. It is important to note that power line frequencies can vary between different regions, and in some areas, such as North America, the power line frequency is typically 60Hz.

To address the 50Hz power line interference in the EEG signals, a notch filter was implemented in the system. The notch filter specifically targets and suppresses the 50Hz frequency, effectively removing the interference caused by the power grid. This ensures that the acquired EEG signals are cleaner and more reliable for subsequent analysis and interpretation. In the study, the system was configured to analyze the frequency range of 0.5-40 Hz, which covers the commonly observed frequency bands in the analysis of patient's brain waves. These frequency bands are associated with specific types of brain wave activities.

c. A System for EEG Energy and Complexity Calculation based on TTEMD and ApEn

The TTEMD algorithm introduces a controllable parameter Δt, representing the length of a time window, as depicted in Figure 4. In this experiment, Δt is set to 1 second (250Hz). To achieve this, we have designed a loop that processes and stores EEG data with an increment of Δt. Simultaneously, by sliding the time window and time step, we apply the TTEMD and ApEn algorithms to analyze the EEG data, enabling the extraction of temporal distributions of brainwave energy and dynamic complexity.

The system retrieves EEG data from the initial window and subsequently applies the TTEMD algorithm to decompose the EEG data within the window, resulting in a series of IMFs. The system then utilizes the ApEn algorithm to calculate the complexity of each IMF. Next, the system computes the energy distribution and complexity distribution for each IMF. Upon completing the processing of the current window, the system stores the results, generates visual representations, and shifts the window to the next position.

