Real-Time Hybrid Ocular Artifact Detection and Removal for Single Channel EEG

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***Abstract*—Electroencephalography (EEG) is a promising technique to record brain activities in natural settings. However, EEG signals are usually contaminated by Ocular Artifacts (OA) such as eye blink activities. Removal of OA is critical to obtain clean EEG signals required for the feature extraction and classification. With the increasing interest in wearable technologies, single channel EEG systems are becoming more prevalent. Such ambulatory devices require real-time signal processing for immediate feedback. This paper presents a hybrid algorithm to detect and remove OA from single channel EEG signal using NeuroMonitor hardware platform. The algorithm first detects the eye blinks (OA zone) using Algebraic approach, and then removes artifact from OA zone using Discrete Wavelet Transform (DWT) decomposition method. De-noising technique is applied only to the OA zone to keep the critical neural information intact. The OA removal algorithm is applied to the online data for 0.5 sec epoch length. The performance evaluation is carried out qualitatively and quantitatively using time-frequency analysis, mean square coherence and other statistical parameters, i.e. Correlation Coefficient and Mutual Information. Processing time for DWT was significantly lower (x25) to that of SWT. This proposed hybrid OA removal algorithm demonstrates real-time execution with sufficient accuracy.**

Keywords—Algebraic Method; Electroencephalograph (EEG); Ocular Artifact; Online removal; Wavelet Transform;

I. INTRODUCTION

Electroencephalography (EEG) records the neurological signals in terms of the electrical signals corresponding to the brain activities. With the raw EEG signals, electrical artifacts arising from eye-blinks and movement of the eyeballs get recorded along with neurological signal. These artifact related to ocular activities are collectively known as Ocular Artifact (OA). Regular EEG signals in the order of microvolts are contaminated by these OA in the order of millivolts. The frequency range of interest for most of the EEG applications lies up to 100 Hz, and typical amplitude are 10μV to 50μV whereas OA occurs within the range of 0 to 16 Hz having higher amplitude. The Fig. 1 shows a typical raw EEG data (FP1) with OA and the cleaned EEG data.

OAs can create inaccuracy or even can cause critical errors for feature extraction and classification effecting diagnosis process or automated brain-computer interfacing (BCI) applications. To improve the automatic processing of EEG signals for accurate clinical and experimental analysis, removal of these artifacts are of prime interest. It is also substantial for remote monitoring and real-time analysis with ambulatory single channel EEG devices.

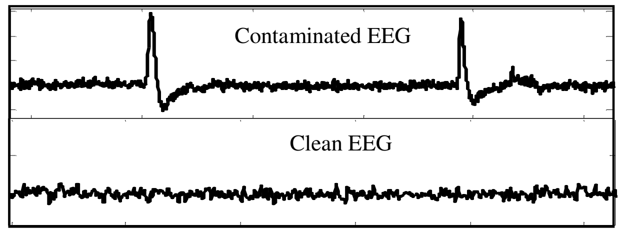


Fig. 1: A representative raw EEG signal (FP1) vs a clean EEG signal

The frequency spectrum of OA overlaps with the EEG frequency band, therefore filtering techniques to remove OA, might also eliminate important neural information. Many techniques have been developed to eliminate OA from EEG signals. Some methods used Wavelet Transform (WT) [1,2,3], Modified Multiscale Sample entropy (mMSE)-wICA [4], EMD (Empirical Mode Decomposition) - CCA (Canonical Correlation Analysis) [5,6] and Algebraic Method (AM) [7] based approaches. WT has been proven to be promising for its ability to work on single channel EEG [1,2,3]. Another technique reported for OA removal from single channel EEG is based on EMD-CCA, where OA template is determined from contaminated EEG using EMD and then CCA is carried out using detected OA template and contaminated EEG signal to de-noise the EEG data [5]. EEMD (Ensemble EMD) – CCA method described in [6] improves the performance by eliminating the mode mixing dilemma existing with [5]. Both algorithms preformed similarly as WT method, but computational cost is higher than WT algorithm. Algebraic method follows operational calculus leading to joint detection algorithm and detects only the OA zone [7]. This method can detect OA but does not remove artifact, and is very fast in processing time compared to WT based algorithm.

