Novel Approaches for the Removal of Motion Artifact from EEG Recordings

Pranjali Gajbhiye, Rajesh Kumar Tripathy, Abhijit Bhattacharyya, Ram Bilas Pachori

***Abstract*—The Electroencephalogram (EEG) signal is contaminated with various noises or artifacts during recording. For the automated detection of neurological disorders, it is a vital task to filter out these artifacts from the EEG signal. In this paper, we propose two novel approaches for the removal of motion artifact from the single channel EEG signal. These methods are based on the multiresolution total variation (MTV) and multiresolution weighted total variation (MWTV) filtering schemes. The multiresolution analysis using the discrete wavelet transform (DWT) helps to segregate the EEG signal into various subband signals. The total variation (TV) and weighted TV (WTV) are applied to the approximation subband signal. The filtered approximation subband signal is evaluated based on the difference between the noisy approximation subband signal and the output of the TV or WTV filter. The processed EEG signal is obtained using the multiresolution wavelet-based reconstruction. The difference in the signal to noise ratio (△SNR) and the percentage of reduction in correlation coefficients (η) are used for evaluating the diagnostic quality of the processed EEG signal. The experimental results demonstrate that the proposed MTV and MWTV approaches have better denoising performance with (average △SNR, and average η) values of (29.12dB, and 68.56%), and (29.29dB, and 67.51%), respectively, as compared to the existing techniques.**

***Index Terms*—EEG Signal, Motion Artifact, Multiresolution Analysis, Total Variation, △SNR, Correlation Coefficient.**

I. Introduction

THE Electroencephalogram (EEG) is a non-invasive diagnostic test used to quantify the brain electrical activity, and it is recorded using a number of electrodes which are placed along the scalp at different locations [1]. This signal is corrupted with various artifacts such as motion, ocular, muscle etc. during ambulatory EEG monitoring [2]–[4]. The motion artifact occurred in the EEG signal due to the movement of the subject during acquisition [3]. The filtering of motion and other artifacts from the EEG signals is necessary for the applications like detection of neural disorders, sleep-related disorders, emotion detection and brain-computer interface (BCI) [5]–[10].

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In literature, different approaches have been reported for the elimination of motion artifacts from the EEG signal [4], [11]. Sweeney et al. [12] have compared the performance of various motion artifact removal techniques using the EEG signal. These techniques are based on different multiresolution analysis methods such as discrete wavelet transform (DWT) [13], empirical mode decomposition (EMD) [14], ensemble empirical mode decomposition (EEMD) [15], and singular spectrum analysis (SSA) [16]. The same authors have also combined EMD with canonical component analysis (EMD-CCA), EMD with independent component analysis (EMD-ICA), EEMD with ICA (EEMD-ICA), and EEMD with CCA (EEMD-CCA) for the filtering of motion artifacts from EEG signal [12]. Recently, Maddirala and Shaik [17] have applied SSA for the filtering of motion artifact from the EEG signal. There, the authors have filtered out the motion artifact based on the selection of the reconstruction components from the EEG signal in the SSA domain. Apart from the elimination of the motion artifacts, various signal processing methods have also been used for the removal of other artifacts from the single channel EEG, and also from other physiological signals [4] [18]. Among them, Patel et al. [19] have applied the combination of EEMD and principal component analysis (PCA) over the EEG signal which is contaminated with ocular artifacts. The filtered signal has been obtained based on the selection of the principal components (PCs) of intrinsic mode function (IMF) matrix of EEG. Similarly, in another study, Maddirala, and Shaik [20] have combined the SSA and the adaptive noise cancellation (ANC) for the elimination of electrooculogram (EOG) artifacts from the single channel EEG signal.

The approaches mentioned above have used DWT, EMD, EEMD, and SSA for the multiresolution analysis of the EEG signal. The EMD, EEMD, and SSA are purely signal dependent, and these techniques require higher computations for the evaluation of the modes or IMFs from the EEG signal. The aforementioned approaches have also less performance for the denoising of motion artifact from the EEG signal [12]. Therefore, the novel approaches which have better denoising performance, and computationally efficient are required for the filtering of various artifacts from the EEG signal. The wavelet-based scheme is found to be an effective multiresolution approach for the analysis and decomposition of the EEG signal [21] [22] [7]. The combination of DWT and thresholding has been used for the filtering of motion artifact and other artifacts from the EEG signal [23] [24]. The EEG signal is highly

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non-stationary in nature, and the thresholding of wavelet coefficients may cause the loss of relevant information during the reconstruction of the signal. The total variation (TV) and weighted TV (WTV) denoising techniques have shown better performance for the analysis of electrocardiogram (ECG) signals [25] [26]. In TV filtering, the filtered signal is evaluated based on the solution of the optimization problem, and this denoising method has the advantage such as the preservation of sharp edges in the filtered signal [27]. In multiresolution domain, the EEG wave patterns are grossly captured using different subband signals and the motion artifact normally affect the low-frequency subband signal of EEG [6] [17]. The TV and WTV denoising approaches have not been used for EEG signal in multiresolution domain. Therefore, we can expect that the use of TV or WTV denoising techniques over the multiresolution domain of the single channel EEG signal will be effective for the elimination of motion artifact. In this paper, the approaches based on the multiresolution TV (MTV) and multiresolution WTV (MWTV) denoising are proposed for the filtering of motion artifact from the EEG signal. The major contributions in this paper are written as follows.

