Denoising of Motion Artifacts in EEG Signals using DWT-EMD Approach

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Denoising of motion artifacts in EEG signals using DWT-EMD approach

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Abstract—Surface Electroencephalography (EEG) is a non-invasive technique used for monitoring and recording the electrical activity of the human brain. Typically, the raw and unprocessed EEG signals are contaminated with various types of physiological artifacts originated from eye blinks and limb movements due to long haul monitoring. The removal of such low frequency motion artifacts in preprocessing techniques could potentially improve the accuracy of diagnosis. In this viewpoint, a multi-resolution analysis such as discrete wavelet transform (DWT) with empirical mode decomposition (EMD) is presented to filter the motion artifacts from the EEG signal. Initially, the low frequency components were separated from EEG signal using DWT decomposition technique and the same are passed to EMD to find intrinsic mode functions (IMFs). Using iterative thresholding algorithm the noisy IMF's are filtered out, and these denoised approximated components are utilized to reconstruct the motion artifact free EEG signal. The proposed technique shows 15.3218 dB of Δ SNR, 41.9859% of Relative root mean square error (RRMSE) and the percentage reduction in correlation coefficient (% η) of 65.8213 by using Physionet data base.

Keywords—EEG signal denoising, DWT, EMD, Interval Thresholding, Δ SNR, RRMSE, correlation coefficient.

1. INTRODUCTION

The surface electroencephalography (EEG) is a low-cost, non-invasive technique used for analyzing the electrical activity of human brain. Typically in clinical research, EEG recordings are preferable due to its high temporal resolution and portability in comparison to contemporary and high cost involved scanning techniques such as CT and MRI for detection and brain diseases such as Alzheimer's disease, epileptic activity, depression, dementia, sleep disorders, and schizophrenia [1]. The EEG records are typically obtained by positioning several surface electrodes on the human scalp using the International standard 10-20 system [2]. Usually, the recorded EEG signals contain different types of physiological and non-physiological artifacts [3]. Unlike, the well-defined physiological artifacts originated from ocular, respiratory and cardiac movements, motion artifacts arising from body movements attributed to head movement, hand movement, talking and chewing are absolutely random and posing challenges in filtering them from EEG signal. Despite the advantages offered by wireless EEG recording systems, the dry contact electrodes and the high degree of freedom in body movements are mostly responsible for motion artifacts in long haul monitoring [4]. The detection and elimination of motion artifacts is essential however challenging to study the EEG signals for better diagnosis.

In literature, various methods such as Empirical mode decomposition (EMD) techniques [5][6], Discrete wavelet transform (DWT) based techniques [9], and singular spectrum analysis (SSA) methods [10] have been applied to suppress the motion artifacts from the noised-EEG signals. Along with the above mentioned, several hybridization techniques such as canonical correlation analysis (CCA) with multi-channel linear prediction (MLP), EMD with CCA, EMD with independent component analysis (ICA), EEMD with ICA (EEMD-ICA) [7], and EEMD with CCA (EEMD-CCA) [9] are also proposed to remove the motion artifacts from the EEG signal. However, the CCA with MLP method proposed failed to remove motion artifacts from the recorded EEG signal due to the linear dependencies of MLP method [8]. Despite the fact of low computational load, the requirements of additional channels in adaptive filtering methods and errors in estimation of modal parameters in Kalman filtering methods are potential drawbacks in achieving better SNR and correlation improvement in motion artifact EEG signals. It is also observed that the EEMD-ICA hybrid algorithm removes the motion artifacts from EEG and show 8.9 dB and 76.5% SNR and correlation improvement respectively [7]. A similar hybrid approach such as a combination of EEMD with CCA is proved to give rise similar results when compared with EEMD-ICA and Wavelet based hybrid algorithms [9]. In comparison with computational intense EEMD based algorithm modified singular spectrum analysis (SSA) technique show better results in terms of improved Δ SNR and % η of 0.91507dB and 11.388 respectively. Despite of 6-times reduced complexity when compared with EEMD-CCA, The SSA method shows negligible improvement in SNR [10]. Further to address the low improvement in SNR limitation in SSA method, a modified grouping method is presented and achieved 12.97dB and 58.23% of SNR and RRMSE respectively. However, performance of the Grouped SSA algorithm depends on the proper selection of percentage of overlapped segments [11]. One of the recent works carried out

by V. Bono et.al, 2016 presented a Hybrid wavelet and EMD approach with commercially available 19-channel pervasive EEG system Enobio corrupted by eight types of artifacts [12]. It is observed that the WPTMD performance metrics consist of RMSE and SNR are show similar results when compared to WPTICA and FASTER methods for real-time data however show better results in RMSE for the semi simulated data. Hence it is believed that WPTMD algorithm is capable of realizing better RMSE.