In this paper, we propose a hybrid algorithm to detect and thereby remove OA from online EEG data. We combine two methods: (i) Algebraic method – to detect the OA zone [7], (ii) Discrete WT (DWT) to de-noise the detected OA zone [3] so as to obtain the artifact free EEG signal. The proposed fully automated method neither needs recording of additional reference EOG signal nor relies on the other EEG channels. The OA removal algorithm has been implemented in our previously developed 2-channel ambulatory EEG device - NeuroMonitor [9]. The performance of the OA denoising algorithm has been statistically evaluated with time domain metrics - Correlation of Coefficient (CC) and Mutual

Information (MI) and frequency domain metrics - Time-Frequency analysis (TFA) and Magnitude Square Coherence (MSC) estimation.

II. Methodology

In this section, we discuss in detail the methods used for identifying and denoising the ocular zones in the raw EEG data.

A. Algebraic approach for OA zone detection

This section describes briefly the algebraic approach to detect spikes [7]. Due to the eye blink during regular EEG signal recording, spike like artifact is generated, which is considered as irregularity in the neuronal signal. This method detects the abrupt changes and estimate their locations for the given noisy observation $y(t)$, of a piecewise regular signal $x(t)$ [8]. It considers that there exists at most one spike in each interval 'I' [τ, τ + T], where, τ is the origin and T is the length of 'I'. In this interval, Finite Impulse Response (FIR) filter of the order 'M' is applied to extract FIR filter coefficients using sliding window technique, which is repeated 'n' times where 'n' represents the number of sliding windows in interval 'T'. Using algorithms defined in [7] and [8] the second order equation derived as:

$$\boldsymbol{a_k . t_k^2 + b_k . 2t_k + c_k = 0;} \tag{1}$$

In (1), a_k, b_k, and c_k are the output coefficients of FIR filter at time 't_k' in interval [0,T]. If there is discontinuity at 't_k', these coefficients will be non-zero else they will be zero. Accordingly, the Decision function, 'F_n' is calculated and if that value exceeds the threshold, spike exists at time 't_k' otherwise it does not. Due to existence of the noise in actual signal, F_n is compared with threshold instead of zero. Table I shows the required mathematical formulae to implement the algebraic algorithm [7]. The threshold equation is referenced from [3] and 'N' is fixed to 0.001 so as to detect only the OA in the given data (found consistent enough to detect OA in EEG signals of different subjects). The algebraic method to detect OA zone has fast processing time, a key feature suitable for real-time applications.

TABLE I
LIST OF FORMULAE UTILIZED IN THIS WORK

Impulse response equation	$h_k(t_m) = \frac{(-1)^{k+1}}{(v-1)!} \frac{d^2}{dt_m^2}(1+t_m)^{k+2}\, t_m^{v-1}$; $0 \le t_m \le T$ $= 0$; elsewhere
Coefficients calculation using FIR Filter	$v_k(\tau) \approx v_{k,n} = \sum_{m=0}^{M} W_m h_{k,m}\, y_{n+M-m}$
Decision function calculation	1. $F_{k,n} = [v_{k+1,n}]^2 - v_{k,n} v_{k+2,n}$ 2. $F_n = \prod_{k=0}^{K-1} F_{k,n}$; $n = 0,1,2 \ldots$
Threshold equation	$\gamma = N / (\mu + \sigma)$; N = Constant; μ = mean; σ = Standard Deviation

B. Wavelet Transform based de-noising

WT has emerged as one of the robust methods in processing non-stationary signals such as EEG. Two types of WT decomposition methods, Stationary WT (SWT) and Discrete WT (DWT) are evaluated here for their respective performances with the mother wavelet as 'coif5'. For both SWT and DWT, the input signal is convolved with high-pass and low-pass filters to get detail coefficients and approximation coefficients respectively. In SWT, after every decomposition level, signal is up-sampled by a factor of 2 because of which throughout till the final decomposition level, the total no. of detail and approximation coefficients remain same as the no. of original input samples. Whereas with DWT, at every recursive decomposition level, signal is down-sampled by a factor of 2 which results in no. of output coefficients at every level as half of the input signal to that level. Therefore no. of samples to be convolved at every stage, reduces to half compared to the input signal length. Due to the discrepancy of up-sampling and down-sampling at every decomposition level in SWT and DWT respectively, DWT is preferred over SWT for its faster processing time and equivalent efficient de-noising ability, considering real-time implementation aspect of the proposed algorithm. To preserve the low frequency components in non-OA zone, WT is applied only to the detected OA zone (identified by algebraic method) and non-OA zone remains intact ensuring the critical EEG background information persistent in this region.