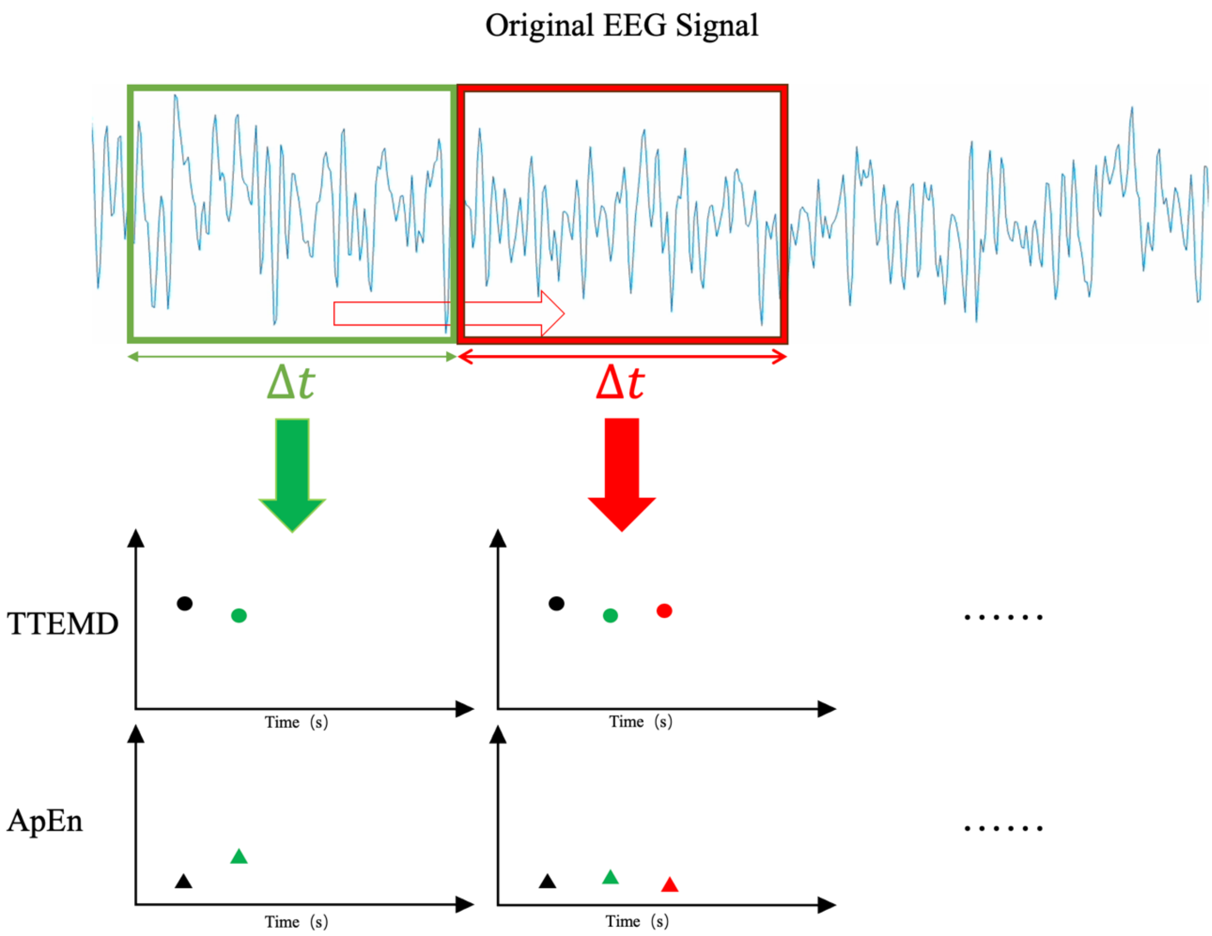

Figure 4. Flowchart of sliding window computation of TTEMD and ApEn.

d. Statistical Analysis

The system consists of two modes: online and offline. The online mode is used for real-time analysis of EEG energy and assessment of consciousness level. The offline mode enables us to analyze existing data. The online mode is particularly useful for continuous monitoring of a patient's consciousness level during surgery or other medical procedures, while the offline mode allows for in-depth analysis of the data collected during the online mode.

The use of both modes provides a comprehensive approach to the assessment of consciousness level and can help medical professionals make more informed decisions regarding patient care. Figure 5 below shows the Graphical User Interface (GUI) of the system.