In this paper instead of taking WPT, DWT is tested due to the low computational intensity and also the fact that mostly the low frequency motion artifacts sub-band will be decomposed to approximation coefficients only. Since the decomposition of detailed coefficients can be avoided to minimize the computational time. Furthermore, the low band signal is passed through EMD with appropriate threshold technique to remove the motion artifacts.

2. METHODOLOGY

In this section the detailed process flow in elimination of motion artifacts from the noised EEG signal is explained. Initially, in the first subsection 2.1, the implemented database for evaluation of the performance of the proposed methodology has been discussed and followed by the second subsection 2.2 discussed about the process flow of proposed DWT-EMD methodology.

2.1 EEG Database

The publicly available EEG dataset from the Physionet database [13][14] is considered to evaluate the performance of the proposed method. This database consist of 3 male and 2 female (Average age: 27) healthy subjects EEG recordings. The EEG signals from the two channels are collected from the frontal cortex from positions FPz and FP1h. The EEG recordings of two channels were labeled as channel 1, free from artifacts and channel 2, contaminated with motion artifacts. The dataset included 23 trails and each trail was 9 minutes long with motion induced by repeatedly disturbing the channel 2 electrode at a two minute interval. The acceleration and EEG signal sampling frequencies between 200 Hz and 2048 Hz respectively.

2.2 Proposed DWT-EMD methodology

There is a low frequency drift observed in the recorded artifact and ground truth signals as shown in the Fig. 1A. Hence, passed through second order Butterworth high-pass filter of cutoff frequency 0.5 Hz due to the fact that the second order Butterworth possesses monotonic frequency response in pass-band region. The drift corrected signals are presented in Fig. 1B which is a 10 min record and the Fig. 1C represents the artifact portion from 193 seconds to 209 seconds. The ground truth and motion artifact EEG signals are recorded from the frontal cortex of all trails while eyes are closed [10].

Fig. 1: A. Motion artifact and Ground truth EEG signals after passing through a low pass filter with cutoff frequency (0.5Hz). B. A portion of Motion artifact and Ground truth EEG signal with presence of artifact.

Further to remove motion artifact, the proposed method effectively combines the DWT and EMD as shown in Fig. 2. The DWT was applied to the artifact EEG signal and decomposed into approximation and detailed sub-bands. Subsequently, the EMD method finds a set of IMFs by decomposing the approximation band coefficients. Among the IMFs, the relevant IMFs contain significant information with low frequency noise are selected. In order to remove the noise components, the selected IMFs are threshold using the interval thresholding method. This method finds the extreme in the interval between two adjacent zero crossings of the IMF and were threshold. The threshold IMFs are added with the signal IMFs. The IDWT was applied to the detailed sub-bands and the filtered IMFs to produce the denoised signal. The performance of the proposed method is assessed with various distortion measures like Δ SNR, RRMSE and percentage reduction in correlation coefficient ($\% \eta$). Each component description of this scheme was explained in detail in the subsequent subsections.

Fig. 2: The block diagram of proposed motion artifact denoising method with DWT-EMD with process flow

2.2.1. Wavelet analysis of EEG signals

The multiresolution analysis [15] is described as the decomposition and reconstruction of a signal with a pair of scaling function and wavelet function. The DWT is a multiresolution analysis, which comprises the time domain representation of a signal $x(t)$ that decomposes the time domain representation of a signal $x(t)$ into a number of time-shifted and scaled versions of a selected mother wavelet. In this work, we have used ‘bior1.5’ [16] mother wavelet and the EEG signal is decomposed into single level sub-bands. The scaling and the wavelet functions [17][18] are given in (1) and (2) respectively.

