

Research Paper: EEG Artifact Removal System for Depression Using a Hybrid Denoising Approach



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ABSTRACT

Introduction: Several computer-aided diagnosis systems for depression are suggested for use by clinicians to authorize the diagnosis. EEG may be used as an objective analysis tool for identifying depression in the initial stage to avoid it from reaching a severe and permanent state. However, artifact contamination reduces the accuracy in EEG signal processing systems.

Methods: This work proposes a novel denoising method based on Empirical Mode Decomposition (EMD) (with Detrended Fluctuation Analysis (DFA) and wavelet packet transform. Initially, real EEG recordings corresponding to depression patients are decomposed into various mode functions by applying EMD. Then, DFA is used as the mode selection criteria. Further Wavelet Packets Decomposition (WPD)-based evaluation is applied to extract the cleaner signal.

Results: Simulations were conducted on real EEG databases for depression to demonstrate the effects of the proposed techniques. To conclude the efficacy of the proposed technique, SNR and MAE were identified. The obtained results indicated improved signal-to-noise ratio and lower values of MAE for the combined EMD-DFA-WPD technique. Additionally, Random Forest and SVM (Support Vector Machine)-based classification revealed the improved accuracy of 98.51% and 98.10% for the proposed denoising technique. Whereas the accuracy of the EMD- DFA is 98.01% and 95.81% and EMD combined with DWT technique equaled 98.0% and 97.21% for the EMD- DFA technique for RF and SVM, respectively, compared to the proposed method. Furthermore, the classification performance for both classifiers was compared with and without denoising to highlight the effects of the proposed technique.

Conclusion: Proposed denoising system results in better classification of depressed and healthy individuals resulting in a better diagnosing system. These results can be further analyzed using other approaches as a solution to the mode mixing problem of the EMD approach.

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Highlights

- Several computer-aided systems are suggested for diagnosing depression.
- EEG may be used as an objective analysis tool for identifying depression.
- Denoising system proposed in this study results in better classification of depressed and healthy individuals.

Plain Language Summary

Depression is a major global burden. For years, EEG-based computer-aided systems were a powerful tool for detecting neurological disorders. However, advanced healthcare facilities based on EEG for identifying depression in the early stage are required to avoid a severe and irreversible state. Thus, preprocessing is an exclusively required step in EEG signal analysis. EEG is sensitive to certain irrelevant sources as well as artifacts, like EOG and EMG. Denoising describes the procedure of removing noise present in the signal. At first, a linear digital filter-based reduction of superimposed noise on the tracings of the EEG was proposed. Then, the efficiency of the regression analysis was demonstrated for single trials of ERP signals and the average potentials. Denoising system proposed in this study results in better classification of depressed and healthy individuals and the results can be further analyzed using other approaches.

1. Introduction

Depression is a major global burden among societies worldwide. EEG-based computer-aided systems were a powerful tool for detecting numerous neurological disorders.

Such systems have presented technical investigations concerning the neuroscience industry for exploring the neuronal mechanics underlying various symptoms of Depression (Acharya et al., 2015; Acharya et al., 2015; Cai et al., 2018; Sharma, Achuth, Deb, Puthankattil, & Acharya, 2018). Advanced healthcare facilities need to be designed using computational and mathematical methodologies based on EEG for identifying depression in the early stage to avoid a severe and irreversible state. Preprocessing is an exclusively required step in EEG signal analysis. The tentative measured signal can be represented as a linear combination of multiple brain events. EEG is sensitive to certain irrelevant sources as well as artifacts, like EOG (ocular artifacts), Electromyography (EMG) due to movement artifacts, and various other technical sources that interfere with the signal at particular scalp electrodeposition; thus, making control over the signal confused. Therefore, there is a necessity for preserving an adequate signal over the noise in biomedical applications (Kaur & Singh, 2015, 2016; Vaid, Singh, & Kaur, 2015).

Denoising describes the procedure of removing noise present in the signal. To challenge this problem, various algorithms were proposed, as shown in Figure 1. These include regression techniques (Awal, Mostafa, Ahmad, & Rashid, 2014; Wallstrom, Kass, Miller, Cohn, & Fox, 2004), autoregressive models (Hoffmann & Falkenstein,

2008), bandpass, and adaptive filtering, singular value decomposition, Kalman filtering, PCA, ICA and EMD (Barua & Begum, 2014; Cluitmans & Van De Velde, 2000; Molla, Tanaka, & Rutkowski, 2012).