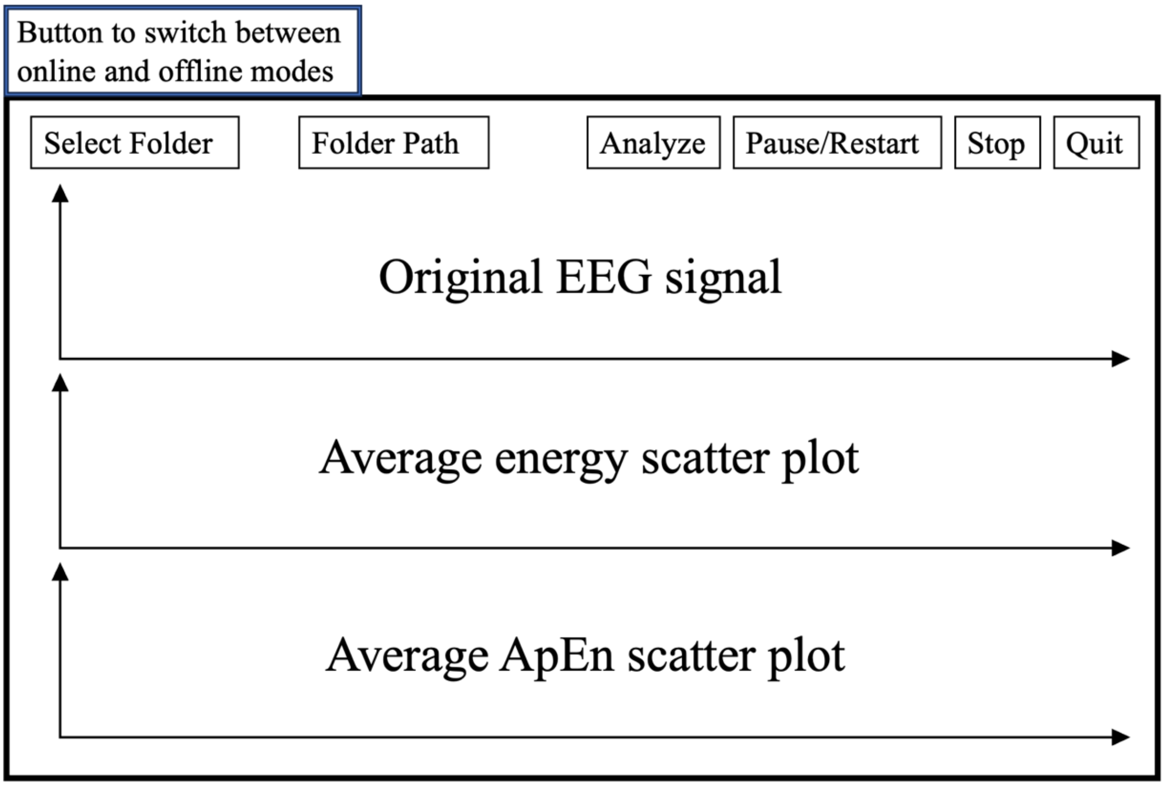

Figure 5. GUI of the system.

III. EXPERIMENT

a. Experiment-result

The data used in this study was obtained from patients with either brain death or coma in the Intensive Care Unit (ICU) at a hospital in Shanghai, China. The study was approved by the hospital's ethics committee and informed consent was obtained from the patients' families. The data acquisition process involved recording the EEG signals directly at the patient's bedside using a clinical EEG system with an international 10-20 electrode placement. The included 6 channels (F7, F8, F3, F4, Fp1, Fp2) and one ground electrode (GND) that was also placed on the forehead, and the remaining two electrodes (A1, A2) which were reference electrodes that were placed on the earlobes. This configuration allowed for the recording of EEG signals with high spatial resolution and low noise interference. A sampling rate of 1000 Hz with electrode impedance is kept below $8\,\mathrm{K}\Omega$.

After obtaining the EEG signals from the subjects, the first step in analyzing the signals is to preprocess them. In our study, we used a bandpass filter to extract the frequency range of interest, which is from 0.5 Hz to 40 Hz. This range covers the typical EEG frequency bands: delta, theta, alpha, beta, and gamma.

In this study, we analyze the EEG energy and ApEn results obtained from offline analysis of EEG data collected from 10 patients diagnosed with brain death and 10 patients with coma. The results showed clear differences between the two groups, indicating that the proposed real-time analysis system has the potential to effectively assess the consciousness level of patients. as shown in Figures 6 and 7. The results clearly indicate significant differences between the two groups. In particular, the EEG energy levels of brain death patients were found to be significantly lower than those of coma patients, while the ApEn values were higher for brain death patients.