$$\phi_{l,k}(n) = 2^{-l/2} \phi(2^{-l}n - k) \quad (1)$$

$$\psi_{l,k}(n) = 2^{-l/2} \psi(2^{-l}n - k) \quad (2)$$

The approximation band and detailed coefficients of each sub-band are evaluated using the mathematical expressions are expressed in (3) and (4).

$$cA_L(k) = \sum_{n=-\infty}^{\infty} x(n) \left[2^{-L/2} \phi(2^{-L}n - k) \right] \quad (3)$$

$$cD_L(k) = \sum_{n=-\infty}^{\infty} x(n) \left[2^{-l/2} \psi(2^{-l}n - k) \right] \quad (4)$$

where, l represents the level of decomposition (1, 2, . . . , L), ‘ n ’ is sample number (1, 2, . . . , N) and ‘ N ’ is the length of the signal and of the EEG signal. The original signal is reconstructed by adding up all the detailed coefficients of each subband and the approximation coefficients of the last subband. The mathematical expressions for the computation of the reconstructed approximation sub-band signal given in (5) and reconstructed detailed sub-band wavelet coefficients given in (6). The mathematical expression for the reconstruction of EEG signal from the approximation and detailed sub-bands is expressed in (7).

$$\bar{x}_A(n) = \sum_{k=-\infty}^{\infty} cA_L(k) \phi_{l,k}(n) \quad (5)$$

$$\bar{x}_{D_l}(n) = \sum_{k=-\infty}^{\infty} cD_L(k) \psi_{l,k}(n) \quad (6)$$

$$\bar{x}(n) = \bar{x}_A(n) + \sum_{l=1}^L \bar{x}_{D_l}(n) \quad (7)$$

Along with DWT process, it is tested for various thresholding methods such as Hard thresholding [19] and Soft thresholding [20] to know the impact on Δ SNR, RRMSE and % η on all 23 trails of EEG signals. The equation (8) represents the hard thresholding function and subsequently the equation (9) describes the soft thresholding function.

$$\bar{w}_{j,k} = \begin{cases} w_{j,k} ; & |w_{j,k}| \geq T \\ 0 & ; |w_{j,k}| < T \end{cases} \quad (8)$$

$$\bar{w}_{j,k} = \begin{cases} \text{sgn}(w_{j,k})(|w_{j,k}| - T) & ; |w_{j,k}| \geq T \\ 0 & ; |w_{j,k}| < T \end{cases} \quad (9)$$

The hard thresholding function retains the coefficient values as either $w_{j,k}$ or zero, depending upon the values of $|w_{j,k}| \geq T$ and $|w_{j,k}| < T$ respectively. The soft thresholding function retains the coefficient values as either the difference between absolute value of coefficient and threshold value with sign of its coefficient or zero, depending upon the values of $|w_{j,k}| \geq T$ and $|w_{j,k}| < T$ respectively.

2.2.2. Empirical Mode Decomposition

EMD was introduced by Huang [5]. It is used for denoising nonlinear and non-stationary signals. It decomposes the signal into several IMFs that contain signal and noise components. However, IMFs should follow the constraints as (i) The maxima and zero crossing numbers should be either equal or differ at most by one and (ii) The average number of the envelope is stated with the help of maxima and minima. This value should be zero. The following steps need to execute the sifting process [21]:

1. Identify the local maxima and minima of $x(t)$.
2. Using cubic spline interpolation, calculate the upper and lower envelopes.
3. Compute the average of the envelopes, $m(t)$
4. Update the revised IMFs, $h_i(t)$
5. Calculate the residue $r(t) = x(t) - h_i(t)$
6. Run the procedure from step 1 to 5 till required condition is satisfied.