- The multiresolution property of DWT is used for the extraction of subband signals from the motion artifact contaminated EEG signal.
- The TV and WTV denoising approaches are applied over the approximation subband or low-frequency range subband signal.
- The filtered approximate signal is obtained based on the difference between the approximation subband signal and output of TV or WTV filter.
- The filtered EEG signal is evaluated using the combination of filtered approximation subband signal and detailed subband signals.

The remainder of this paper is organized as follows. In Section II, the proposed approaches for the filtering of motion artifact from the EEG signal are written. Section III presents the results and discussions of the paper. Finally, the conclusions of this paper are presented in Section V.

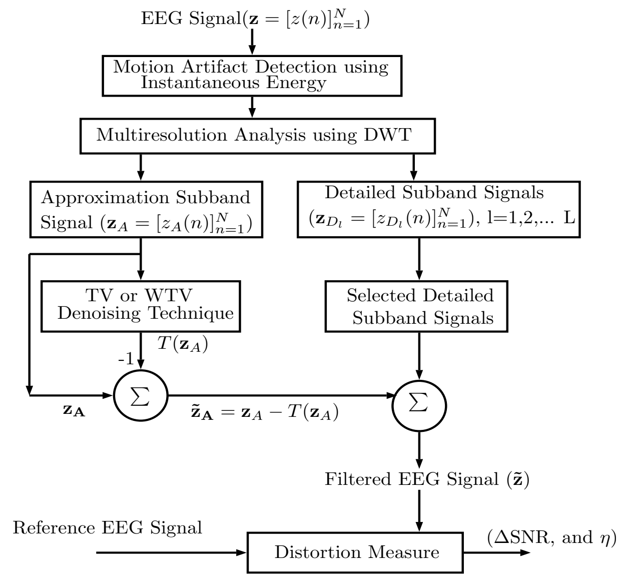

Fig. 1. Block diagram of the proposed approach for the filtering of motion artifacts from EEG signal.

II. METHOD

The block diagram of the proposed denoising approach is depicted in Fig. 1, and it comprises of the detection of motion artifact using instantaneous energy, multiresolution analysis of the EEG signal using DWT, the TV or the WTV denoising technique, and the use of different distortion measures for the evaluation of the performance of the proposed denoising techniques. We have written the detailed descriptions of each component of this block diagram in the following subsections.

A. EEG Signal Collection

In this work, we have collected the motion artifact contaminated EEG signals from a public database which is available in the physionet [11] [12] [28]. This database comprises of functional near-infrared spectroscopy (fNIRS) and EEG signals. The proposed denoising approaches uses two EEG signals which are highly correlated. These two EEG signals are recorded from pre-frontal cortex using two electrodes (Ag-AgCl) from a 256 array electrode cap which is positioned on the subject's scalp [11]. Sweeney et al. [11] have followed the experimental protocol for the recording of EEG signals. Twenty-three EEG recordings are available in the database, and the sampling frequency of each EEG signal is 2048 Hz. Each recording contains two EEG signals such as, one noisy EEG signal which is contaminated with the motion artifact, whereas the other signal is the reference EEG signal (noise free EEG signal or ground truth). The average correlation coefficent is high when the motion artifact is not present in the EEG interval [11]. Similarly, when the EEG signal has motion artifact, the average correlation coefficent value reduces. The superimposition of the reference EEG signal (Black) and motion artifact contaminated EEG signal (Red) are depicted in Fig. 2 (a). In this study, the reference EEG signal is used for the validation of the proposed denoising approaches. The gain of the amplifier has been mentioned as 1000 for each EEG record in the database. Therefore, we have multiplied a factor of 0.001 to each EEG record for further analysis. The annotated sample ranges or frames for the occurrence of motion artifact in the EEG signal for each subject have been mentioned in the database. The performance of the proposed denoising techniques is evaluated over all the frames of the EEG signal for each subject. We have also evaluated the performance of the proposed approaches using real-time EEG signals which are recorded at a hospital in New Delhi, India [1] [29]–[36]. A total of 150 EEG signals (50 interictal, 50 ictal and 50 preictal) are used in this work. The sampling frequency of

[1]https://www.researchgate.net/publication/308719109_EEG_Epilepsy_Datasets

each EEG signal in this new dataset is 400 Hz and each signal contains 1024 samples [37]. These EEG signals are recorded using 16 electrodes (International 10-20 electrode system) which are placed on the scalp of each subject [37]. In this study, we have artificially distorted the EEG signals by adding the motion artifact. The proposed denoising approaches are used to filter-out the motion artifact from the distorted EEG signal.

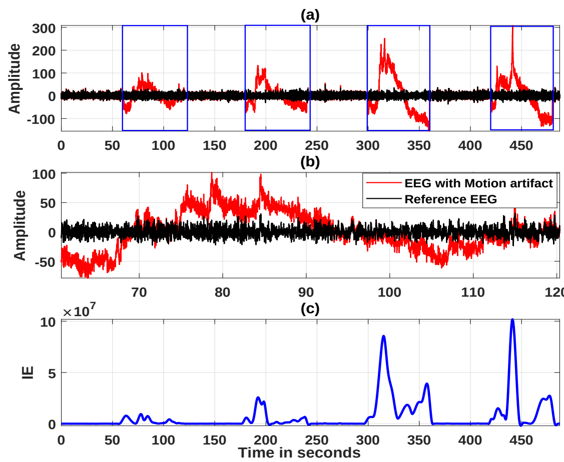

Fig. 2. (a) Superimposition of the reference EEG signal (Black) and motion artifact contaminated EEG signal (Red). (b) Zoomed view of first window in Fig. 2 (a). (c) Envelope of the instantaneous energy of motion artifact contaminated EEG signal.

