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Analysis and Comparison of Artifact Removal Techniques for Epilepsy EEG Signal

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Abstract

Objective: Accurate epilepsy diagnosis demands precise EEG analysis, hindered by non-neuronal artifacts. This study evaluates artifact removal methods, specifically Independent Component Analysis (ICA) and Empirical Mode Decomposition (EMD), aiming to enhance signal quality. We introduce a hybrid approach, combining ICA and EMD. **Methods:** ICA and EMD are applied to preprocess epilepsy EEG recordings. Quantitative evaluation metrics, including Signal-to-Noise Ratio (SNR), Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Standard Deviation (SD), are calculated and compared for both methods. **Findings:** ICA outperforms EMD, showing higher SNR and PSNR, notably in BONN and CHB-MIT datasets. ICA achieves significant reductions in MSE, RMSE, and SD. The hybrid approach surpasses existing methods, supported by quantitative data. **Novelty:** Rigorous application of ICA and EMD to diverse datasets quantitatively establishes ICA's superiority. The hybrid approach, backed by quantitative evidence, proves effective beyond epilepsy EEG. Conclusion: This abstract provides clear, quantitative support for ICA's superiority and the hybrid approach's efficacy, offering valuable insights into artifact removal in EEG analysis.

Keywords: Epilepsy; Artifact removal; EEG; ICA; DWT; EMD; Performance metrics

1 Introduction

The neurological disorder known as epilepsy, which is characterized by abnormal brain activity, causes recurrent involuntary movements and associated difficulties that have a substantial effect on sufferers and their families. With around 50 million people worldwide afflicted, prompt identification becomes critical to successful seizure therapy. Numerous diagnostic instruments, including CT scans, MRIs, fMRIs, PET scans, high-density EEGs, and SPECTs, are vital to this procedure. Despite the widespread use of EEG, its laborious nature has prompted the development of automated seizure detection techniques that make use of deep learning, machine learning, and signal processing. In order to accurately detect epilepsy in its early stages, these techniques usually entail several stages, such as preprocessing, segmentation, feature extraction, and classification [1].

Epileptic EEG recordings are susceptible to diverse artifacts, categorized into physiological, electrode-related, and environmental types. These include muscle, eye, and respiratory activities, each exhibiting distinct characteristics. Identifying and mitigating these artifacts are crucial for accurate interpretation in epilepsy studies, necessitating meticulous monitoring and advanced signal processing techniques [2]. While EEG offers advantages like portability, affordability, and high temporal resolution, challenges such as spatial resolution limitations and signal-to-noise ratio constraints exist. Despite its versatility in neuroscience, psychology, cognitive science, and clinical research, EEG recordings often encounter artifacts, compromising accuracy. Various methods, both manual and automated, have been developed to address these challenges, emphasizing the importance of mitigating artifacts before EEG signal analysis [3].

In the domain of epilepsy detection, the pre-processing stage holds significant importance. To comprehend the various techniques employed in this critical stage, an in-depth literature review spanning the years 2017 to 2023 has been conducted by researchers.

In [4] a method to remove eye-related artifacts (EOAs) from multichannel EEG signals Using ICA and multivariate EMD is proposed identifies and eliminates EOAs effectively. The technique successfully cleans EEG signals, preserving essential information with minimal loss, as shown in simulated and real data. Comparative analysis indicates significant improvements in signal-to-noise ratio and mean square error reduction compared to other techniques.

In [5] canonical correlation analysis and ensemble empirical mode decomposition ie CCA-EEMD a novel method used for automatically removing EOG artifacts and preserving essential information in the EEG signals. Experimental results across seven subjects show its superiority over commonly used methods. In [6] an innovative method for reducing noise and eliminating artifacts from EEG signals, taking into account the contamination caused by non-cerebral sources such as eye movement and muscular aberrations. The hybrid approach uses the General Linear Chirplet Transform to identify and rectify Artifactual Independent Components and Fast-Power ICA for blind source separation. Results from simulated EEG signals indicate the technique's effectiveness in identifying and removing non-cerebral artifacts, ensuring contamination-free signals.

In [7] an unsupervised ICA-based algorithm for EEG artifact removal proposed, utilizing new unsupervised artifact detection, ICA, and a statistical criterion for automatic selection of artifact-related independent components (ICs). The technique is tested using both real and synthetic EEG data (SEEG and AEEG), with an emphasis on online applications. In [8] authors reviewed different EEG artifact removal techniques, and they explored artifact types, methods, and data properties. Specific artifacts were targeted, some methods required reference channels, and techniques like BSS and Wavelet offered high accuracy but complexity. A comparative analysis helped choose methods based on application.