In the initial years, a linear digital filter-based reduction of superimposed noise on the tracings of the EEG was proposed. Kalman filter was used as the optimal filter for removing the EMG noise. The performance of the filters is satisfactory; also from the clinical standpoint, obtaining a marked reduction of noise without distorting the useful information contained in the signal (Bartoli & Cerutti, 1983). Then, the efficiency of the regression analysis was demonstrated for single trials of ERP (Event-Related Potentials) signals and the average potentials (Semlitsch, Anderer, Schuster, & Presslich, 1986). In addition to providing the regression factors, it offers reduced coherence among the eye blink activity and ongoing EEG activity (Semlitsch et al., 1986).

The Blind Source Separation (BSS) algorithms, such as Principal Component Analysis (PCA) and Independent Component Analysis (ICA) were apparent as influential artifact removal methodologies. However, PCA and ICA have certain disadvantages, e.g., these fail to cope with high order statistical dependence. Moreover, these are inefficient for the removal of artifacts in case artifacts have the corresponding magnitude, like brain signals (Makeig, Bell, Jung, & Sejnowski, 1996). In our study, a BSS-SVM-based artifact removal method for removing the ocular and ECG artifacts was presented (Shoker, Sanei, & Chambers, 2005). Here, SOBI-based components were identified from the raw EEG, and SVM was used to

extract the features from these Independent Components (ICs). Then, a series of experiments on simulated EEG recordings for 5 different configurations of EEG electrodes found that SOBI is more effective than the other BSS-based algorithms for denoising (Kierkels, Van Boxtel, & Vogten, 2006; Kaur & Singh, 2016).

There is another technique of Wavelet Transform (WT)-based thresholding that provides more efficient multi-resolution exploration. It has been concluded to perform superior, compared to standard Low Pass Filters (LPF), median filters, and moving average filters (Lahmiri & Boukadoum, 2015). However, the limitation of Gibbs phenomena exists in WT. Additionally, other limitations of the wavelets include the manual setting of the level of decomposition and wavelet basis is needed that may add false harmonics as signals are nonlinear and non-stationary. The distortions might be introduced in the reconstructed signal that may be because of unsuitable breakdown, leading to less efficient denoising (Zeng, Song, Yan, & Qin, 2013). Discrete Wavelet Transform (DWT) was explored for ECG denoising for power line interference, the EMG, and the baseline drift (Alfoouri & Daqrouq, 2008).

The limitations in wavelet are overlapping spectrum and ICA are lacking redundancy in the number of signals, compared to sources. A large body of literature was conducted taking a combination of various techniques using wavelets and ICA methods; accordingly, they reported the best performance for removing artifacts along with preserving the nominal data loss (Alfoouri & Daqrouq, 2008; Ghandeharion & Erfanian, 2010). Wavelet-Based thresholding is applied to demixed ICs rather than on the raw EEG data (Nazarpour, Wongsawat, Sanei, Chambers, & Oraintara, 2008). A more robust technique was offered to combine Wavelet and ICA without the need to identify the thresholds (Ghandeharion & Erfanian, 2010).

Another transform was growing for the applications of denoising, Empirical Mode Decomposition (EMD). The main advantage of EMD is no need to postulate the mother wavelet and the level of decomposition, compared to WT. EMD was successful for the removal of fractional and white Gaussian noise. However, it has the limitation of mode-mixing. Another restriction of EMD is in defining the stopping conditions of the sifting procedure (Mert & Akan, 2014; Zeng, Song, Yan, & Qin 2013). As a result, hybrid techniques, like EMD with wavelet thresholding and EMD-ICA, etc. were reported in the literature. For example, a study discovered a new technique where a noisy signal was decomposed using EMD then DWT thresholding was followed (Kabir &

Shahnaz, 2012). Noise-Free Intrinsic Mode Functions (IMFs) and the residue were added to regenerate the signal. This leaves scope for additional upgrading. Like EMD, an unweighted summation of IMFs filtered after DWT thresholding may overlook the capability of carrying different structural information (Kabir & Shahnaz, 2012). The frequency and the effect of the decomposed signal decrease with an increase in the mode of IMF. Besides, residue contains a little bit of signal information; thus, adding it in the reconstructive step adds slight to the process of artifact removal.