B. Motion Artifact Detection

In this study, the motion artifact presence in the EEG signal is detected using instantaneous energy. The instantaneous energy of the motion artifact contaminated EEG signal, $\mathbf{z} = [z(n)]_{n=1}^{N}$ is given as,

$$E(n) = |z(n)|^2 \tag{1}$$

The reference EEG, the motion artifact contaminated EEG and the instantaneous energy of the motion artifact contaminated EEG are depicted in Fig. 2 (a), Fig. 2 (b) and Fig. 2 (c), respectively. It is observed that the instantaneous energy is high when the motion artifact is appeared in the sample range of the EEG signal. Therefore, we have selected different sample ranges of EEG signal for the filtering using proposed denoising approaches.

C. Multiresolution Analysis of EEG

In this study, we have performed the multiresultion analysis of the EEG signal using DWT [22]. The EEG signal, $\mathbf{z} = [z(n)]_{n=1}^{N}$ with the sampling frequency as 2048 Hz is decomposed into $L = 8$ levels using DWT for the evaluation of one approximation band ($cA_L(k)$) and eight detail subbands ($cD_l(k)$ with $l = 1, 2, ..., L$ wavelet coefficents. This decomposition is performed based on the use of the low-pass filter (scaling function) and high-pass filter (wavelet function) in which the impulse responses are obtained using the dilation and the translation of the

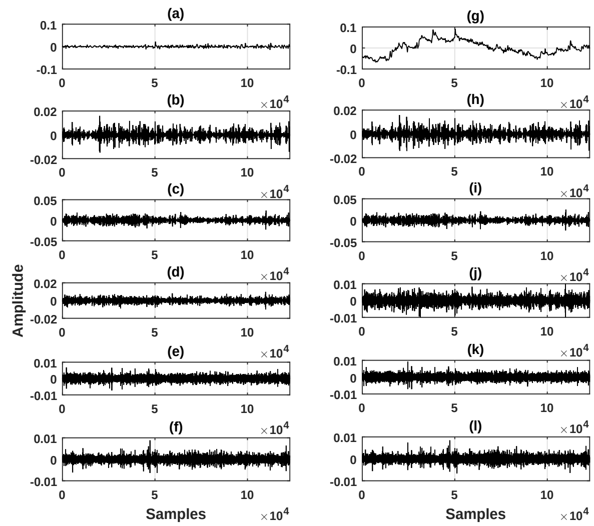

Fig. 3. (a) Approximation subband signal ($z_A(n)$) for original EEG. (b)-(f) Detailed subband signals ($z_{D_8}(n)$), $z_{D_7}(n)$), $z_{D_6}(n)$), $z_{D_5}(n)$) and $z_{D_4}(n)$)) for original EEG. (g) Approximation subband signal ($z_A(n)$) for motion artifact contaminated EEG. (h)-(l) Detailed subband signals ($z_{D_8}(n)$), $z_{D_7}(n)$), $z_{D_6}(n)$), $z_{D_5}(n)$) and $z_{D_4}(n)$)) for motion artifact contaminated EEG.

mother wavelet ('db4') [38] [22]. The low-pass filter or the scaling function, and the high-pass filter or the wavelet function are denoted as $\phi_{L,k}(n) = 2^{\frac{-L}{2}}\phi(2^{-L}n - k)$, and $\psi_{l,k}(n) = 2^{\frac{-l}{2}}\psi(2^{-l}n - k)$, respectively [39]. For the input EEG signal, the mathematical expressions for the evaluation of both approximation band wavelet coefficients vector ($\mathbf{cA}_L = [cA_L(k)]_{k=1}^{N_{A_L}}$), and l^{th} detail subband wavelet coefficients vector ($\mathbf{cD}_l = [cD_l(k)]_{k=1}^{N_{D_l}}$) are given by,

$$cA_L(k) = \sum_{n=-\infty}^{\infty} z(n)[2^{\frac{-L}{2}}\phi(2^{-L}n - k)] \tag{2}$$

$$cD_l(k) = \sum_{n=-\infty}^{\infty} z(n)[2^{\frac{-l}{2}}\psi(2^{-l}n - k)] \tag{3}$$

where n is the sample number of the EEG signal with $n = 1, 2...N$ and N is the length of the EEG signal. The k corresponds to the wavelet coefficent number in the approximation and detail subbands. Similarly, L is denoted as the wavelet decomposition level. The N_{A_L} and N_{D_l} correspond to the sizes of the approximation band wavelet coefficients vector, and the l^{th} detail subband wavelet coefficients vector, respectively [40]. The signal synthesized using the subband wavelet coefficients vector for l^{th} detail subband is given by

$$z_{D_l}(n) = \sum_{k=-\infty}^{\infty} cD_l(k)\psi_{l,k}(n) \tag{4}$$

Similarly, the reconstructed approximate subband signal is computed using the mathematical expression as follows

$$z_A(n) = \sum_{k=-\infty}^{\infty} cA_l(k)\phi_{L,k}(n) \tag{5}$$

Moreover, the EEG signal is synthesized using the approximation and the detailed subband signals as [39]