In [9] a unique technique that combines spatial constraint independent component analysis (SCICA) with EEMD to remove ocular artifacts from EEG recordings is proposed. EEMD extracts Implicit Mode Functions (IMFs), distinguishing between artifact-free and artifactual IMFs using a Correlation Coefficient-based algorithm. ICA, guided by Kurtosis and mMSE thresholds, processes artifactual IMFs, with spatial constraints modifying the mixing matrix. Restored IMFs contribute to reconstructing the artifact-free EEG signal. Comparative analysis demonstrates the method's superior performance over state-of-the-art techniques in ocular artifact removal from EEG. In [10] [11] a novel EEMD based ICA approach (EICA) proposed for reducing EOG artifacts from multichannel EEG signals.

1.1 Research gap:

The existing literature provides a comprehensive overview of artifact removal methodologies in epilepsy EEG signals, ranging from traditional techniques to hybrid approaches and advanced machine learning methods. Commonly applied techniques include EMD, DWT, ICA, and PCA.

However, despite the breadth of methods, notable limitations persist. Some approaches are overly focused on general artifact removal, lacking specificity. ICA requires visual expertise, time, and specific data and channel considerations. PCA may struggle when artifacts mimic genuine brain activity, and wavelet transforms face challenges with overlapping spectra. EMD encounters mode mixing issues, and studies often rely on visual inspection or simulated EEG data, hindering direct comparisons. Even the database selection for this research is also a great challenge for the researcher's. The absence of a universally effective method for eliminating all artifact types poses a challenge in identifying an optimal choice.

This research aims to bridge a gap in existing studies by undertaking a thorough comparative analysis of Independent Component Analysis (ICA) and Empirical Mode Decomposition (EMD) methods. The study introduces a novel hybrid approach, combining ICA and EMD, to enhance the de-noising of EEG signals effectively, specifically focusing on epilepsy EEG signals. The evaluation involves the application of standard performance metrics, providing a more nuanced insight into the efficacy of these methods in artifact removal for epilepsy EEG signals. The standard databases, CHB-MIT Scalp EEG Database and the Bonn EEG Time Series Database, serve as valuable sources for assessing the proposed hybrid approach.

The rest of this work is summarized as follows: The suggested technique is explained in Section 2, and the findings and discussions are covered in Section 3. The study work's conclusion is covered in Section 4.

2 Methodology

The following methodology been proposed in order to remove the artifacts from the epilepsy EEG signal.

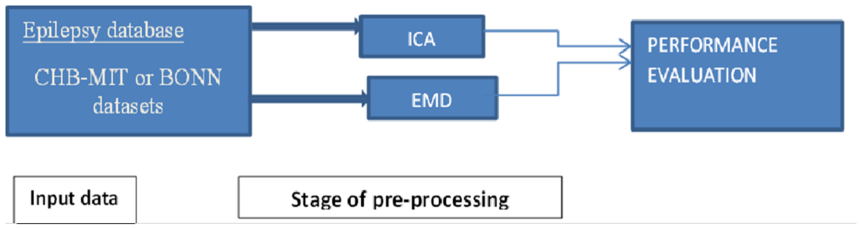


Fig 1. Proposed methodology for artifact removal

2.1 Database description

The CHB-MIT Scalp EEG Database and the Bonn EEG Time Series Database are two well-known online databases that are used in this work to analyze epileptic signals. 22 pediatric patients with uncontrollable seizures had their EEG recordings tracked for several days following the cessation of anti-seizure medication. These recordings are included in the CHB-MIT Scalp EEG Database[11][12]. Annotations on the beginnings and endpoints of 182 seizures are available in the database.

One hundred single EEG channels, each lasting 23.6 seconds and captured at 173.61 Hz, spanning the frequency range of 0.5 Hz to 85 Hz, are available in the Bonn EEG Time Series Database[13][14]. There are five sets in the database: A, B, C, D, and E. Surface EEG recordings of healthy subjects with their eyes open and closed are found in sets A and B. Intra cerebral EEG recordings from seizure-producing regions both inside and outside of epileptic patients are included in sets C and D. Intracranial EEG recordings made during epileptic seizures are included in Set E. Each set consists of 100 text files with 4097 ASCII-coded samples of a single EEG time series.