The proposed WT based OA removal algorithm involves the following steps:

1. Apply DWT only to the detected OA zone to decompose it up to eight levels using *coifman* (coif5) as a basis function.
2. The detail coefficients of decomposition levels 5 to 8 (frequency range of 1-16Hz) are compared with the threshold equation "(σ * 1.5)", where σ denotes the median absolute deviation of the signal. If the coefficient value exceeds the threshold value, it is replaced with zero else retains as it is.
3. Finally, inverse discrete wavelet transform is applied to reconstruct the clean EEG signal from the decomposed signal.

C. Overall hybrid approach

Overall algorithm proposed in this paper implements Algebraic approach to detect the OA zone and DWT based de-noising technique applied only to the detected OA zone for eye blink removal, refer Fig 2. Algorithm is found to be suitable for real-time implementation for single channel EEG signal OA removal. Also the proposed method completely preserves the EEG information in the non-OA zones.

Some key considerations for implementing hybrid algorithm are mentioned below:

a. For the algebraic method, to ensure that there exists at the most one eye blink (irregular point) in 'T', the length of the interval 'T' has been taken as 0.29 sec, which gives sufficient resolution as eye blinks are typically longer than 0.3 sec. (the average eye blink duration is generally

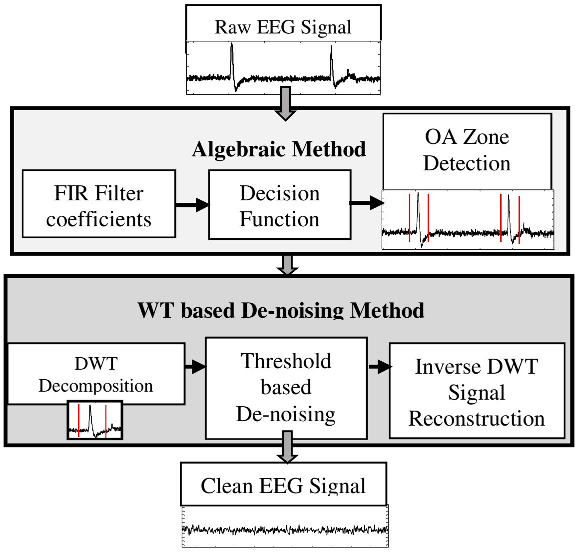


Fig.2: Proposed overall EEG de-noising algorithm

0.2 to 0.4 sec [10]). The FIR filter delay which is generally half of the filter order is adjusted while calculating the exact OA zone locations.

b. Due to the filter delay, there are chances that the eye blinks occurring at the end of the epoch, get undetected by the algorithm. It has been avoided by overlapping the epochs with the ratio of ~31%, to ensure the correct OA zone detection by testing over several datasets.

c. Algorithm is tested for online EEG data streaming and epoch data length of 128 samples (i.e. 0.5 sec data - using 256 sps) is considered in the real-time to execute the entire de-noising algorithm.

D. *Performace evaluation*

For the validation of the developed OA removal technique, Time-Frequency Analysis (TFA), Magnitude Square Coherence (MSC) plot and two statistical parameters: Correlation of Coefficient (CC) and Mutual Information (MI), are utilized.

TFA is carried out using EEGLAB function. It provides the information of energy of the frequencies exiting at a given time simultaneously. MSC plot is generated using the MATLAB function '*mscohere'*. MSC gives the estimate of the frequency coherence between the two signals x and y, where values between 0 and 1 indicates how well signal x corresponds to y at each frequency.

CC computes the similarity between the raw and corrected EEG signals. MATLAB (MathWorks Inc., Natwick, MA) function '*corrcoef*' is used to determine it and result ranges between *0* being *no match at all* and 1 being *exact match.* CC is separately computed for non-OA zone and OA zone to clearly show the correlation in respective area**.** MI measures how much one random variables tells us about another. The higher the value of MI metric, the better the mutual information content. The open source MATLAB function *minfo.m* developed by Dr.Jason Palmer (available at: http://sccn.ucsd.edu/~jason/minfo.m) is used to compute MI.