The result of the sifting process is splitting $x(t)$ into IMFs and a residue signal. The original signal $x(t)$ can be reconstructed by adding the IMFs and residue signal which is given in (10).

$$x(t) = \sum_{i=1}^N h_i(t) + r_N(t) \quad (10)$$

The IMFs of the noisy signal obtained through EMD are presented in Fig. 3. The IMFs are representing the frequency components in reciprocal order where the increase in IMF index consists of the low frequency components and vice-versa. In this study, all the trails have resulted in 10 IMFs and the most significant artifact information are appeared from IMF5 and above. In order to eliminate the low frequency artifacts in the IMFs kurtosis is calculated for all trails. Kurtosis is a fourth order moment used to measure the peakedness of a real random variable [22] and is expressed in (11). It is found that the average value of kurtosis is maximum at IMF index 5 in all trails. Hence the thresholding algorithm is applied to IMFs above index 5 to filter the noise.

$$K_4 = \frac{E[(h_i(t))^4]}{(E[(h_i(t))^2])^2} - 3 = \frac{E[(h_i(t) - \mu_{h_i(t)})^4]}{\sigma_{h_i(t)}^4} - 3 \quad (11)$$

Fig. 3: The IMFs of the noisy signal obtained through EMD

2.2.3. Thresholding of the IMFs for denoising

The EMD decomposes the signal into number of IMFs. The decomposed IMFs consists of both signal and noise components. The vital components of the IMFs are extracted by thresholding the noise dominated IMFs [21]. The IMFs are threshold using the interval thresholding method. It preserves the integrity of the waveforms that goes beyond the threshold values. The Equation (12) is used for thresholding the IMFs.

$$\hat{h}_i(z_j^k) = \begin{cases} h_i(z_j^k) \frac{|h_i(r_j^k)| - T_j}{h_i(r_j^k)}, & |h_i(r_j^k)| > T_j \\ 0, & |h_i(r_j^k)| \leq T_j \end{cases} \quad (12)$$

From the above equations, z_j^k is the k^{th} interval between two adjacent zero-crossings in the j^{th} IMF, r_j^k is the extrema in interval z_j^k , and $\hat{h}_i(z_j^k)$ is the threshold IMF. The threshold value T_j for the j^{th} IMF is estimated using the universal threshold and is given by $T_j = A\sqrt{E_j 2\ln(L)}$, where E_j is the estimated energy density of the j^{th} IMF and expressed in (13).

$$E_j = \begin{cases} \left[\frac{\text{median}(\text{abs}(h_j(t)))^2}{0.6745} \right]^2; & j = 1 \\ \frac{E_1}{\beta} \rho^{-j}; & j = 2, 3, \dots, N \end{cases} \quad (13)$$

where β and ρ are constants and are 0.719 and 2.01 respectively.

3. RESULTS

In this section, the denoised EEG signal quality obtained by using the DWT-EMD method was measured with the change in SNR ratio (ΔSNR) [18] pre and post artifact removal, percentage reduction in correlation coefficient ($\% \eta$) [18] and the RRMSE [11] metrics. The metrics are defined as follows:

1. The difference in SNR $\Delta\text{SNR} = \text{SNR}_{AF} - \text{SNR}_{BF}$, where SNR_{AF} is the SNR evaluated after the artifact filtering.

$$\text{SNR}_{AF} = 10 \log \left[\frac{\|x_{art}(n)\|_2^2}{\|x_{art}(n) - x_{den}(n)\|_2^2} \right] \quad (14)$$

and SNR_{BF} is the SNR evaluated before the artifact filtering.

$$SNR_{BF} = 10 \log \left[\frac{\|x_{art}(n)\|_2^2}{\|x_{art}(n) - x_{gth}(n)\|_2^2} \right] \quad (15)$$

2. Percentage reduction in correlation coefficient (% η)

$$\eta = \left[1 - \frac{1 - \rho_{AF}}{1 - \rho_{BF}} \right] \times 100 \quad (16)$$

Where ρ_{BF} and ρ_{AF} are the correlation coefficients of pre and post filtering the motion artifacts and are expressed in (17) and (18).

$$\rho_{AF} = \rho(x_{art}(n), x_{gth}(n)) \quad (17)$$

$$\rho_{AF} = \rho(x_{art}(n), x_{den}(n)) \quad (18)$$

3. Relative root mean square error (RRMSE) is an indicator and is calculated taking the ratio of RMSE to RMS of measured data.

$$RRMSE = \frac{RMS((x_{art}(n) - x_{den}(n)))}{RMS(x_{art}(n))} * 100 \quad (19)$$