$$z(n) = z_A(n) + \sum_{l=1}^{L} z_{D_l}(n) \tag{6}$$

In the context of nonstationary EEG signal processing, wavelets have been explored for multiscale analysis [22], feature extraction [41], denoising [42] etc. The 'db4' wavelet basis function has been widely used in wavelet transform based EEG signal processing [21]. In this work, we have used 'db4' wavelet basis for the multiresolution analysis of EEG signal. The original EEG signal and the motion artifact contaminated EEG signal are depicted in Fig. 2 (b) in black and red colors, respectively. It is evident that, due to the presence of motion artifact, there are variations in the amplitude values and the shape of the EEG signal. The subband signals (approximation subband signal and five detail subband signals) are depicted in Fig. 3 (a)-(f), and Fig. 3 (g)-(l), respectively. The frequency ranges for approximation subband signal ($z_A(n)$) and five detail subband signals ($z_{D_8}(n)$, $z_{D_7}(n)$, $z_{D_6}(n)$, $z_{D_5}(n)$ and $z_{D_4}(n)$) for both original and motion artifact contaminated EEG signals are [0.5-4 Hz], [4-8 Hz], [8-16 Hz], [16-32 Hz], [32-64 Hz], and [64-128 Hz], respectively [43] [44]. It is observed that the motion artifact noise is present in the approximation subband signal and hence, the suitable filtering approach can be applied to this subband signal for the elimination of motion artifact. In this study, we have applied TV and WTV denoising algorithms over the approximation subband signal. For the reconstruction of the processed EEG signal from the subband signals, we have excluded the high-frequency subband signals ($z_{D_3}(n)$, $z_{D_2}(n)$ and $z_{D_1}(n)$) as these subband signals do not capture the EEG relevant information [12].

D. TV and WTV Denoising Techniques

In this work, both TV and WTV denoising techniques are used over the approximation subband signal ($z_A(n)$) of the motion artifact contaminated EEG. In TV denoising, the processed approximation subband signal ($\tilde{z}_A(n)$) is evaluated by solving the following optimization problem as [45] [46]

$$\underset{\tilde{z}_A(n)}{\arg\min}[\frac{1}{2}\sum_{n=1}^{N}|z_A(n)-\tilde{z}_A(n)|^2+\lambda\sum_{n=1}^{N-1}|z_A(n)-\tilde{z}_A(n)|] \tag{7}$$

Similarly, for WTV denoising technique, the optimization problem is formulated as [26]

$$\underset{\tilde{z}_A(n)}{\arg\min}[\frac{1}{2}\sum_{n=1}^{N}|z_A(n)-\tilde{z}_A(n)|^2+\lambda\sum_{n=1}^{N-1}w(n)\,|z_A(n)-\tilde{z}_A(n)|] \tag{8}$$

where λ is the regularization factor. The $w(n)$ is the weight value at n^{th}sample and it is assigned using the Teager-Kaiser energy (TKE) of the signal, $z_A(n)$ [26]. Thus, the weight value is evaluated as,

$$w(n) = [(0.01 \times T(z_A(n))) + \epsilon] \tag{9}$$

where $T(z_A(n)) = [z_A^2(n) - z_A(n-1)z_A(n+1)]$ is the TKE of the approximation subband signal [47]. The TKE suitable for the analysis of non-stationary signals with lower computation complexity [48]. The ϵ is considered as the small positive constant and its value is chosen as 0.001. The optimization problems in Equation (7) and Equation (8) are solved based on the majorization-minimization approach [45]. The processed approximation subband signal is iteratively estimated from the motion artifact contaminated approximation subband signal as [45],

$$\tilde{\mathbf{z}}_A^{t+1} = \mathbf{z}_A^t - \mathbf{D}^T(\frac{1}{\lambda}\text{diag}(|\mathbf{D}\tilde{\mathbf{z}}_A^t|) + \mathbf{D}\mathbf{D}^T)^{-1}\mathbf{D}\mathbf{z}_A \tag{10}$$

where t is the t^{th} iteration, and in this work, we have considered λ and total number of iterations as 2.5 and 5000, respectively. The $\mathbf{z}_A = [z_A(n)]_{n=1}^N$ and $\tilde{\mathbf{z}}_A = [\tilde{z}_A(n)]_{n=1}^N$ are the vectorial representation of the motion artifact contaminated and processed approximation subband signals. $\mathbf{D}$ is termed as the first order difference matrix and the size of this matrix is $(N-1) \times N$ [49]. The processed EEG signal is obtained using the multiresolution based wavelet reconstruction as follows:

$$\tilde{z}(n) = \tilde{z}_A(n) + \sum_{l=4}^{L} z_{D_l}(n) \tag{11}$$

where $\tilde{z}_A(n)$, and $\tilde{\mathbf{z}} = [\tilde{z}(n)]_{n=1}^N$ are the processed approximation subband signal and the processed EEG signal, respectively.