2.2 Stage of Pre-processing

2.2.1 Independent Component Analysis (ICA)

Blind Signal Separation (BSS) in Blind Signal Processing (BSP) is a powerful technique for effectively isolating source signals from mixtures without relying on prior information or training data. Its applications span diverse fields, including medical imaging, engineering, image processing, speech recognition, communication systems, and even astrophysics[15][16]. In audio engineering, BSS goes beyond speech recognition, proving valuable for tasks like automatic transcription and identifying both speech and musical instruments[15][16]. This versatility highlights BSS's significant contribution to advancements across scientific and technological disciplines.

A standout method within the diverse landscape of BSS is ICA[15][17]. Renowned for its conceptual simplicity and high-quality results, ICA has gained widespread popularity across various applications. In audio engineering, where BSS applications extend beyond speech recognition, methods like ICA become invaluable, finding utility in tasks ranging from automatic transcription to identifying both speech and musical instruments. The multifaceted applicability of BSS, exemplified by methods like ICA, underscores its pivotal role in propelling advancements across a spectrum of scientific and technological disciplines.

When the number of source signals, denoted by the letter "p," is equal to or more than the number of channels, denoted by the letter "n," which stands for the microphones or sensors, standard ICA is intended to operate on a multichannel signal. Using n values of observed signals (signals generated by microphones or sensors) x_1,..., x_n, ICA determines a p $\times$ n mixing matrix A for n $\geq$ p only and statistically independent components (source signals) S_1,..., Sp. A common linear ICA model is shown in Equation (1).Equation (2)

$$x = As \tag{1}$$

where, A is a n × p mixing matrix, s = (s_1,….., s_p) T is a vector of source signals, and x = (x_1,….., x_n)T is a vector of observed signals (Figure 1). Equation (2) represents ICA's solution to the separation problem:

$$\widehat{S} = Wx = WAs \tag{2}$$

Where (F_1,... μ_n) = ⊠T is an estimate of s, while matrix W, often known as the filtering matrix, is an estimate of A's inverse. The filtration matrix W is a member of the non-singular matrices det (W) $\neq$ 0 general linear group GI (n) when n = p.

Pre-processing steps that involve whitening the observed signal (z = Bx = Bas), where B is the whitening matrix with unitary variance and de-correlation Cz = E(zzT)=I, typically result in a reduction of the computational cost of ICA[15]. Equation (3) is derived under the assumption that source signals Cs=I.

$$I = C_z = E(zz^T) = BAE(ss^T)(BA)^T = BA(BA)^T \tag{3}$$

This proves that the matrix (BA)T=(BA)-1, or BA, is orthogonal (s to z is translated using the orthogonal matrix BA). Therefore, if σ = QTZ = QTBAS = US, then the matrix U = QT BA is a permutation matrix, and a new filtering matrix Q (after whitening) must likewise satisfy the orthogonality criteria[18].

ICA has the following limitations:

1. It assumes statistical independence among the generated components.
2. It requires a non-Gaussian distribution in the generated independent components.
3. The number of independent components must match the observed mixtures.

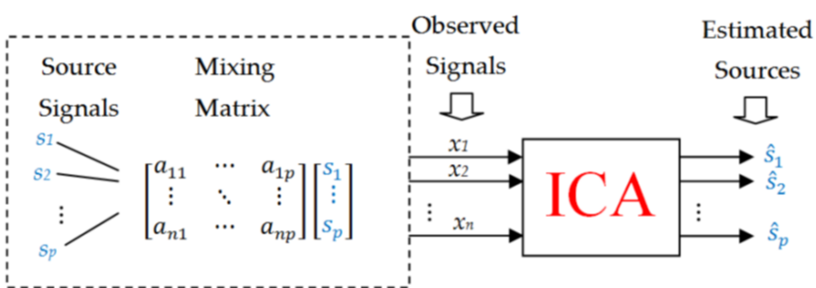


Fig 2. Standard independent component analysis block diagram[15]

Among the techniques most frequently employed for EEG artifact removal is the ICA method covered above. This study looked at how ICA was implemented for the BONN and CHB-MIT databases, as seen in Figures 5 and 6, respectively which is discussed in detail in the results and discussion section.

2.2.2 Empirical Mode Decomposition (EMD):

EMD is a time-domain filter that is dynamic and data-responsive. Its objective is to break down a signal at a local time scale into a number of Intrinsic Mode Functions (IMFs). Every IMF captures the distinct qualities of the original signal within its particular time frame. EMD distinguishes itself as a data-responsive multi-resolution method by dissecting a signal into physically meaningful components. It is useful for breaking down non-stationary and non-linear signals into discrete parts at different resolutions[18] [19]. By using the notion of scale separation, EMD, like a dynamic filter bank in the time domain, efficiently finds inherent modes of oscillations in any given dataset. The intrinsic mode function, which is the phrase used to describe each discrete oscillatory mode, is precisely described as follows[19].