The proposed DWT-EMD method is tested for the available 23 trails of the EEG database along with the combination of soft and hard thresholding methods. The mean metrics are calculated for the complete range of the signal. The ground truth, motion artifact and the denoised EEG signal are obtained using the DWT-EMD method and its second artifact portion (193s-209 seconds) for the trail 10 are depicted in Fig. 4A and Fig. 4B respectively. Subsequently, various decomposition level results are depicted in Fig. 4C, Fig. 4D, Fig. 4E respectively. Fig. 4F represent the results when artifact signals pass through EMD by suppressing the DWT. Fig. 4G, Fig. 4H represents the results when artifact signals pass through DWT and subsequently pass through hard and soft thresholding methods and Fig. 4I, Fig. 4J represents the results of DWT-HT and DWT-ST are applied to EMD method. A qualitative analysis show that the responses obtained in Fig. 4I, Fig. 4J are adding drift in the artifact filtered output.

Fig. 4: A. The drift corrected signals for trail 10 which contains Motion artifact signal (Green), Ground truth signal (Blue) and Denoised EEG signals with DWT-EMD with level-1 decomposition Method (Pink). B. A portion represents the second motion artifact region along with ground truth and Artifact removed EEG signal with DWT-EMD with level-1 decomposition. C. Reconstructed EEG signal with DWT-EMD with level-2 decomposition. D. Reconstructed EEG signal with DWT-EMD with level-3 decomposition. E. Reconstructed EEG signal with DWT-EMD with level-4 decomposition. F. Reconstructed EEG signal with EMD method alone. G. Reconstructed EEG signal with DWT- hard threshold method. H. Reconstructed EEG signal with DWT- soft threshold method. I. Reconstructed EEG signal with DWT-HT along with EMD method. J. Reconstructed EEG signal with DWT-ST along with EMD method.

TABLE 1. THE Δ SNR, RRMSE AND $\% \eta$ VALUES OF ALL SUBJECTS USING THE DWT-EMD APPROACH

EEG Signal	Δ SNR	RRMSE	$\% \eta$
Trail 1	-3.2817	44.1865	82.8505
Trail 2	10.2443	38.7398	84.4439
Trail 3	12.9461	41.5078	79.9641
Trail 4	8.6264	45.3605	79.4381
Trail 5	17.1102	41.7675	79.5717
Trail 6	15.4846	40.8052	80.9708
Trail 7	19.1010	39.5429	84.6670
Trail 8	24.1939	35.5276	81.9338
Trail 9	19.1900	36.0537	74.7069
Trail 10	18.4516	38.0198	68.9668
Trail 11	23.3451	33.9791	79.3296
Trail 12	7.0008	58.2967	39.1005
Trail 13	15.0156	46.3405	57.2255
Trail 14	22.0694	41.1586	43.5526
Trail 15	22.6189	35.0862	20.1798
Trail 16	16.6717	41.7965	73.7240
Trail 17	17.3039	38.6684	77.3269
Trail 18	16.9057	42.0636	60.2274
Trail 19	14.1398	40.3704	76.2030
Trail 20	10.6769	50.1507	42.7793
Trail 21	14.1876	44.8224	48.6880
Trail 22	14.9458	46.6040	47.9997
Trail 23	15.4545	44.8287	50.0405
Average	15.3218	41.9859	65.8213
Standard Deviation	4.50931	5.3816	17.9851

The relative comparison of the performance indices between the existing methods and the proposed method is tabulated in Table 2.