E. Distortion Measures

In this work, we have evaluated the performance of the proposed MTV and MWTV denoising approaches using two different distortion measures as the difference in the signal to noise ratio (ΔSNR), and the percentage reduction in the correlation coefficient (η). The ΔSNR is given by [12],

$$\Delta SNR = SNR_{AF} - SNR_{BF} \tag{12}$$

where SNR_{AF}, and SNR_{BF} are termed as the SNR values before filtering (BF) and after filtering (AF), respectively. The SNR_{BF}, and the SNR_{AF} are computed as follows:

$$SNR_{BF} = 10 \times \log[\frac{\|\mathbf{z1}\|_2^2}{\|\mathbf{z1}-\mathbf{z}\|_2^2}] \tag{13}$$

$$SNR_{AF} = 10 \times \log[\frac{\|\mathbf{z1}\|_2^2}{\|\mathbf{z1}-\tilde{\mathbf{z}}\|_2^2}] \tag{14}$$

where $\mathbf{z1}$, $\mathbf{z}$, and $\tilde{\mathbf{z}}$ are the reference EEG, the motion artifact contaminated EEG, and the processed EEG signals, respectively. The percentage reduction in the correlation coefficient (η) is evaluated using the following mathematical expression as [12],

$$\eta = [1 - \frac{1-\rho_{AF}}{1-\rho_{BF}}] \times 100 \tag{15}$$

where $\rho_{AF} = \rho(\mathbf{z1}, \tilde{\mathbf{z}})$ and $\rho_{BF} = \rho(\mathbf{z1}, \mathbf{z})$ are the correlation coefficients evaluated before and after filtering of the motion artifact from the EEG signal.

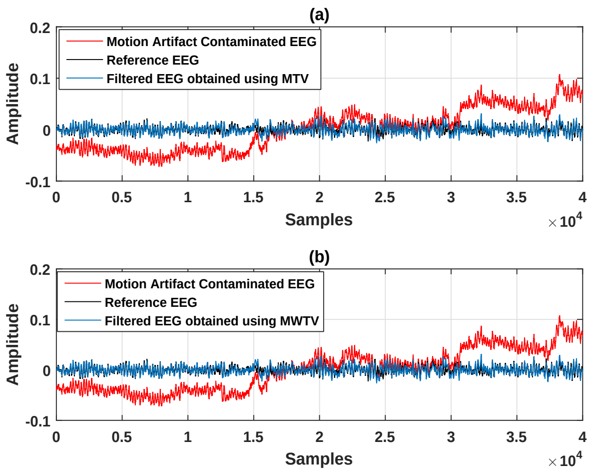

Fig. 4. (a) Motion artifact contaminated EEG (red color), reference EEG (black color) and filtered EEG (blue color) signals for the subject EEG-1 (using MTV denoising approach). (b) Motion artifact contaminated EEG (red color), reference EEG (black color) and filtered EEG (blue color) signals for the subject EEG-1 (using MWTV denoising approach).

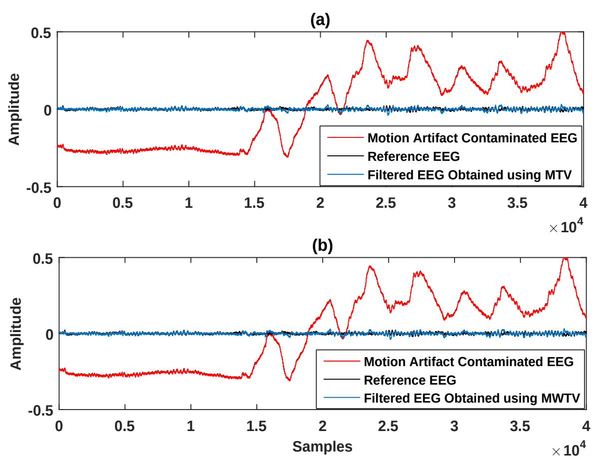

Fig. 5. (a) Reference EEG (black color) and filtered EEG (blue color) signals for the subject EEG-8 (using MTV denoising approach). (b) Motion artifact contaminated EEG (red color), reference EEG (black color) and filtered EEG (blue) signals for the subject EEG-8 (using MWTV denoising approach).

III. Results and Discussion

In this section, the performance of the proposed MTV and MWTV denoising approaches (as outlined in Fig. 1) is evaluated using all 23 number of EEG signals. The average values of ΔSNR and the η values are computed by considering all frames or sample ranges of EEG signals for each subject. The filtered EEG signals obtained using the MTV approach, the reference EEG signals, and the motion artifact contaminated EEG signals for the subjects (EEG-1 and EEG-8) from the database are depicted in Fig. 4 (a) and Fig. 5 (a), respectively. Similarly, Fig. 4 (b) and Fig. 5 (b) depict the reference EEG and the filtered EEG signals for the subjects (EEG-1 and EEG-8) using MWTV denoising techniques. It has been observed that for both the subject cases, the motion artifacts are eliminated from the noisy EEG signals. The correlation coefficient between the filtered EEG signal and the reference EEG signal for the subject (EEG-1) is obtained as 0.86 using the MTV denoising method. When the MWTV denoising approach is used, the correlation coefficient value is improved to 0.87. Similarly, the ΔSNR is also improved from 19.28dB (MTV denoising) to 19.81dB using MWTV denoising approach.