Another finding proposed BSS-EMD based method to recover the loss of information. However, again, such performance is limited by dependence on the quality of ICA-separated ICs. Therefore, another study that used SSSA as a BSS algorithm along with EMD provided better results (Zeng et al., 2013). Mert et al. introduced Detrended Fluctuation Analysis (DFA) as stopping criteria for determining noisy IMFs obtained by EMD (Mert & Akan, 2014). Safieddine et al. proposed a comparison between deterministic (EMD & wavelet approaches) and stochastic (ICA & cross-correlation analysis, i.e., CCA) approaches which concluded that 2T-EMD should be preferred for denoising for lower SNR data (Safieddine et al., 2012).

Bono, Jamal, Das, and Maharatna (2014) introduced two-hybrid techniques of Wavelet Packet Transform (WPT)-ICA and WPT-EMD. Another study provided the comparison of EMD, WT, and Kalman filters (Salis et al., 2013).

A critical review of some of the existing systems for NFT is provided in Table 1. Several artifact removal techniques were presented. Regression-Based techniques were supported for denoising; however, they are limited by the disadvantage of bidirectional contamination. As a solution to the problem of bidirectional contamination, low pass filtering and adaptive filters were offered before applying the regression (Croft & Barry, 2000; Munia, Haider, Schneider, Romanick, & Fazel-Rezai, 2017; Salis et al., 2013; Suchetha & Kumaravel, 2013) our scope was a comparative analysis of the performance of three standard denoising methods like continuous Empirical Mode Decomposition (EMD). However, adaptive filters require defining reference techniques for modeling. Then, PCA found a growing attraction concerning denoising; however, in the case of approximately, the same magnitude with the brain signal of interest, more reliable algorithms of ICA were recognized as providing major contribution compared to PCA. Artfactual ICs identification in the case of ICA was considered in numerous investigations. To cover up these issues of artfactual ICs,

Table 1. A comparative analysis of existing EEG denoising methods

References	Method	Physiological Signals	Outcome
DiMatteo, Genovese and Kass (2001)	B- splines before applying regression and subspace projection	fMRI Image	Provides better results The problem of defining a reference prototype
Wallstrom et al. (2004)	Regression-based and PCA, ICA component-based methods	EEG	Using the adaptive filter, the performance of regression-based artifact correction improves. PCA proved to be effective in denoising the EEG signal with minimum spectral distortion Limitation of spectral distortion from ICA-based correction procedures and bidirectional contamination
Shoker et al. (2005)	BSS- SVM	EEG	Efficient Denoising
Kierkels et al. (2006)	BSS algorithms	EEG	SOBI effective than other BSS algorithms
Castellanos and Makarov (2006)	wICA	EEG	Conserves both spectral as well as coherence characteristics unlike ICA leading to overestimation of power spectrum and underestimation of coherence property
Phlypo et al. (2007)	JSSE	EEG	Reducing the distortion and interference of the artifacts than FastICA, SOBI, and JADE algorithms The problem of spectral distortion by ICA
Alfoouri and Daqrouq (2008)	DWT	ECG	Better SNR and MSE The limitations of Gibbs phenomena, adding false harmonics and less efficient denoising
Nazarpour et al. (2008)	Robust minimum variance beamformer (RMVB)	EEG	Low cost and more effective
Wu and Huang (2009)	EEMD	Noise assisted Data	More accurate Lack of mathematical formulation
Ghandeharion and Erfanian (2010)	Mutual information with ICA and wavelet denoising	EEG	No need to define the threshold values or offline training
Suchetha and Kumaravel (2013)	EMD	ECG	Beter than adaptive filtering Mode- mixing problem
Bono et al. (2014)	WPT- ICA & WPT- EMD	EEG	Suitable for artifact removal without any proper information about the artifacts
Mert and Akan (2014)	EMD- DFA	-	Efficient at low SNR values
Aneesh et al. (2015)	VMD	Power quality signal	Efficient denoising More accurate
Kærgaard et al. (2016)	EEMD-BLMS and DWT-NN	ECG	Efficient denoising
Liu et al. (2017)	VMD	Seismic Data	More robust and well- defined time- domain analysis The problem of defining the procedure of selection of modes