TABLE 2. RELATIVE COMPARISON OF PERFORMANCE INDICES OF EXISTING AND PROPOSED METHODS

Method	Δ SNR (dB) ($\mu \pm \sigma$)	RRMSE (%) ($\mu \pm \sigma$)	η (%) ($\mu \pm \sigma$)
EEMD [9]	6.98	79.46	43.2
EEMD-ICA [9]	8.22	68.81	52.3
EEMD-CCA [9]	8.21	76.89	52.2
SSA [10]	11.16	62.85	61.35
Ov-SSA [11]	12.97	59.23	NA
DWT Hard thresholding	-1.9038 $\pm$ 1.1683	39.5850 $\pm$ 10.9527	4.8476 $\pm$ 4.6049
DWT Soft thresholding	2.9648 $\pm$ 1.9539	48.3927 $\pm$ 10.4412	2.68017 $\pm$ 3.9219
DWT Hard thresholding - EMD	-55.3805 $\pm$ 6.3662	44035.2 $\pm$ 8723.03	0.0077 $\pm$ 0.0189
DWT Soft thresholding - EMD	-37.8005 $\pm$ 6.1447	5699.11 $\pm$ 3362.49	0.0282 $\pm$ 0.0272
EMD method	14.8686 $\pm$ 5.0888	45.2720 $\pm$ 5.1458	62.8132 $\pm$ 17.2872
Proposed DWT (L1)-EMD method	15.3218$\pm$4.5093	41.9859$\pm$5.3816	65.8213$\pm$17.9851
Proposed DWT (L2)-EMD method	10.9919 $\pm$ 3.3350	38.5999 $\pm$ 6.1244	57.858 $\pm$ 18.2989
Proposed DWT (L3)-EMD method	4.3619 $\pm$ 2.0829	29.6558 $\pm$ 5.4691	47.16175 $\pm$ 16.0576
Proposed DWT (L4)-EMD method	1.5479 $\pm$ 1.0090	22.3686 $\pm$ 4.9761	43.9667 $\pm$ 18.6347

μ is mean and σ is the standard deviation; L1, L2, L3, L4 are decomposition levels, NA is Not Applicable.

In Table 2, the performance metrics of the proposed DWT-EMD method are compared with the existing methods. In the proposed method the motion artifact EEG signal is decomposed into level-1 to level-4. The performance of the DWT-EMD method in terms of average and standard deviation values with and without DWT decomposed artifact signal are computed for all trails. From the analysis, it is found that the values of level-1 decomposition have better Δ SNR, RRMSE and $\% \eta$. Subsequently for level-2 to level-4 the RRMSE value shows better performance whereas the average values of Δ SNR and $\% \eta$ are falling down. The proposed method results are satisfactory for level-1 when compared to the existing methods.

4. DISCUSSION

The elimination of motion artifacts and to get a clean EEG signal is very much essential to diagnose the various brain disorders. To address the suppression of motion artifacts problem various methods have been implemented in literature as discussed in introduction paragraph. In this study, A wavelet supported EMD method is proposed and tested for its performance metrics such as Δ SNR, RRMSE and $\% \eta$. In this method, bi-orthogonal wavelets are used to determine the performance metrics due to the linear phase characteristic and support the construction of symmetric wavelet functions. The linear phase characteristic and symmetric wavelet functions are used for the better signal reconstruction in EEG signals. In this work, both orthogonal and bi-orthogonal wavelets are used to study the performance of the proposed algorithm. The artifact signals are tested and found that the bi-orthogonal wavelet gives better results for all metrics. The results obtained by DWT Hard thresholding and DWT Soft thresholding methods fail to reconstruct the artifact removed EEG signal. The artifact removed signals are shown in Fig. 4G, Fig. 4H. DWT-HT method could not successfully remove the artifacts and resulted in poor performance. DWT-ST method is relatively gives better performance of Δ SNR compare to DWT-HT but the Δ SNR is much lower than the methods proposed in literature which are shown in Table 2.

Further to test the performance indices of EMD method alone, the signals are pass through EMD filter alone and obtained results are depicted in Fig. 4F and the performance metrics are given in Table 2. The EMD method is self-sufficient to improve the Δ SNR, RRMSE and $\% \eta$ which are far better than the published methodologies given in Table 2. The artifact removed output signal clearly shows that the artifacts are effectively eliminated and the performance indices gives more satisfactory results compared to earlier discussed methods. The EMD method decomposes the signal into IMFs which are representing the frequency components. The kurtosis is applied and identified the peakedness of each IMF. Since the lower indexed IMFs till the highest peak value are representing high frequency components, interval thresholding method is applied to the IMFs consisting of low frequency components are enable to get denoised EEG signal and the performance indices values are quantified as shown in Table 2.