- The mean value must be zero and the count of extremes and zero-crossings must either match exactly or show a difference of no more than one over the whole dataset.
- The mean value of the envelopes determined by the local minima and maxima must both equal zero at any given position.

The input signal is broken down into multiple intrinsic mode functions (IMF) and a residue using the EMD method.

$$I(n) = \sum_{m=1}^{M} IMF_m(n) + Res_M(n)$$

where the multicomponent signal is denoted by I(n). The residue corresponding to M intrinsic modes is represented by ResM(n), while the intrinsic mode function is denoted by IMFm(n).

$Log_2 N$, where N is the total number of data points, roughly limits the overall amount of IMF components. This satisfies every requirement for using the Hilbert transform to establish a meaningful instantaneous frequency. Empirical Mode Decomposition (EMD) converts the original signal x(t) into a set of IMF iteratively using the Shifting algorithm, as described below.

The following is a description of the stepwise EMD algorithm:

Step 1: Set the initial values to $-r_0(t) = x(t)$, i = 1, $r_i(t) = r_0(t)$.

Step 2: The process for extracting the ith IMF

a) Set up: J = 1, $h_0(t) = r_i(t)$.

b) Eliminate all local minimum and maximum values of h_{J-1} (t)

c) Use a cubic spline of $h_{J-1}(t)$ to interpolate the local peaks and minima to produce the upper and lower envelopes.

d) Determine the upper and lower envelopes' means, $m_{J-1}(t)$..

e) $h_J(t) = h_{J-1}(t) - m_{J-1}(t)$

f) Set if the stopping requirement is met if imf i(t) = $h_J(t)$ else go to (b) with J = J +1

Step 3: $r_{i+1}(t) = r_{i-1}(t) -$ imf i(t)

Step 4: If r_{i+1} (t) still has at least 2 extremes then go to 2 with i = i + 1 else the decomposition procedure ends. And ri(t) is the residue.

Finally, when EMD procedure is completed after n iterations, the original signal can be reconstructed as:

$$X(t) = \sum_{j=1}^{n} imf_i + r(t) \tag{5}$$

In this case, r(t) represents the ultimate residue, which functions as a monotonic object free of frequency components and is often referred to as the trend. In the meantime, the non-negative number n depends on x(t), and the collection of mono components describes the detail. The Empirical Mode Decomposition (EMD) process flowchart, which shows the sequential steps of the process, is depicted in Figure 5.

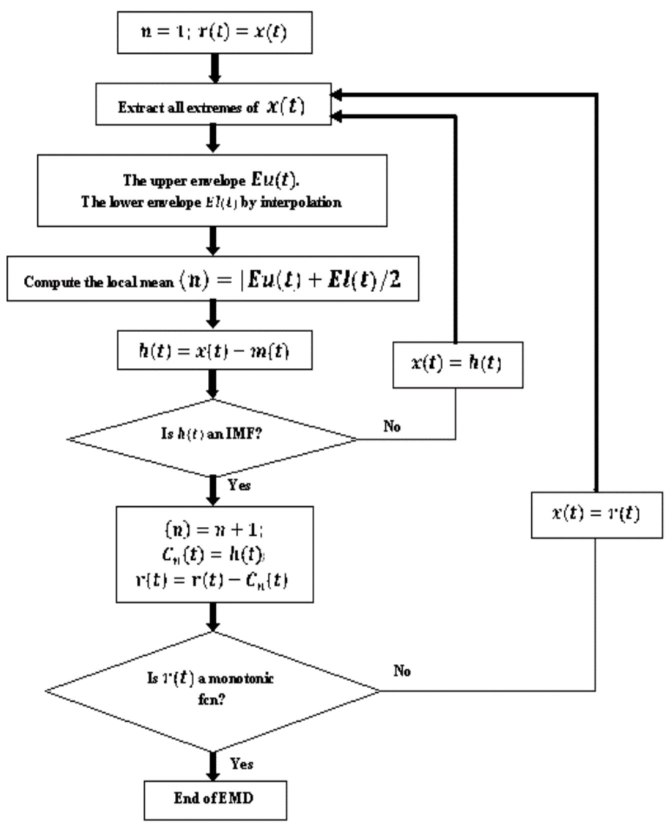


Fig 3. Empirical Mode Decomposition Flowchart [courtesy- (19–21)

The waveform representations, specifically Figures 6 and 7, illustrate the outcomes of the pre-processing methodology utilizing Empirical Mode Decomposition (EMD) for the CHB-MIT and BONN databases. A discerning examination of these figures reveals noteworthy insights which are discussed in results and discussion section in detail.