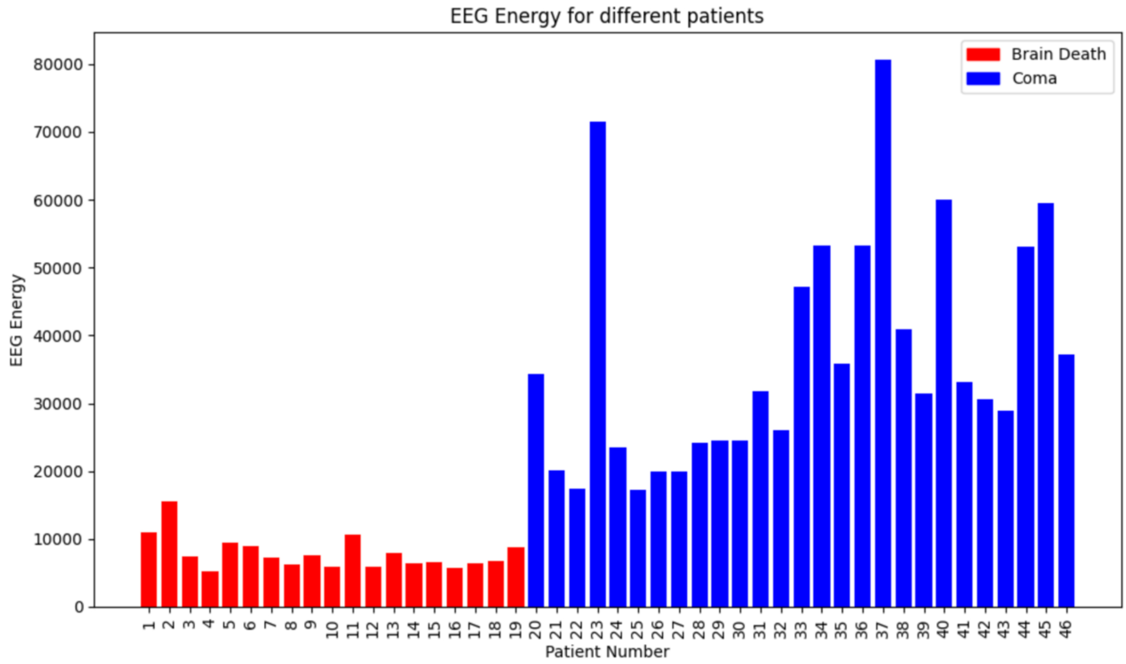

Figure 6. EEG Energy Analysis Results for Comatose and Brain Death.

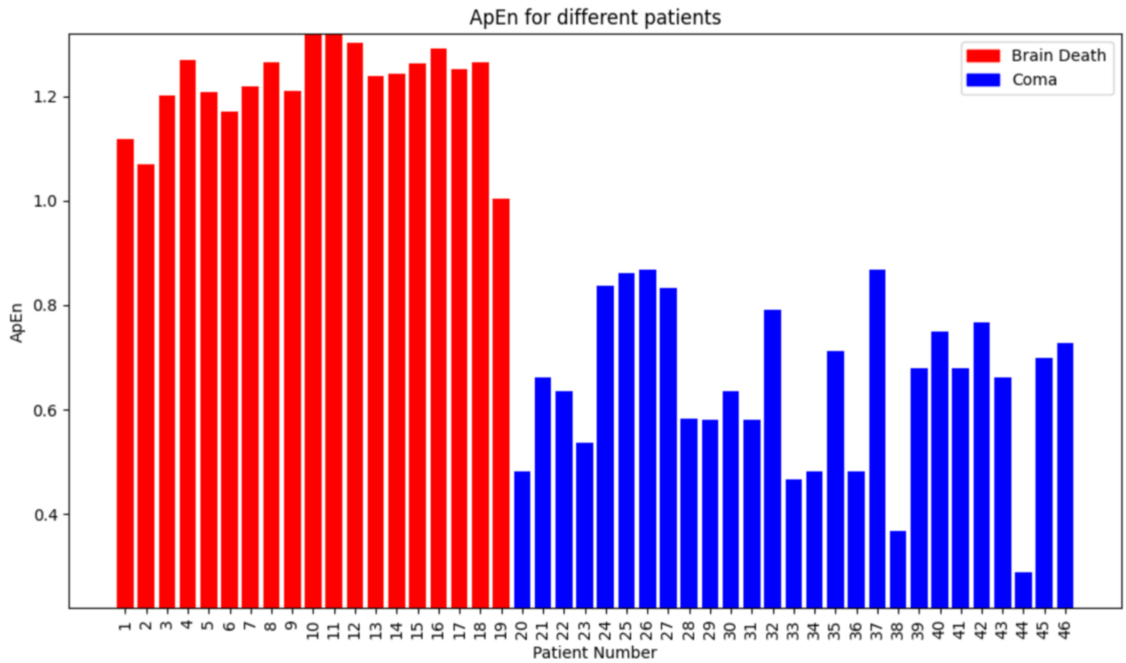

Figure 7. ApEn Analysis Results for Comatose and Brain Death.

Figure 8 displays the results of offline data analysis obtained from a patient who transitioned from a state of deep coma to brain death. The figure highlights the notable differences in brainwave energy and ApEn between the states of deep coma and brain death.