The ΔSNR and the η values of all EEG recordings evaluated using the proposed MTV and MWTV filtering approaches are shown in Table I. It is observed that the average ΔSNR values are high for the subjects (EEG-3, EEG-4, EEG-5, EEG-11, and EEG-23) using the MTV denoising approach. Apart from the EEG signals from these subjects, the average ΔSNR values of the EEG signals for all other subjects are high using the MWTV denoising technique. The weight values in MWTV denoising helps in the smoother minimization of the cost function as compared to the MTV denoising [26]. Due to this reason, EEG signals from these 18 subjects have higher ΔSNR values. Moreover, for the MWTV denoising case, only EEG signals from subjects (EEG-1, EEG-6, EEG-7, EEG-8, EEG-9, EEG-17) have higher η values as compared to other subjects. Higher η values are also observed for EEG signals from all other subjects using the MTV denoising technique. The within-frame variations of ΔSNR and η values for the EEG signals from the subjects (EEG-6, EEG-7, EEG-9, and EEG-17) are depicted in Fig. 6 (a)-(d), and Fig. 6 (e)-(h), respectively. Similar frame sizes are considered for the EEG signals of all subjects. It is observed that the MWTV denoising technique has higher mean values for ΔSNR and η using the EEG signals of these four subjects. The within-frame variations in the ΔSNR values are less for the EEG signals from the subjects (EEG-7, EEG-9, and EEG-17) using the MWTV denoising approach as compared to the WTV denoising. Moreover, the within-frame variations in the η values are high for the EEG signals from all four subjects using the MWTV denoising approach. For the new dataset, the within-class variations of the ΔSNR and η values for EEG signals of interictal, ictal and preictal classes evaluated using proposed MTV and MWTV denoising approaches are depicted in Fig. 7 (a)-(b) and Fig. 7 (c)-(d), respectively. It is observed that the ΔSNR and η values are improved after filtering of the motion artifact from the distorted EEG signal. The average η values for all EEG classes are found to be more than 90%. These higher η values reveals that the proposed approaches are suitable to eliminate motion artifact from EEG signal. The variations of ΔSNR and the η values with number of wavelet decomposition levels are shown in Fig 8 (a) and Fig 8 (b), respectively. It is evident that the when number of wavelet decomposition level is 7, the ΔSNR and the η have higher value as compared to other decomposition levels. The difference between the ΔSNR and η values are less when the decomposition level varied from $L = 7$ to $L = 8$. Therefore, either $L = 7$ or $L = 8$ can be considered as optimal decomposition level in this work for the decomposition of EEG signal. Similarly, the Fig 8 (c) and Fig 8 (d) depict the variations of ΔSNR and the η values with the regularization parameter for MTV and

TABLE I
THE MEAN (μ) AND THE STANDARD DEVIATION (σ) VALUES OF ΔSNR AND η FOR ALL SUBJECTS USING PROPOSED APPROACHES.

Subject	**MTV Denoising**		**MWTV Denoising**	
EEG	ΔSNR dB ($\mu \pm \sigma$)	η (%) ($\mu \pm \sigma$)	ΔSNR dB ($\mu \pm \sigma$)	η (%) ($\mu \pm \sigma$)
EEG-1	24.77 ± 4.31	87.96 ± 3.66	24.81 ± 4.11	88.40 ± 1.62
EEG-2	27.88 ± 1.70	87.96 ± 3.35	27.89 ± 1.78	87.29 ± 3.60
EEG-3	28.20 ± 2.24	79.73 ± 4.81	27.87 ± 2.11	77.06 ± 5.01
EEG-4	27.58 ± 2.93	84.72 ± 1.22	27.50 ± 2.78	83.50 ± 1.99
EEG-5	37.37 ± 1.03	88.70 ± 2.60	37.05 ± 0.70	87.22 ± 3.20
EEG-6	28.83 ± 4.89	81.09 ± 1.49	29.14 ± 5.17	81.29 ± 2.59
EEG-7	32.36 ± 2.27	86.53 ± 0.83	32.63 ± 1.83	86.60 ± 1.66
EEG-8	34.61 ± 4.23	82.21 ± 0.74	34.98 ± 4.28	82.22 ± 1.10
EEG-9	31.26 ± 1.84	76.02 ± 3.14	31.71 ± 1.55	76.33 ± 4.22
EEG-10	34.00 ± 3.30	72.80 ± 3.85	34.11 ± 3.47	71.59 ± 3.94
EEG-11	35.42 ± 1.60	80.07 ± 0.50	35.25 ± 1.26	78.16 ± 1.82
EEG-12	22.85 ± 3.81	63.90 ± 6.97	23.06 ± 3.98	61.31 ± 8.85
EEG-13	27.28 ± 2.20	55.77 ± 3.26	27.67 ± 2.39	54.58 ± 3.24
EEG-14	30.47 ± 5.59	50.14 ± 1.81	30.94 ± 5.53	46.68 ± 2.54
EEG-15	29.63 ± 2.17	45.36 ± 13.42	30.11 ± 2.28	42.36 ± 13.13
EEG-16	30.67 ± 4.38	68.77 ± 4.39	31.13 ± 4.24	68.60 ± 3.57
EEG-17	28.70 ± 1.73	70.98 ± 1.57	29.22 ± 1.79	71.86 ± 2.73
EEG-18	29.75 ± 3.08	60.50 ± 5.81	30.04 ± 3.02	57.93 ± 6.40
EEG-19	28.40 ± 1.35	73.84 ± 5.47	28.47 ± 1.43	72.35 ± 5.86
EEG-20	23.63 ± 1.37	40.87 ± 10.49	23.64 ± 1.26	38.82 ± 8.74
EEG-21	26.26 ± 3.06	42.55 ± 3.36	26.49 ± 3.01	41.21 ± 3.76
EEG-22	25.01 ± 1.79	50.19 ± 7.07	25.15 ± 1.98	49.08 ± 6.75
EEG-23	24.87 ± 1.62	46.23 ± 12.95	24.86 ± 1.47	43.63 ± 13.53
Average	29.12 ± 2.72	68.56 ± 4.47	29.29 ± 2.67	67.31 ± 4.78