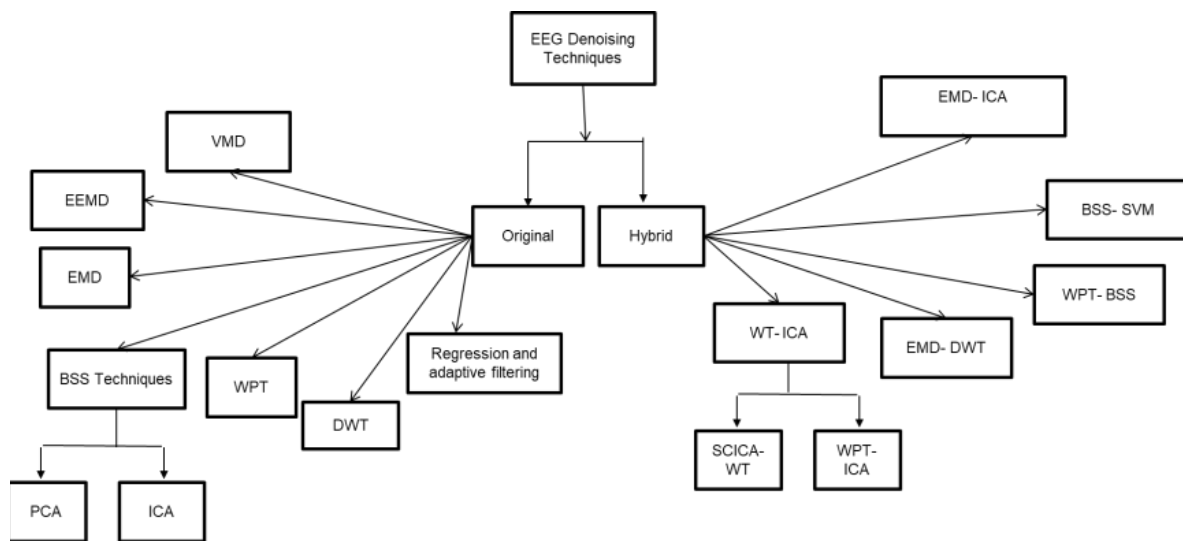


Figure 1. Existing denoising algorithms

wavelet transforms were offered. Another recent denoising methodology of EMD has been proposed afterward. In previous studies, using EMD inspired by wavelet transforms, ignoring various IMFs after wavelet-based thresholding could lead to ignoring information carrying the capacity of IMFs leading to inefficient denoising results. This work focuses on the performance comparison of EMD using DFA followed by WPD to denoise the EEG data with the conventional approaches; it was found more efficient than conventional approaches. A new classification method based on EMD and WPT was implemented. To assess the performance of the proposed algorithm, depression patients and normal individuals were classified using SVM and Random Forest.

Empirical mode decomposition

EMD is a recursive process of breaking down a signal into the sum of various finite intrinsic oscillatory functions called IMFs (Intrinsic Mode Functions), i.e., empirically identified based on their feature time scales in

the signal. A signal $S(t)$ can be represented as a finite sum of IMFs as in Equation (1).

$$(1) S(t) = \sum_{k=1}^N s_k(t)$$

We define IMF as an AM-FM (amplitude modulation-frequency modulation) function written as Equation (2)

$$(2) s_k(t) = S_k(t) \cos \phi_k(t) \quad S_k(t), \phi_k'(t) > 0 \quad \forall t$$

It is assumed here that $\phi_k'(t)$ and $S_k(t)$ are varying lower than. The s_k IMF executes as a harmonic component. The algorithm is easily adjustable and the original function's nonstationary part can be extracted. The stopping criteria are defined by a process called sifting that is carried out in the following steps (Kabir & Shahnaz, 2012; Kiamini, Alirezace, Perseh, & Ahmadi, 2009; Krupa, Mohd Ali, & Zahedi, 2009).

- Local maxima and local minima are defined from the input signal. Then, using the cubic spline line method, upper and lower envelopes were identified.