The observed disparities in brainwave energy and ApEn values provide valuable insights into the distinctive characteristics of these two states. The data analysis reveals a significant decrease in brainwave energy and an altered pattern of complexity as the patient progresses from deep coma to brain death. These findings contribute to our understanding of the physiological changes associated with the transition from deep coma to brain death. They underscore the potential of brainwave energy and ApEn as quantitative measures for assessing the level of consciousness and differentiating between these critical states.

Our real-time EEG-based system leverages the TTEMD and ApEn algorithms to extract energy and complexity measures from EEG data, which are then fed into our meticulously trained SVM model. The model is trained using a wealth of EEG data labeled as "coma" and "brain death". Once the model is trained, it is run with a large volume of new EEG data and the predictive scores it generates for the brain states — coma or brain death — are recorded. We then perform statistical analyses on these predictive scores, which allows us to establish the positions of the two standard lines representing coma and brain death states in the GUI. When new EEG data is processed in the system, we can differentiate and compare coma and brain death states more effectively. The advantage of this approach lies in its provision of a clear, intuitive visualization that aids healthcare professionals in determining whether a patient's condition aligns more closely with a coma or brain death. The system offers an enhanced, holistic interpretation of a patient's neurological condition in real-time, facilitating informed and timely decision-making, thereby contributing to improved patient management.

It is noteworthy that during the real-time recording process of EEG, we often encounter issues such as channel signal loss, excessive noise, and high amplitude fluctuations. To mitigate these problems, we have implemented a threshold setting in our system. This enables automatic detection and discarding of problematic data. Correspondingly, an 'X' indicator is displayed on the GUI whenever such data is discarded. The threshold setting also allows for the preservation of data that has relatively less impact on the system's accuracy. This methodology not only enhances the precision of our system but also substantially reduces the misjudgments caused by factors such as noise. If a significant number of 'X' indicators are displayed, it is a prompt for the physician to examine the current EEG recording environment and check for potential issues with the EEG connections.