Later the combined effect of DWT and EMD with hard and soft thresholding methods are experimented and observed that the DWT decomposition levels and hard and soft thresholding methods have impact on signal denoising or artifact removal. In case of DWT-HT-EMD and DWT-ST-EMD methods are fail to reconstruct the artifact removed signal due to drift effect. The output signal values are very large and give rise to high negative value of Δ SNR, high positive value of RRMSE and very low (near zero) value of $\% \eta$. These methods are failed to remove the artifacts as the output signals values are very high. Hence both the methods are not considered. The results of DWT-HT-EMD and DWT-ST-EMD methods are shown Fig. 4I and Fig. 4J respectively. Further to examine effect of decomposition levels the proposed DWT-EMD method is applied and tested to motion artifact contaminated EEG signals from level-1 decomposition to level-4 decomposition and the qualitatively results are shown in Fig. 4B to Fig. 4E respectively. The Fig. 4B clearly indicates the suppression of motion artifacts. It is observed that the denoised signals and the groundtruth signals are highly correlated. As the decomposition level is increasing, the suppression of motion artifacts is significantly reduced as shown in Fig. 4C, Fig. 4D and Fig. 4E. This specific reduction in correlation coefficient is attributed to the fact the motion artifacts are lower frequency components and are present in the approximation band. The DWT decomposes the EEG signal into approximation and detailed subbands and the approximation subband is further decomposed for higher level decomposition. This leads to the reduction of samples of the approximation band to half. But this causes insufficient number of samples in the approximation band to further filter the artifacts. Hence the performance of the proposed method reduced with the number of decomposition levels. The values of the metrics are gradually decreased and failed to eliminate the artifacts in motion artifact contaminated EEG signal. Even though the reduction in RRMSE value is relatively acceptable, the reduction in Δ SNR and $\% \eta$ is vulnerable. Therefore level-1 decomposition is considered for this proposed methodology. From Table 2 comparing the proposed DWT-EMD method (level-1) decomposition with the existing methods, out of the 23 trails 17 trails have greater Δ SNR compared with Ov-SSA [11] method. Except trail12, the remaining 22 trails yield low values of RRMSE. The average $\% \eta$ value of DWT-EMD method (level-1) decomposition yields better result than all existing methods. From Table 2, the metrics, SNR of the proposed approach is better than the existing methods. However, there is a reduction in percentage RRMSE in the proposed work and the $\% \eta$ reductions are 37.47%, 26.82%, 34.90%, 20.86%, and 17.24% with reference to cited references [9], [10] and [11] respectively. The $\% \eta$ is increased by 22.62%, 13.52%, 13.62% and 4.47% with reference to cited references [9] and [10] respectively.

5. CONCLUSION

This paper has presented a multiresolution analysis by using DWT-EMD approach for the elimination of motion artifacts from the EEG signals. The noise contaminated signal was decomposed into approximation

and detailed sub-bands. The EMD method decomposed the approximation band into IMFs. The interval thresholding was applied to the selected IMFs and achieved the filtering process. The filtered signal and detailed sub bands are reconstructed to obtain the denoised signal. The proposed approach showed better performance with a low RRMSE and higher η average values of 41.9859 and 65.8213 and an average 15.3218dB Δ SNR. This approach can further be enhanced by applying suitable filtering techniques for betterment of Δ SNR in the elimination of motion artifacts.

Compliance with ethical standards

Financial Disclosure

The authors certify they have no affiliations with or involvement in any organization or entity with any financial or non-financial interest in the subject matter or materials discussed in this manuscript.

Conflict of interest

The authors declare that they have no conflict of interest.

Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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Supplement Information

TABLE S1 – COMPARISON OF IMPROVEMENT OF SNR, RRMSE AND $\% \eta$ VALUES FOR DIFFERENT WAVELETS OF DWT WITH EMD BY USING MOTION ARTIFACT EEG DATABASE