III. DATA ACQUISITION AND ANALYSIS

This section discusses the data acquisition protocol and processing techniques used in the implementation of the algorithm. The block diagram depicting the implementation and evaluation procedure of the hybrid algorithm is shown in Fig. 3.

A. *Data acquisition*

NeuroMonitor is an ambulatory EEG device used to capture raw EEG signal and transmit it wirelessly to remote device [9]. It is a miniature, lightweight, two-channel referential montage based EEG device that is practically deployable in real-life settings and can wirelessly transmit data using Bluetooth at the baud rate of 115.2 kbps in online mode, while being concealed within head accessories like a cap/headband having sampling rate of 256 sps.

In this study, EEG data has been recorded using our custom NeuroMonitor EEG device [9] from three subjects with electrodes placed on the prefrontal cortex at FP1 and FP2 channel locations (based on 10-20 International electrode system) referenced with the ground electrode on the left mastoid. For the first 10 seconds, subjects were in the relaxed state closing the eyes. During the next 35 seconds, subjects were instructed to blink every 5 sec. The recorded data is transmitted wirelessly using Bluetooth and received at the console by the GUI developed in MATLAB [9].

B. *Data processing*

The MATLAB acquisition software receives 128 samples epoch (0.5 sec) of the raw EEG signal at a time from each channel. The proposed OA removal algorithm is then executed on the received block of EEG epoch in real-time for both channels sequentially. The algorithm first detects the eye blink zones using algebraic method, and applies DWT decomposition to remove the OA only if it exists. If the eye blink doesn't get detected in the current epoch by algebraic method, the software continues to capture the next EEG epoch to repeat the process till the stop command is issued from the GUI to stop the receiver. Finally the raw EEG signal and processed clean EEG signal are stored for further offline performance evaluation.

IV. RESULTS AND DISCUSSION

In Fig. 4 the output of Algebraic method is shown where the spike zones are detected exactly over the actual eye blinks as desired. As the initial step DWT and SWT were compared for their respective performances. Fig. 5 shows the time domain diagram for DWT before and after cleaning EEG for Subject 1 Channel 1 (FP1). It was observed that de-noising using SWT showed more residues of eye blinks after cleaning, while DWT can introduce sharp transitions. This fact is also observed in the CC comparative bar charts for DWT and SWT in Fig. 6 and it also plots processing time comparison where it is apparent that the processing time of DWT is much faster than SWT (by about 25 times).

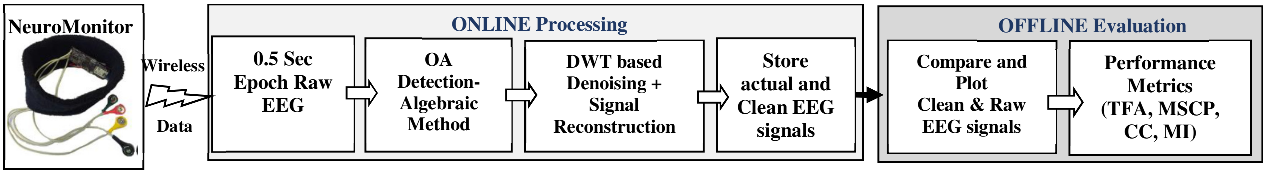


Fig. 3: Block diagram depicting the hybrid algorithm for OA removal

MI results for the same dataset were evaluated as 1.1277 for DWT and 1.0992 for SWT, which are nearly similar.

The MSC plot for FP1 Channel of Subject 1 with DWT denoising is shown in Fig. 7. It was observed that frequency coherence for Subject 1 has less coherence in lower frequencies between 1-16 Hz, and nearly 1 for all higher values. However, for other two datasets, it was found that the performance is subject dependent, where even though WT decomposition levels were selected for frequency range of 1-16 Hz, less than 1 MSC values are observed for higher than 16Hz frequencies. TFA was showing compatible results and respective eye blink artifacts were eliminated with enough accuracy. The TFA plot between raw and reconstructed denoised signal in Fig. 8 depicts that the hybrid algorithm not only cleans the signal well but keeps the other signal frequencies intact.

Table II tabulates the first four blinks CC and MI for all the datasets. For Subject 3, the eye blinks sizes and shapes were little different and therefore *coif5* wavelet basis appears to perform poorly.