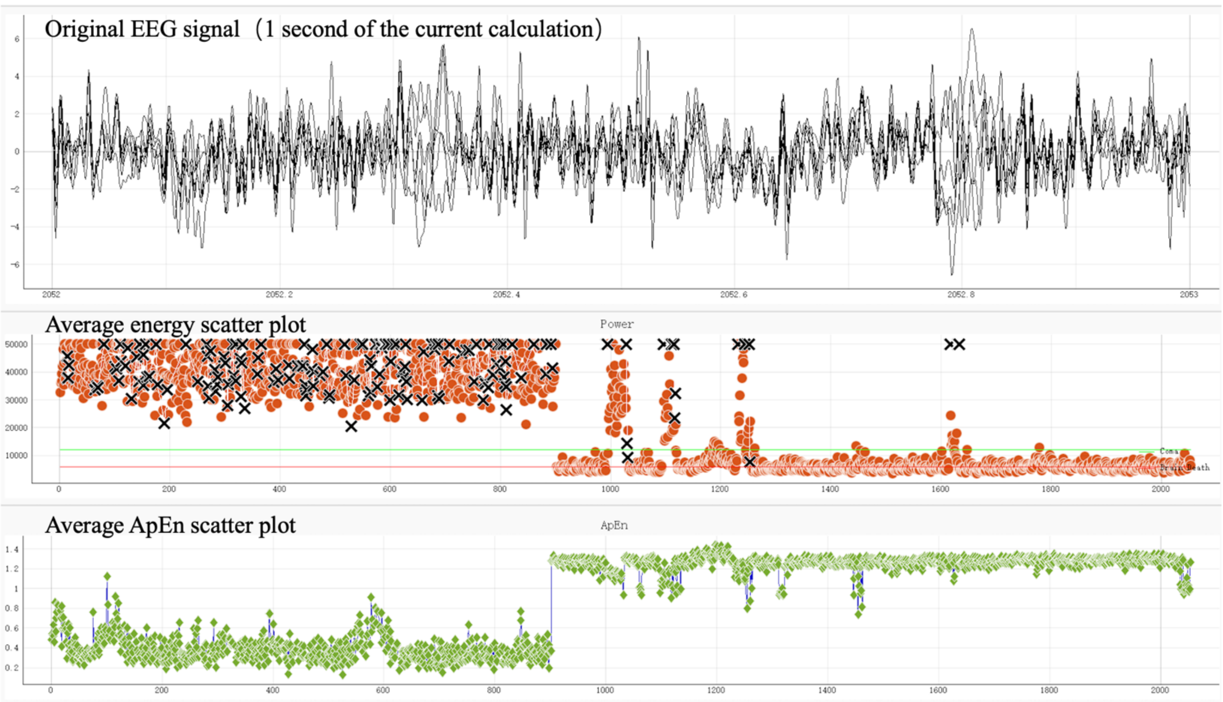

Figure 8. GUI Display of Coma to Brain Death Transition.

b. Results

The results of our study provide insights into the potential use of energy analysis in assessing the level of consciousness in patients with impaired brain function. Our analysis of the TTEMD and ApEn values of EEG signals from comatose and Brain Death revealed significant differences between the two groups, suggesting that the level of energy in the brain may be a useful indicator of brain function. In addition, the results of our analysis on the comatose patients showed a positive correlation between the level of energy in the brain and the level of consciousness, which supports the hypothesis that energy analysis can be used to assess the level of consciousness in these patients.

However, it should be noted that our study has some limitations. First, the sample size was relatively small, which may affect the generalizability of our results. Future studies with larger sample sizes are needed to confirm the findings of our study. Second, our study only focused on comatose and Brain Death, and the applicability of our findings to other patient populations, such as patients under anesthesia or in a vegetative state, remains to be explored.

Overall, our study provides preliminary evidence of the potential of energy analysis in assessing the level of consciousness in patients with impaired brain function. Further research is needed to validate our findings and explore the clinical applications of this approach.

In contrast to previous studies in this domain, our work introduces novel aspects that substantially enhance the accuracy and reliability of EEG signal analysis. Most of the prior studies focus primarily on the acquisition and interpretation of EEG signals, but they have not adequately addressed the prevalent challenges such as channel signal loss, excessive noise, and high amplitude fluctuations. Our study, on the other hand, has implemented a threshold mechanism that automatically detects and discards problematic data, thereby drastically reducing the impact of these issues on the analysis outcomes.

Furthermore, the SVM-based approach we have used for distinguishing between brain-dead and coma patients shows significant improvement over the traditional methods used in the previous studies. Previous methods often rely on manual interpretation and do not consistently provide a clear distinction between the brain states. The use of SVM in our study provides an automated, objective, and highly accurate means of differentiation. Moreover, the real-time implementation of our system and the provision for immediate feedback to the clinician set our study apart from the prior works. While many previous studies have focused on post-processing and analysis of EEG signals, our study emphasizes on real-time analysis, which has more practical implications in clinical settings.

In conclusion, the methodologies and systems introduced in our study provide significant improvements over previous works in terms of both the precision of EEG signal analysis and the practicability of implementation in real-world clinical settings.

IV. CONCLUSION

The present study demonstrates the feasibility of analyzing EEG energy patterns to assess levels of consciousness in patients with disorders of consciousness. Our results indicate that by using time-frequency analysis and entropy measures, we can differentiate between states of consciousness in patients with disorders of consciousness. Importantly, the proposed system offers real-time analysis and portability, making it potentially useful for clinical settings.

While there are some limitations to the present study, such as the relatively small sample size and the lack of generalizability to other patient populations, the results suggest promising avenues for future research. Further exploration of the proposed system may provide additional insights into the relationship between EEG energy patterns and consciousness and may ultimately lead to more effective diagnostic and treatment strategies for patients with disorders of consciousness. Overall, the present study contributes to the growing body of research exploring the use of EEG-based measures to assess consciousness in patients with disorders of consciousness. By offering a novel approach that emphasizes the importance of analyzing EEG energy patterns, our study highlights the potential of EEG-based measures to improve our understanding of the neurophysiology of consciousness and ultimately improve patient outcomes.

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Conflicts of Interest

The author has no conflict of interest about anything in this article.

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