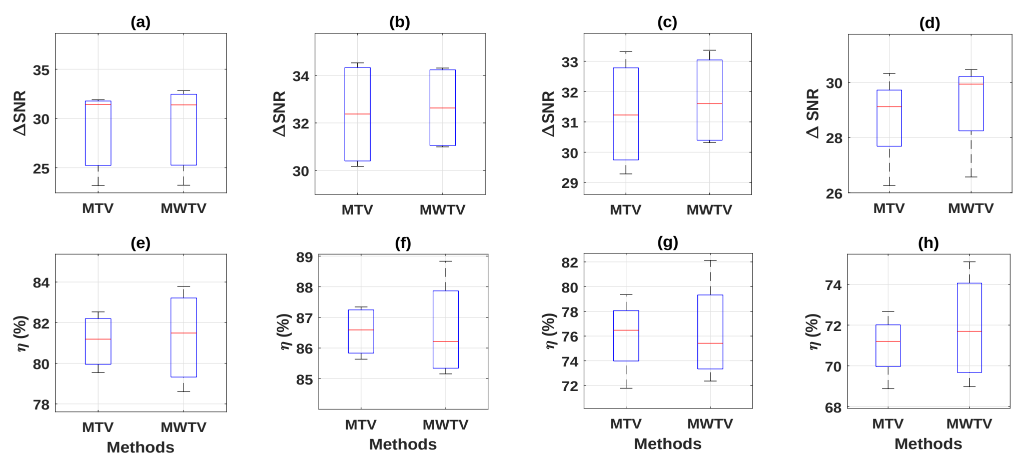

Fig. 6. (a) Within-frame variations of ΔSNR values for EEG-6 case. (b) Within-frame variations of ΔSNR values for EEG-7 case. (c) Within-frame variations of ΔSNR values for EEG-9 case. (d) Within-frame variations of ΔSNR values for EEG-17 case. (e) Within-frame variations of η values for EEG-6 case. (f) Within-frame variations of η values for EEG-7 case. (g) Within-frame variations of η values for EEG-9 case. (h) Within-frame variations of η values for EEG-17 case.

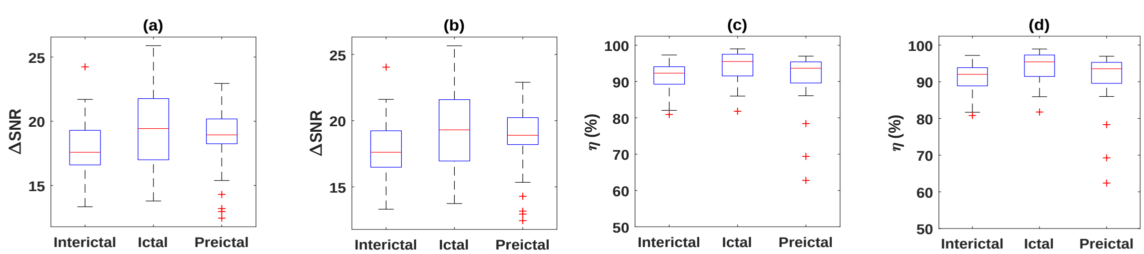

Fig. 7. (a) Within-class variations of ΔSNR values of the filtered EEG signals for interictal, ictal and preictal classes using MTV denoising scheme. (b) Within-class variations of ΔSNR values of the filtered EEG signals for interictal, ictal and preictal classes using MWTV denoising scheme. (c) Within-class variations of η values of the filtered EEG signals for interictal, ictal and preictal classes using MTV denoising scheme. (d) Within-class variations of η values of the filtered EEG signals for interictal, ictal and preictal classes using MWTV denoising scheme.

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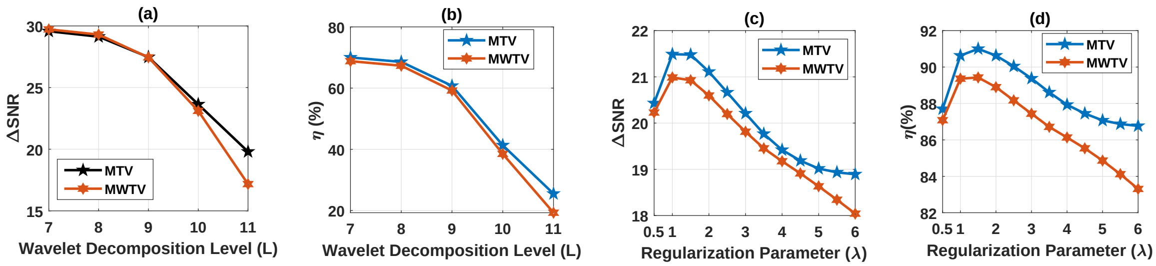

Fig. 8. (a) Variation of ΔSNR with number of wavelet decomposition levels. (b) Variation of η (%) with number of wavelet decomposition levels. (c) Variation of ΔSNR with the regularization parameter. (d) Variation of η (%) with the regularization parameter.

MWTV denoising approaches. It is evident that the ΔSNR and the η are high for λ value equal to 1.5. Henceforth, $\lambda = 1.5$ is the optimal regularization parameter for the proposed MTV and MWTV denoising approaches for EEG signal.