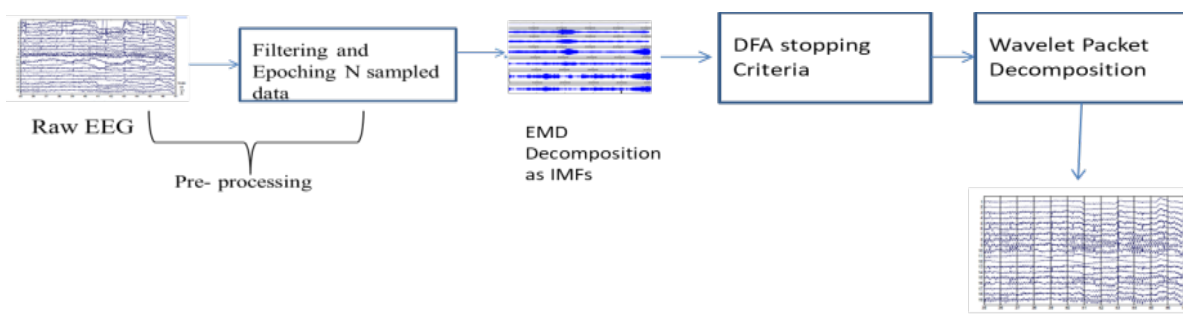


Figure 2. The flowchart of the proposed methodology

Table 2. Comparing the proposed denoising techniques with the conventional respecting SNR and MAE corresponding to different levels of white Gaussian noise

Variables	Denoising Method	$\sigma=0$ dB	$\sigma=5$ dB	$\sigma=10$ dB	$\sigma=15$ dB	$\sigma=20$ dB
SNR	DWT	4.20	5.1492	10.18	15.82	20.12
	EMD only	4.21	5.03	12.32	15.34	21.29
	EMD- DWT	1.23	5.944	12.04	16.582	22.583
	EMD-DFA- WPD	20.24	18.54	18.04	16.29	17.06
MAE	DWT	13.7209	45.492	101.18	115.82	202.12
	EMD only	13.6731	45.03	101.32	115.34	202.29
	EMD- DWT	13.23	44.944	101.04	116.582	202.583
	EMD-DFA- WPD	12.24	44.04	100.04	115.89	203.06

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- Take the average of an envelope to mean denoted as $h(t)$. Subtract the input signal and the envelope mean and denote it as the first IMF if it satisfies the two conditions defined above to be met by IMFs. Else, take it as the next input for carrying the next iteration process to find the next IMF.

- Repeat the above steps until a stopping criterion is met.

Wavelet packet decomposition

It has lately come into view in different field applications as a new helpful means for signal processing. WPT is the comprehensive structure of DWT. The standard wavelet transform is limited to wavelet bases that move towards the lower frequencies by a power of 2. Thus, it might not be able to give the finest results. However, some other combination of bases might give better desirable results. Discrete wavelet transform gives approximate transformation to the sampled or discrete signals. In the case of WPD, the sampling of low pass and high

pass coefficients is conducted to attain $d[n]$ and $a[n]$ as detail and approximate coefficients. This recursive process is performed with approximate coefficients till a preferred level of decomposition is attained. Wavelet packet decomposition was used in various applications related to emotion recognition in Brain-Computer Interface (BCI) applications. The technique of wavelet packet decomposition provided better results, compared to other existing methods in the terms of accuracy in the space time-frequency domain.

2. Methods

The main aim of this work was to perform decomposition of EEG signal into IMFs by using DFA-based stopping criteria. Then, these IMFs are further analyzed using wavelet packet decomposition. Finally reconstructed signal is analyzed for performance (Figure 2). For the present study, a real EEG dataset prepared by Hospital Universiti Sains Malaysia (HUSM), Kelantan, Malaysia was analyzed. It contains EEG signals of 34 MDD (Major Depressive Disorder) patients and 30 healthy

Table 3. The statistical analysis of SNR, MAE between the reconstructed and original signal between different approaches

EEG Spectral Measure	ANOVA		t-test	
	P	P1	P2	P3
SNR	0.03	<0.001	<0.001	<0.001
MAE	0.01	<0.001	<0.001	<0.001

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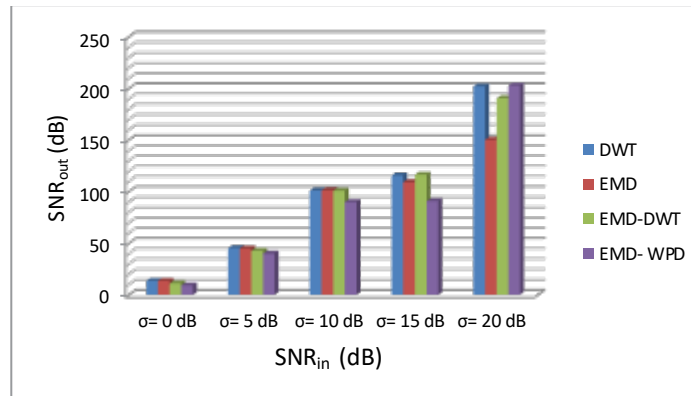


Figure 3. The variation of SNR at the output corresponding to different levels of white Gaussian noise

subjects. The sampling rate of data is 256 Hz (Mumtaz, Xia, Yasin, Ali, & Malik, 2017).