2.2.3 Hybrid method

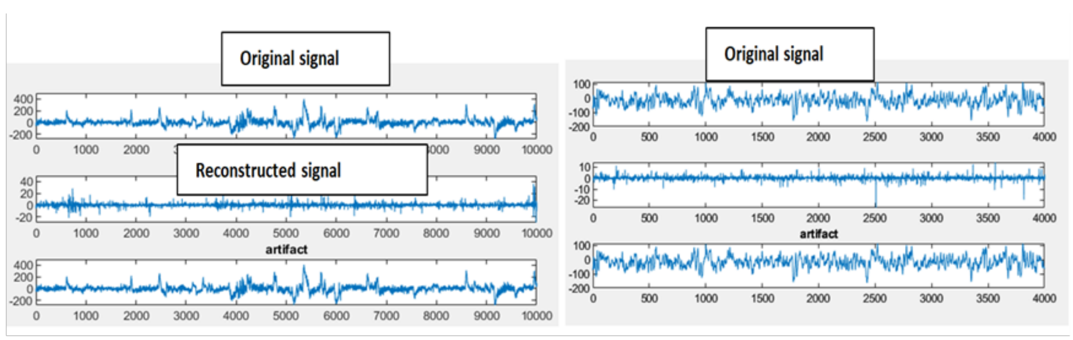
In this artifact removal hybrid approach for EEG data, ICA is first applied to the raw EEG signals to isolate brain activity from unwanted artifacts. The resulting cleaned signals post-ICA is then processed using EMD, which dissects each channel into Intrinsic Mode Functions (IMFs) and a residue. Working on individual channels, the method identifies and eliminates artifacts, providing a targeted and comprehensive artifact removal process. The entire procedure is visually represented in a figure, illustrating the progression from raw EEG signals through ICA cleaning and EMD decomposition, showcasing the effective removal of artifacts at each stage. This fusion of ICA and EMD offers a powerful technique for enhancing the quality and reliability of EEG data for subsequent analyses [20] [22].

Fig 4. Block Diagram of Hybrid (ICA + EMD) Technique

3 Results and discussion

The waveform figures, specifically Figure 5 represent the outcomes of the pre-processing phase using Independent Component Analysis (ICA) for the CHB-MIT and BONN databases, respectively. Upon careful examination of the figures, distinct patterns emerge.

In Figure 5**(a)**, corresponding to the CHB-MIT database, the original signal is visibly intertwined with artifacts, manifesting as spikes or irregularities in the waveform. However, the transformative power of ICA becomes evident in the reconstructed signal. Here, the prevalence of artifacts is notably diminished, marked by a reduction in the number of spikes and it also reflected in the evaluation parameter such as increase in the SNR value. This suggests a successful removal or mitigation of unwanted interference through the ICA pre-processing.

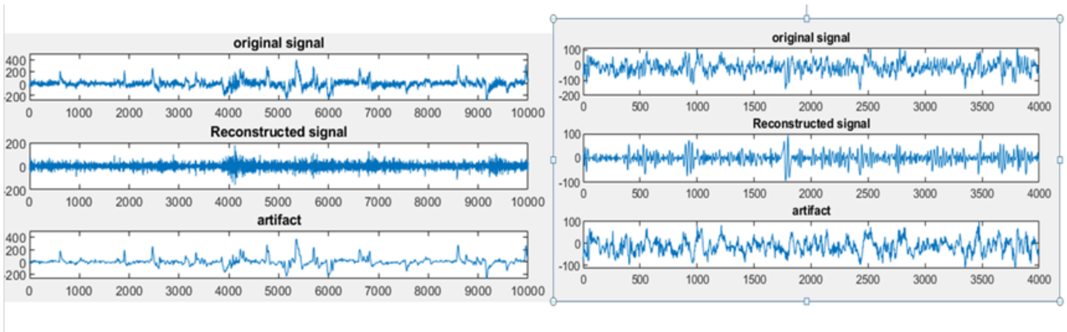


a) b)

Fig 5. Waveforms of Epilepsy EEG signal before and after de-noising for ICA technique for CHB-MIT Database (a) and BONN dataset (b)

Similarly, in Figure 5**(b)**, representing the BONN database, a comparable observation unfolds. The original signal, laden with artifacts, undergoes a discernible transformation in the reconstructed signal. This altered waveform exhibits a significant reduction in the presence of spikes and artifacts, indicating an effective cleansing of the signal through the application of ICA.