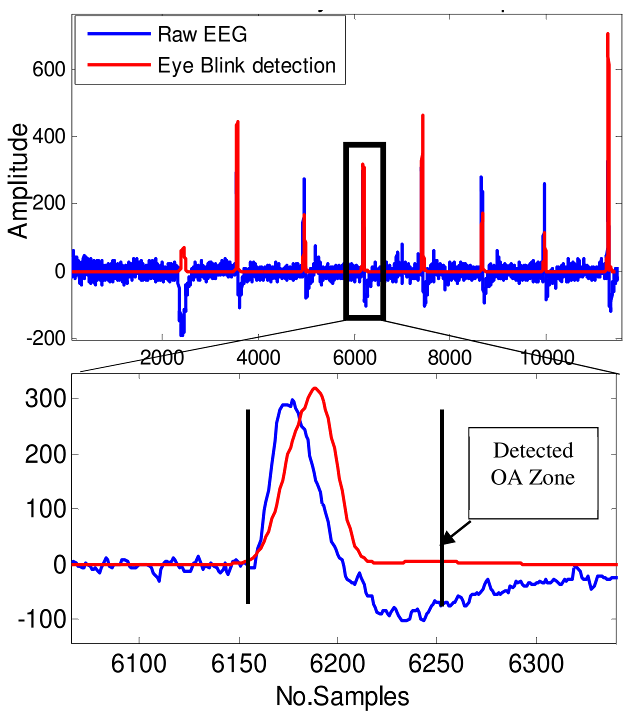
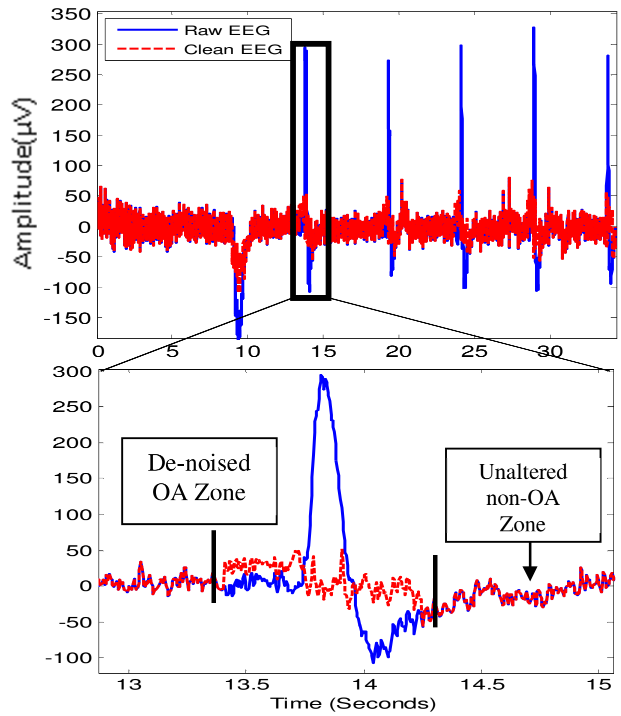


Fig. 4: Plot depicting Raw EEG and eye-blink detection zone using proposed Algebraic OA zone detection technique.