For performing the analysis, various values of signal-to-noise ratio are considered by adding the white Gaussian noise to the recorded signal. The additive white Gaussian noise is a basic prototype to present the behavior of naturally occurring random processes having the same intensity at various frequencies. First of all, the decomposed IMFs were selected according to scores defined by DFA. Then, the thresholded IMFs are further decomposed using WPD. Next, these wavelet denoised components are combined with selected IMFs to give the final output signal. To conclude the efficacy of the proposed technique, Signal to Noise Ratio (SNR) and Mean Absolute Error (MAE) were identified at different levels of added white Gaussian noise. If $y(t)$ is the original input signal and $\hat{y}(t)$ is the denoised signal with sampling number represented as T .

SNR, a term encountered in signal processing, is an essential element in describing the quality of the neural information processed from the raw EEG signals. It is frequently used to assess the performance of various physiological systems, to compare and estimate denois-

ing protocols, and to monitor the overall performance of the system. It is defined as the ratio of the related signal divided by the level of the noise. Here, the signal is the amplitude of the EEG signal and the noise is the residual unwanted background activity in the EEG signal that distorts the signal. Thus, SNR in decibels is defined by Equation (3):

$$(3) SNR_{Out} = 10 \log_{10} \left\{ \frac{\sum_{t=1}^T [y(t)]^2}{\sum_{t=1}^T [y(t) - \hat{y}(t)]^2} \right\}$$

MAE is used similar to MSE to evaluate the denoising algorithm. MAE is the maximum value of the absolute error signal. It is also defined by using the aforementioned symbols as the Equation (4):

$$(4) MAE = \frac{\sum_{t=1}^T |y(t) - \hat{y}(t)|}{T}$$

Feature Extraction and Classification: For validation purposes, three features namely, Mean, Shannon entropy, and Hjorth parameter widely used in studies related to depression detection (Castellanos & Makarov, 2006; Phlypo, Boon, D'Asseler, & Lemahieu, 2007) followed by rejection of those deemed artificial. We show that a "leak" of cerebral activity of interest into components marked as artificial means that one is going to lost that

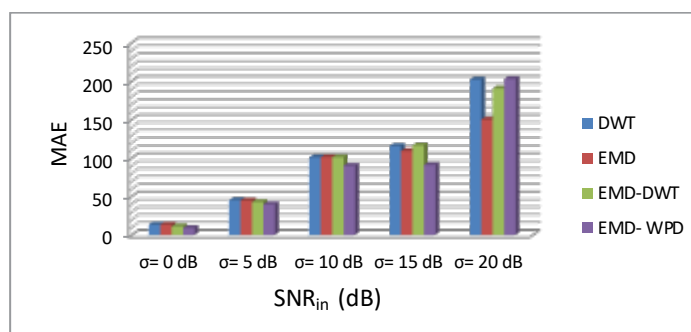


Figure 4. The variation of MAE at the output corresponding to different levels of white Gaussian noise

Table 4. Accuracy evaluation of different denoising techniques using random forest and SVM based classification

Techniques	Random Forest		SVM	
	F1 Score	Accuracy (%)	F1 Score	Accuracy (%)
DWT	94.29	97.8	93.9	94.09
WPT	92.7	96.7	90.1	94.7
EMD- DFA	91.07	98.0	90.83	97.21
EMD-DWT	96.83	98.01	93.89	95.81
EMD-DFA-WPD	97.81	98.51	94.37	98.07

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activity. To overcome this problem we propose a novel wavelet enhanced ICA method (wICA) were measured from the denoised signals. These features are briefly described as follows:

Mean

This time-domain feature is represented as the central point corresponding to a set of data points. If $x(t)$ represents the data with T samples, the mean is defined as Equation (5):

$$(5) \mu = \frac{1}{T} \sum_{t=1}^T |x(t)|^2$$

Another time-domain feature termed as Hjorth Parameters is defined using statistical calculations. It consists of three parameters namely, activity, mobility, and complexity.