Essentially, the figures provide as visual aids for the effectiveness of the ICA pre-processing for both databases. The sharp difference between the original and reconstructed signals highlights how effective ICA is in mitigating artifacts and improving signal quality. Fewer abnormalities in the adjusted waveforms indicate that significant information was successfully extracted from the EEG data, paving the way for more precise and trustworthy analysis down the road.



a) b)

Fig 6. Waveform of EEG signal before and after de-noising for the EMD technique for CHB-MIT Database (a) and BONN database (b)

In Figure 6**(a)**, pertaining to the CHB-MIT database, the original signal exhibits discernible artifacts, manifesting as spikes within the waveform. The transformative impact of EMD becomes apparent in the reconstructed signal. Here, the prevalence of artifacts is notably reduced, characterized by a diminished occurrence of spikes. This observation strongly suggests the successful removal or mitigation of unwanted interference achieved through the EMD pre-processing.

Similarly, Figure 6**(b)**, corresponding to the BONN database, echoes a parallel narrative. The original signal, marked by artifacts, undergoes a discernible transformation in the reconstructed signal. This altered waveform exhibits a significant reduction in the presence of spikes and artifacts, indicative of an effective cleansing of the signal through the application of EMD.

Importantly, the figures not only serve as visual testimonials of the efficacy of EMD in pre-processing but also reveal a quantifiable improvement in performance. This is reflected in the Signal-to-Noise Ratio (SNR) value, a key performance parameter. The increase in the SNR value underscores the enhanced quality of the reconstructed signal, affirming a substantial reduction in artifacts and noise.

In essence, the figures provide a compelling visual and quantitative narrative of the successful pre-processing outcomes using EMD for both the CHB-MIT and BONN databases. Fewer abnormalities in the modified waveforms indicate that significant information was extracted from the EEG data, and they also highlight the improved performance that resulted from a decrease in artifacts and an increase in the SNR value.

3.1 Pre-processing using HYBRID of EMD and ICA for CHB-MIT and BONN database results

The EEG waveform pictures (Figure 7 **(a)** and **(b)**) present the results of a new pre-processing method that combined Independent Component Analysis (ICA) and Empirical Mode Decomposition (EMD) in a hybrid way for the CHB-MIT and BONN databases. These illustrations provide an engrossing visual story of the revolutionary effects of this creative hybrid method.

In Figure 7**(a)**, representing the CHB-MIT database, the original EEG signal is initially entangled with artifacts, evident in the presence of spikes within the waveform. The implementation of the hybrid EMD-ICA technique, however, introduces a noteworthy transformation. The reconstructed signal reveals a substantial reduction in artifacts, marked by fewer spikes. This visual observation emphasizes the successful removal or mitigation of unwanted interference achieved through the synergistic application of both EMD and ICA.

Similarly, in Figure 7**(b)** corresponding to the BONN database, a parallel narrative unfolds. The original EEG signal, initially burdened with artifacts, undergoes a distinctive transformation in the reconstructed signal. This altered waveform exhibits a significant reduction in the presence of spikes and artifacts, underscoring the efficacy of the hybrid EMD-ICA technique in enhancing signal quality [20].

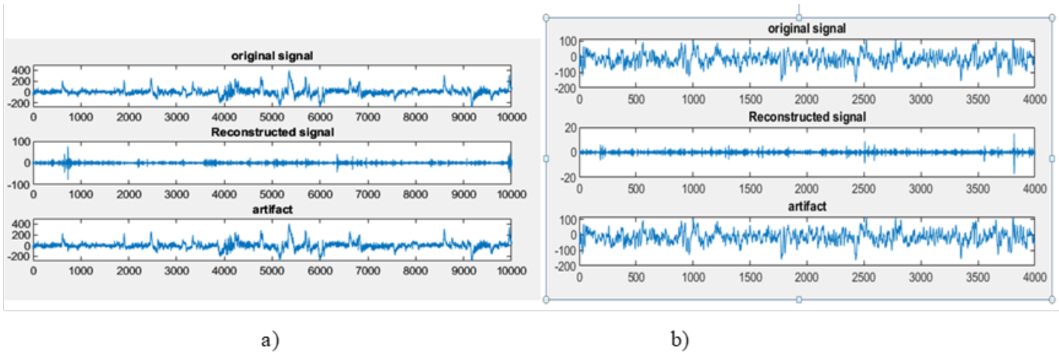


Fig 7. Waveform of EEG signal before and after de-noising for the HYBRID of EMD and ICA technique for a) CHB-MIT Database and b) BONN database

Crucially, these figures not only provide a visual testament to the success of the hybrid approach in artifact removal but also introduce a quantitative measure of performance improvement. The Signal-to-Noise Ratio (SNR) value, a vital performance parameter, experiences a noticeable increase. This enhancement in SNR reinforces the superior quality of the reconstructed signal, affirming a substantial reduction in artifacts and noise.