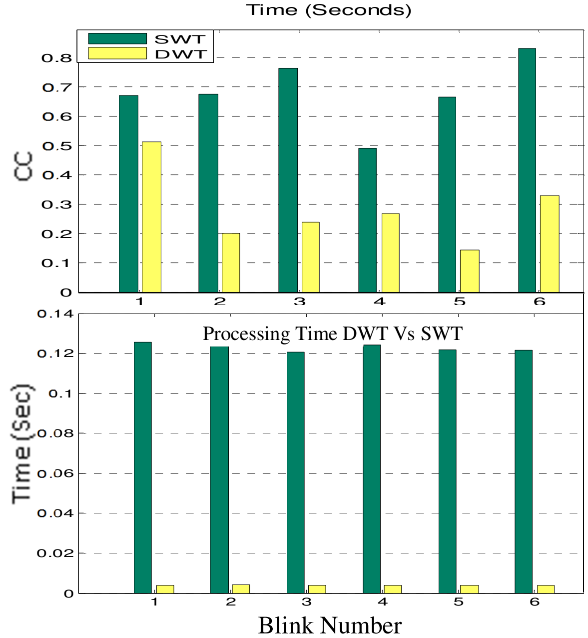


Fig. 6: CC and processing time comparison FP1 subject-1 with coif5 wavelet

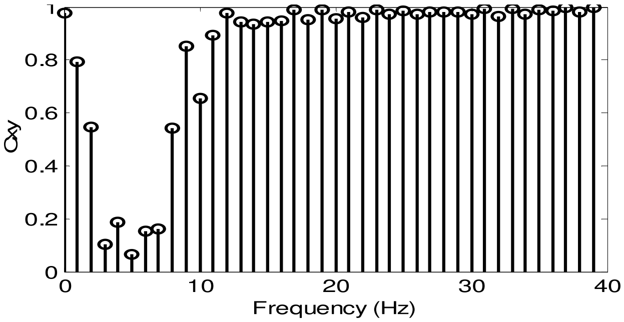


Fig. 7: Magnitude square coherence (DWT) plot of Subject-1 FP1.

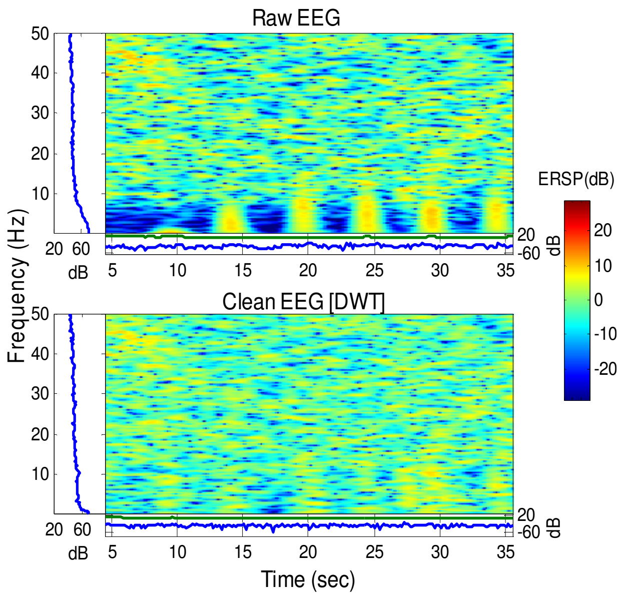


Fig. 8: Time–Frequency Analysis plot of Subject-1 FP1 EEG Data.

TABLE II.
PERFORMANCE METRICS FOR CC AND MI WITH DWT DENOISING

		Correlation of Coefficient				MI
Subject		Blink 1	Blink 2	Blink 3	Blink 4	
1	FP1	0.5129	0.1989	0.2378	0.2675	1.1277
	FP2	0.5258	0.2019	0.2392	0.2479	0.9182
2	FP1	0.0071	0.6064	0.2678	0.3079	0.9059
	FP2	0.1649	0.7082	0.0681	0.2540	0.9249
3	FP1	0.8238	0.2592	0.2174	0.7229	0.7798
	FP2	0.8419	0.7128	0.2147	0.6443	0.8118

It is to be noted that CC and MSC for the non-OA zone were ‘1’, which indicates that the entire EEG information in terms of amplitude and frequency both, in non-OA zone were intact and completely preserved.

V. CONCLUSION

In this paper, a hybrid algorithm to remove OA from single channel EEG data is proposed which comprises of algebraic method based OA detection, followed by DWT decomposition based OA removal. DWT is chosen over SWT mainly for its faster operational speed. The Correlation of Coefficient and Magnitude squared coherence plot indicates that the raw EEG signal completely matches with the corrected EEG signal in non-OA zone. In the OA zone, the neuronal information were retained while artifacts were significantly suppressed. This shows effectiveness of applying WT de-noising only to the Eye blink zone rather than entire signal. The proposed algorithm is executed in online mode for real-time EEG signal data processing. The work demonstrates satisfactory performance with 0.5 sec epoch, where OA is removed successfully in real-time. Overlapping of epochs ensured accurate detection of eye blinks without missing them at the edge of the epoch. The subject based varied performance for WT based removal is noticed, which requires further investigation. Even though, this work shows that the proposed hybrid algorithm efficiently removes eye blinks in real-time settings with the desired accuracy for single channel EEG. This hybrid approach can also be applied for any number of multichannel EEG systems making it versatile in nature.

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