Activity (A): It is defined as Equation (6):

$$(6) A = \frac{\sum_{t=1}^T ((x(t) - \mu)^2)}{T}$$

Mobility (M): If the derivative of $x(t)$ is $X(t)$, then mobility is given by Equation (7)

$$(7) M = \frac{\sqrt{X(t)}}{\sqrt{x(t)}}$$

Complexity(C): It is defined as Equation (8)

$$(8) C = \frac{M(X(t))}{M(x(t))}$$

Shannon Entropy: It is the measurement of uncertainty or probability p of the signal value and is defined by Equation (9) as

$$(9) E = -\sum_{t=1}^T p \log(p)$$

Classification: In this research work, Random Forest (RF) and Support Vector Machine (SVM) classifiers were used for classifying signals into depressed and healthy individuals.

The RF classifier is more accurate in generating the classification results even in the presence of noise. Other advantages of using this algorithm are higher operational efficiency which makes it more efficient for training on the EEG data. The RF classifier being the ensemble algorithm selects a random subset of a training set and generates a set of decision trees. Then, these decision trees are used to create the final test class.

SVM makes use of an assumed space in the form of linear functions based on optimization theory. It acts as a learning system that provides the best hyperplane acting as a separator between two classes of the input space. This system defines margin as the distance among hyperplane and adjoining array (known as support vector)

Table 5. Classification performance, compared with and without Denoising using Random Forest and SVM-based classification

Classifier Performance	Without Denoising (%)	Denoising Using Proposed Technique (%)
RF	96.98	98.51
SVM	94.83	98.07

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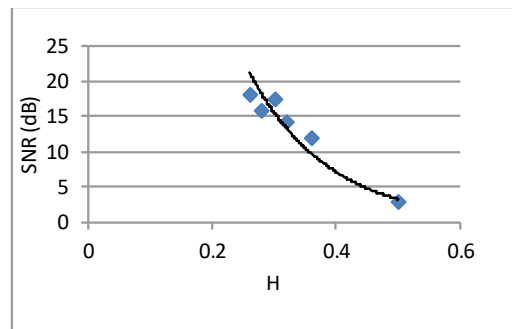


Figure 5. The variation of SNR at different values of H

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of each class. The learning in SVM involves the power to trace the hyperplane.

To evaluate the performance of the denoising system for EEG signals of depression patients, the classification results are analyzed for these two classifiers. The results using various classifiers and the output are classified as depressed and normal. The parametric evaluation is conducted by calculating the classification accuracy and F1 score. Classification accuracy is defined as the number of accurate estimates made divided by the overall estimates made. More is the classification accuracy; more precise is the proposed system. Accuracy is measured by another metric known as the F1 score, i.e., calculated from precision and recall. A single value is assigned by calculating the harmonic mean from these two attributes. The F1 score was calculated along with the accuracy for this unbalanced class.

To better correlate the results, and to assess the performance of the proposed algorithm, statistical analysis using Repeated-Measures Analysis of Variance (RM-ANOVA) and a t-test analysis was performed on the denoising results. This statistical analysis was performed to check whether the proposed method outperforms other methods with the value of significance set at $\alpha=0.05$. The significant differences among the techniques were evaluated using SNR and MAE as the dependent variable. The statistics were calculated for these two variables among the artifactual signals and the denoised signals.

3. Results

EEG signals with varying values of SNRs present that higher values of SNR and lower values of MAE are observed for the presented work. It indicates EMD-DFA-WPD is a better denoising algorithm. Table 2 concludes the SNR and MAE values of the techniques for different SNR levels of white Gaussian noise denoted as σ .

The obtained results indicated improved signal-to-noise ratio and lower values of MAE for the combined EMD-DFA-WPD technique, compared to EMD, DWT, and EMD with DWT technique (Figures 3 & 4). EMD performs better than wavelet technique for lower SNR levels; however, EMD-DFA-WPD is providing higher SNR and lowest MAE than all the conventional techniques although its performance is better for lower levels of white Gaussian noise.