In summary, the figures vividly illustrate the benefits of the hybrid EMD-ICA technique in pre-processing EEG signals for both the CHB-MIT and BONN databases. The refined waveforms, characterized by diminished irregularities, signify the extraction of meaningful information from the EEG data, showcasing the potential of this innovative approach for enhanced signal quality and improved performance.

3.2 Performance evaluation

The suggested algorithm's effectiveness in removing artifacts has been assessed in terms of the degree of artifact reduction and the degree of distortion it introduces into the relevant signal, particularly in relation to seizure occurrences. A pre-defined reference channel, such as FCz or Cz, is present in many EEG caps. In order to quantify this assessment, the Cz channel is selected as the reference channel, and a number of efficiency measures have been computed in the time and spectral domains. Here is a description of the metrics[23]:

1. Signal-to-noise ratio (SNR): This might be thought of as the ratio of "everything you want to measure in your analysis" to "everything else picked up by the EEG signal." It is commonly given in decibels. SNR prior to de-noising the EEG signal is provided by,

$$SNR\_Before = 10log_{10}\left[\frac{\sigma^2{}_{Xref}}{\sigma^2{}_{ebr}}\right] \tag{6}$$

Where, $\sigma^2{}_{Xref}$ and $\sigma^2{}_{ebr}$ is the variance of reference signal and noisy signal before artifact removal. SNR after denoising EEG signal is given by,

$$SNR\_After = 10log_{10}\left[\frac{\sigma^2{}_{Xref}}{\sigma^2{}_{ear}}\right] \tag{7}$$

Where $\sigma^2{}_{ear}$ is the variance of signal before artifact removal. ΔSNR is the difference in SNR before and after artifact removal is given by the following formula,

$$\Delta SNR = 10log_{10}\left[\frac{\sigma^2{}_{Xref}}{\sigma^2{}_{ebr}}\right] - 10log_{10}\left[\frac{\sigma^2{}_{Xref}}{\sigma^2{}_{ear}}\right] \tag{8}$$

2. Peak SNR (PSNR): The fidelity of a signal's representation depends on the ratio between the maximum strength of the signal and the power of corrupting noise. The decibel scale is typically used to express PSNR as a logarithmic amount since many signals have a very wide dynamic range. It is stated as

$$PSNR = 10log_{10}\left[\frac{max^2}{MSE}\right] \tag{9}$$

Where, max is the maximum amplitude of the reference signal and MSE is the mean square error which is discussed below.

3. Mean Square Error (MSE): It calculates the average squared errors between the noisy signal and the reference signal prior to denoising the EEG signal, as well as the average squared errors between the denoised signal and the reference signal following denoising. Prior to denoising, MSE is provided by

$$MSE\_Before = \frac{1}{N}\sum\nolimits_{n=0}^{N-1}\left[X_{ref} - X_B\right]^2 \tag{10}$$

Where, N is total length of the signal, X_ref and X_B is the reference signal and the noisy signal respectively. MSE after denoising is given by,

$$MSE\_After = \frac{1}{N}\sum\nolimits_{n=0}^{N-1}\left[X_{ref} - X_A\right]^2 \tag{11}$$

Where, X_A is the estimated (denoised) signal.

4. Root Mean Square Error (RMSE): The EEG signal's square root represents the average square error between the noisy and reference signals prior to denoising, as well as the average square error between the denoised and reference signals following denoising. Prior to denoising, RMSE is provided by,

$$RMSE\_Before = \sqrt{\frac{1}{N}\sum\nolimits_{n=0}^{N-1}\left[X_{ref} - X_B\right]^2} \tag{12}$$

RMSE after denoising is given by,

$$RMSE\_After = \sqrt{\frac{1}{N}\sum\nolimits_{n=0}^{N-1}\left[X_{ref} - X_A\right]^2} \tag{13}$$

5. Spectral Distortion (SD): It's the ratio of the power spectral density of the noisy signal to the reference signal before denoising and after denoising the EEG signal to the reference signal after denoising. SD is supplied prior to denoising,

$$SD\_Before = \frac{\sum_{f=1}^{Fs/2}\left(P_B(f)\right)^2}{\sum_{f=1}^{Fs/2}\left(P_{ref}(f)\right)^2} \tag{14}$$

Where, Fs is the sampling frequency, $P_B(f)$ and $(P_{ref}(f)$ is the power spectral density of noisy signal and reference signal respectively.