Sl. No.	Wavelets	Δ SNR	RRMSE	$\% \eta$
1.	Haar	14.9489 $\pm$ 4.2429	41.8691 $\pm$ 5.3701	65.1181 $\pm$ 18.8634
2.	db-2	15.0639 $\pm$ 4.3720	41.9209 $\pm$ 5.3866	65.2524 $\pm$ 18.2248
3.	db-4	14.8747 $\pm$ 4.2033	41.9382 $\pm$ 5.3570	64.9211 $\pm$ 18.8959
4.	db-5	15.1934 $\pm$ 4.4673	42.0749 $\pm$ 5.3148	65.4208 $\pm$ 18.2669
5.	db-6	14.9097 $\pm$ 4.3381	41.9686 $\pm$ 5.3297	64.8504 $\pm$ 19.2125
6.	db-7	15.0468 $\pm$ 4.2490	41.9721 $\pm$ 5.4589	65.3632 $\pm$ 18.8201
7.	db-8	14.902 $\pm$ 4.0098	41.9780 $\pm$ 5.4595	65.1514 $\pm$ 18.5838
8.	db-9	14.8874 $\pm$ 4.1887	42.0004 $\pm$ 5.5396	64.9744 $\pm$ 18.8215
9.	db-10	14.8874 $\pm$ 4.1887	42.058 $\pm$ 5.4285	65.3685 $\pm$ 18.4601
10.	sym-4	15.1856 $\pm$ 4.4332	41.9694 $\pm$ 5.3892	64.5298 $\pm$ 18.8237
11.	sym-5	14.6727 $\pm$ 4.4870	42.0555 $\pm$ 5.4217	65.4972 $\pm$ 18.1840
12.	sym-6	15.3074 $\pm$ 4.6700	41.9902 $\pm$ 5.5379	64.7770 $\pm$ 18.5447
13.	sym-7	14.7916 $\pm$ 3.9933	41.9401 $\pm$ 5.4695	64.8178 $\pm$ 18.6666
14.	sym-8	14.8399 $\pm$ 4.0760	41.934 $\pm$ 5.5111	64.4893 $\pm$ 18.3268
15.	Sym-9	14.6020 $\pm$ 4.3928	42.0336 $\pm$ 5.3629	65.3551 $\pm$ 18.5319
16.	sym-10	14.9686 $\pm$ 5.7679	41.9461 $\pm$ 5.4574	65.2168 $\pm$ 18.7291
17.	coif11	14.2818 $\pm$ 4.5789	41.9375 $\pm$ 5.3715	63.4051 $\pm$ 19.4226
18.	coif 2	14.7171 $\pm$ 4.1255	42.0045 $\pm$ 5.3485	64.5504 $\pm$ 18.8328
19.	coif 3	14.8459 $\pm$ 4.1276	42.0340 $\pm$ 5.3205	64.7386 $\pm$ 18.9363
20.	coif 4	14.8083 $\pm$ 4.0587	42.0564 $\pm$ 5.3626	64.7232 $\pm$ 18.7144
21.	coif 5	14.8899 $\pm$ 4.1286	41.9941 $\pm$ 5.3248	64.8479 $\pm$ 18.8940
22.	Bior 1.1	14.9489 $\pm$ 4.2429	41.8691 $\pm$ 5.3701	65.1181 $\pm$ 18.8634
23.	Bior 1.3	15.2506 $\pm$ 4.3826	41.9076 $\pm$ 5.4257	65.8168 $\pm$ 18.5894
24.	Bior 1.5	15.3218 $\pm$ 4.5093	41.9859 $\pm$ 5.3816	65.8213 $\pm$ 17.9851
25.	Bior 2.2	15.1874 $\pm$ 4.5314	42.3511 $\pm$ 5.3262	65.3323 $\pm$ 18.8691
26.	Bior 2.4	15.161 $\pm$ 4.5218	42.3244 $\pm$ 5.3184	65.1851 $\pm$ 19.0260
27.	Bior 2.6	15.1753 $\pm$ 4.4717	42.3918 $\pm$ 5.3721	65.3231 $\pm$ 18.9865
28.	Bior 2.8	15.2270 $\pm$ 4.5303	42.4430 $\pm$ 5.3877	65.4291 $\pm$ 18.8587
29.	Bior 3.7	15.2955 $\pm$ 4.4904	42.7765 $\pm$ 5.2848	65.627 $\pm$ 18.9684
30.	Bior 3.9	15.2789 $\pm$ 4.4687	42.7459 $\pm$ 5.3180	65.6573 $\pm$ 18.8683
31.	Bior 4.4	15.0575 $\pm$ 4.3497	42.0689 $\pm$ 5.3514	65.2516 $\pm$ 18.8770
32.	Bior 5.5	14.9727 $\pm$ 4.1825	41.942 $\pm$ 5.36229	63.3411 $\pm$ 17.9867
33.	Bior 6.8	14.9332 $\pm$ 4.1361	42.1120 $\pm$ 5.3607	64.9819 $\pm$ 19.0348