We have compared the denoising performance of the proposed approaches with existing methods, and the comparisons are shown in Table II. It has been observed that the MTV and MWTV denoising approaches have higher performance as compared to existing techniques for the filtering of motion artifacts using the EEG signals from the same database. Moreover, it is also observed that the SSA based method proposed by Maddirala and Shaik [17] has higher variations in the η values (standard deviation as 21.68). The SSA method requires the window length and the number of reconstruction components as priors for the analysis of the EEG signal. For larger duration EEG signal the SSA, EMD, EEMD methods require higher computational time for the evaluation of modes. The DWT is being simple and computationally efficient multiresolution analysis technique for the decomposition of the EEG signal. Sweeney et $al.$ [12] have also applied the DWT and thresholding for the filtering of the motion artifacts from the EEG signal. The ΔSNR and η values reported from their method are less than the proposed approach. The TV and WTV denoising approaches preserve the discontinuities while filtering the motion artifact from the approximation subband signal of EEG. The shape of the filtered EEG signal is also matched with the reference EEG signal using the proposed denoising approaches. We have also compared the computational complexity of the proposed approaches with the state-of-the-art methods for the motion artifact elimination from the EEG signals. The computational complexity values have been reported as $O(T_eT_s(41T_{IMF}N))$, $O(5NT_o^2+5NT_o+19\frac{T_o^3}{3})$, $O(T_eT_s(41T_{IMF}N)+5NT_o^2+5NT_o+19\frac{T_o^3}{3})$, and $O(M^2R+M^3+M^2(1+R)+NM)$, respectively for EEMD, CCA, EEMD-CCA and SSA based methods for the removal of motion artifacts from EEG signal [17]. Where T_e and T_s are the number of ensemebles and number of sifting operations, respectively in EEMD based method. T_{IMF} is termed as the number of intrinsic mode functions (IMFs) obtained using the EEMD of EEG signal. For CCA, the parameter T_o corresponds to the number of observations. The N is termed as the number of samples in the EEG signal. The M and R are denoted as the total number of rows and columns in the multivariate matrix which is formulated using the initial step of SSA of EEG signal. The computational complexities for DWT and TV denoising approach are $O(N)$ and $O(N^2)$, respectively [50] [51]. Similarly, the computational complexity for WTV based denoising technique with TKE operator as weight value is $O(N^2+3N)$. Where $O(3N)$ is the computational complexity of TKE operator for the signal with length N (For each sample of TKE , there are two multiplication and one addition). Thus, the computational complexity of the proposed MTV and MWTV approaches are $O(N^2+N)$ and $O(N^2+4N)$, respectively. It is evident from these observations that the computational complexity of the proposed approaches are less than the existing techniques for the removal of motion artifact from EEG. Therefore, the proposed approaches are suitable for the real-time processing of EEG signal for the filtering of motion artifact. The elimination of the artifacts from the multichannel EEG signals is a challenging problem in neural signal processing [52]. For EEG signals in first database, we have verified that the performance of the proposed method is reduced by increasing the number of decomposition level. Similar variations in the ΔSNR and η values are also observed for the real-time EEG signals in the new database using the proposed approaches. In the future, the method can be studied by varying the sampling frequency during the recording of EEG signal. For multichannel EEG signal, the proposed denoising approaches can be performed over each channel EEG signal for the elimination of motion artifact. Recently, the multivariate extension of empirical wavelet transform (EWT) has been used for the detection of epileptic seizure using EEG signal [53]. Therefore, the multivariate total variation denoising can be performed over multivariate EWT domain for the elimination of motion artifact from the multichannel EEG signal. The motion artifact contaminated EEG signal has higher energy value as compared to the cleaned EEG signal. The energy can be used as the measure to identify the motion artifact in EEG signal. In the future, the machine learning algorithms can be implemented for the automated detection of artifacts from the EEG signal. In this study, the weights are assigned as TKE values for MWTV denoisng approach. Therefore, the adaptive WTV can be implemented for the filtering of motion artifact from EEG signal. In the future, novel signal processing approaches can be developed for the elimination of artifacts from the multichannel EEG signals.

TABLE II
COMPARISON WITH EXISTING MOTION ARTIFACTS REMOVAL METHODS.

Methods	**ΔSNR (dB)**	**η (%)**
DWT and thresholding [12]	8.08 ± 4.01	55.3 ± 35.40
EMD and IMF selection [12]	7.28 ± 3.67	43.2 ± 31.20
EEMD and IMF selection [12]	8.21 ± 3.82	52.2 ± 36.30
EMD-ICA [12]	7.47 ± 3.53	44.1 ± 30.80
EMD-CCA [12]	7.32 ± 3.67	43.4 ± 31.30
EEMD-ICA [12]	8.22 ± 3.81	52.3 ± 36.20
EEMD-CCA [12]	8.21 ± 3.82	52.2 ± 36.40
SSA [17]	11.16 ± 3.80	61.35 ± 21.68
Proposed MTV denoising	29.12 ± 2.72	68.56 ± 4.47
Proposed MWTV denoising	29.29 ± 2.67	67.31 ± 4.78

IV. CONCLUSION

The approaches based on the MTV and MWTV denoising techniques have been proposed in this paper for the elimination of motion artifact from the EEG signal. The TV and WTV techniques are applied over the approximation subband signal of the EEG signal which is contaminated with motion artifact. The filtered EEG signal is obtained based on the difference of the motion artifact contaminated approximation subband signal, and the output of TV or WTV filter followed by the wavelet-based reconstruction. The proposed approach demonstrated a better performance with a higher average ΔSNR and the η values of 29.29 dB and 67.31% when compared with existing approaches. The approach can be implemented in real time for the filtering of motion artifact from the EEG signal. New methods based on the use of different multivariate signal processing approaches can be developed for the elimination of other artifacts from the EEG signals recorded using multiple electrodes.

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