3.3 Performance evaluation results and discussion

Certain techniques aim to reduce artifacts by limiting eye movements and blinking during the data gathering process or by eliminating trials that contain artifacts from the data analysis. Table 1 offers a thorough comparison of the aforementioned methods for the performance evaluation parameters of the two datasets comparing to the existed methods[20].

Table 1. Detailed comparisons between the mentioned techniques for CHB-MIT and BONN datasets compared with existing works

Dataset/Metrics	Existing techniques EMD and DFA (20)	CHB-MIT DATASET Proposed work results			BONN DATASET Proposed work results		
		EMD	ICA	HYBRID ICA+EMD	EMD	ICA	HYBRID ICA+EMD
SNR_Before	-10 (SNR input)	-14.039	-14.039	-14.039	-9.792	-9.792	-9.792
SNR_After	4.40101	-4.416	-0.061	-0.032	-4.439	-0.0303	-0.0141
ΔSNR	**9.60**	-9.622	-13.978	-14.006	-5.353	-9.762	-9.777

Continued on next page

Table 1 continued

PSNR_After	0.798324 (correlation)	17.71	19.892	19.907	13.874	16.079	16.087
MSE_Before		4163.18	4163.18	4163.18	2523.151	2523.151	2523.151
MSE_After	1.79867	1376.409	832.751	830.013	1247.384	750.673	749.272
RMSE_Before		64.523	64.523	64.523	50.231	50.231	50.231
RMSE_After	1.3411	37.099	28.86	28.81	35.318	27.398	27.373
SD_Before		66.008	66.008	66.008	7.798	7.798	7.798
SD_After		0.0081	0	0	0.691	0	0

Both dataset's performance measures are similar in that they use channel F7 to analyze both noisy and de-noised signals and use the same reference channel, Cz. Notably, all approaches have improved the Signal-to-Noise Ratio (SNR) and Peak Signal-to-Noise Ratio (PSNR), with ICA showing a more notable improvement for the BONN and CHB-MIT datasets. Additionally, the Standard Deviation (SD) is practically lowered to 0 for the ICA technique, and the Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) have decreased. When comparing individual ICA and EMD approaches to the Hybrid model (ICA + EMD), the former has shown better outcomes.

Analysis of execution time reveals that EMD outperforms other techniques, demonstrating shorter execution times, while ICA, being a more complex algorithm involving intricate mathematical computations, exhibits longer execution times. In contrast, EMD employs simpler approaches such as identifying maxima, minima, and calculating averages, making it less complex overall.

The existing literature highlights various authors who have incorporated artifact removal techniques, integrating this phase with subsequent epilepsy detection stages. However, it is noted that there is a lack of separate evaluations to determine the optimal process and technique. This article addresses this gap by quantifying the obtained results using performance parameters compared with the existed works.

Among the methods, Independent Component Analysis (ICA) stands out, delivering superior Signal-to-Noise Ratio (SNR). Empirical Mode Decomposition (EMD) exhibits weaker performance, but a hybrid ICA and EMD model proves formidable, excelling across multiple metrics. This research illuminates EEG signal processing intricacies and underscores hybrid approaches' potential for effective artifact removal, paving the way for enhanced neural signal analysis methodologies.

4 Conclusion

In conclusion, the analysis of EEG signals reveals persistent challenges despite diverse artifact elimination techniques. Internal interferences remain formidable obstacles, necessitating specialized methods. While simpler measures provide partial relief, the complexity of EEG signals requires advanced approaches. Evaluation of methods exposes a nuanced landscape of pros and cons, contributing to understanding EEG signal processing. The importance of suitable metrics for algorithm validation is emphasized, offering a comprehensive framework.

Future scope

Future research in EEG artifact reduction should explore advanced hybrid models, potentially incorporating machine learning techniques, to optimize artifact reduction further. The success of the hybrid ICA and EMD model suggests promising directions. Additionally, investigating real-time applications and adaptability to dynamic EEG recordings could enhance practical utility in dynamic environments or continuous monitoring.

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