Furthermore, EMD is applied along with DFA with a value of Hurst exponent H for white Gaussian noise. The value of the Hurst exponent is defined accordingly and adjusted for analysis. The parameter α known as the scaling exponent represents the roughness of the series. Higher values of α represent smooth time series i.e., slow fluctuations (Mert & Akan, 2014). EMD based denoising requires a reliable threshold to determine which oscillations called intrinsic mode functions (IMFs). DFA slope $\alpha=0.5$, $\alpha=1.0$, and $\alpha=1.5$ depending upon the type of noise to be white Gaussian noise, pink or Brownian noise respectively. To cope-up with the problem of mode-mixing, the value of the scaling exponent was set to be 0.75. The value of the Hurst exponent varies as 10.5, 1.0, and 1.5 for white Gaussian noise, pink, and Brownian noise. Figure 5 plots the performance of the proposed algorithm for different values of H demonstrating better performance at 0.37.

Table 3 lists the statistical analysis data to assess the performance of the proposed algorithm. The RM-ANOVA results revealed that the proposed algorithm outperforms at $P<0.001$. Additionally, t-test analysis provided the comparison of parameters where p1 represents EMD-DFA-WPD vs. DWT, p2 represents EMD-DFA-WPD vs. EMD, p3 represents EMD-DFA-WPD vs. EMD-DWT. It concludes that the algorithm performs best compared to other algorithms. Better classification results are obtained for the proposed methodology. RF and SVM classifiers were used to assess the accuracy (Table 4). The best accu-

accuracy of 98.51% is achieved for RF and 98.07% for SVM for EMD-DFA-WPD than other approaches. EMD-DWT gives 98.01% and 95.81% accuracy values for RF and SVM. Additionally, the best F1 score values were observed for the proposed technique compared to the other conventional approaches. Moreover, the classification performance for both the classifiers was compared with and without denoising to highlight the effectiveness of the proposed technique (Table 5).

Although the proposed method yields better suppression of artifacts respecting the evaluation parameters of SNR for different values of white Gaussian noise added at different values of noise along with better classification results. Besides, more efficient algorithms can be developed by increasing the levels of decompositions. Furthermore, EMD lacks mathematical formulation and the mode-mixing problem. As a solution, various newer techniques were offered. Therefore, this analysis can be extended for analyzing other levels of decompositions. Moreover, more efficient algorithms than EMD, such as MEMD, EEMD, and VMD (Aneesh, Kumar, Hisham, & Soman, 2015; Kærgaard, Jensen, & Puthusserypady, 2016; Liu, Cao, & Wang, 2017; Molla et al., 2012). We propose to utilize recently developed a multivariate extension of Empirical Mode Decomposition (EMD can be used for further analysis to eliminate the mode mixing problem).

4. Discussion

There is a need to separate raw EEG signals from various noise sources using an appropriate artifact removal algorithm, leading to minimal neural information loss. Furthermore, there is insufficient evidence of denoising systems for EEG signals of depression patients. We addressed an approach for suppressing artifacts that imposes a challenge to the common preprocessing techniques in EEG processing systems corresponding to depression patients. The present study aimed to develop a reliable EEG preprocessing phase of removing the noise present in EEG signals of depression patients. The removal of these most common noise sources is critical to improving the performance of the EEG-based diagnosing systems for depression. EMD is gaining great success in the field of signal processing. In previous studies using EMD inspired by wavelet transforms, ignoring various IMFs after wavelet-based thresholding could lead to ignoring information carrying the capacity of IMFs leading to inefficient denoising results. In this paper, a denoising model was proposed for EEG signals using hybrid technique EMD and WPD, where the IMF selection criteria in EMD are identified by the DFA algorithm. Unlike the conventional EMD-based EEG denoising ap-

proaches that neglect multiple IMFs containing noise as well as neural information, we proposed to perform a windowing in the EMD domain to reduce the noise from a few IMFs, yielding a comparatively cleaner EEG signal. Compared to other conventional methodologies, the proposed method provides better SNR.

5. Conclusion

A new classification method based on EMD and wavelet packet transform was used. To assess the performance of the proposed algorithm, depression patients and healthy individuals were classified using SVM and Random Forest. Better accuracy is observed for the observed technique than the other approaches. In the future, more efficient algorithms can be developed by increasing the levels of decompositions and considering other partially variational algorithms to decrease the problem of mode mixing by EMD.

Ethical Considerations

Compliance with ethical guidelines

There were no ethical considerations to be considered in this research.

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Authors' contributions

All authors equally contributed to preparing this article.

Conflict of interest

The authors declared no conflicts of interest.

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