Multivariate Variational Mode Decomposition based approach for Blink Removal from EEG Signal

Rahul Gavas, Dibyanshu Jaiswal, Debatri Chatterjee, Venkata Viraraghavan, Ramesh Kumar Ramakrishnan
TCS Research and Innovation, Tata Consultancy Services Limited, India
Email: (rahul.gavas,dibyanshu.jaiswal,debatri.chatterjee,venkatasubramanian.v,ramesh.kumar)@tcs.com

Abstract—**Electroencephalography (EEG) signals contain ocular artifacts which degrades the overall performance of any neuro-engineering based analysis or applications like brain computer interfaces. In general, independent component analysis (ICA) is used for removing blinks. However, that requires expert intervention. This paper aims at cleaning the eye blink related artifacts automatically without any manual interventions. We propose a novel approach based on multivariate extension of variational mode decomposition (VMD), called MVMD, for the said purpose. The mode-alignment property of MVMD has been utilized to align the joint/common oscillations across multiple channels of a given single mode. The detection of blinks is found to be better in the components of MVMD over the raw EEG signal. The proposed approach is first validated on synthetically generated EEG data and then it is tested on two publicly available real EEG datasets. Results confirm usability of the proposed approach over ICA technique. An average correlation of 0.938 ($\pm$0.0221) and 0.9869 ($\pm$0.0094) are obtained for the synthetically generated and high end EEG data, respectively, in the non-blink regions. We obtained approximately 90% classification accuracy in detecting fatigue on CogBeacon dataset. This accuracy is comparable with that obtained using state of the art approach, with the added advantage of not requiring manual interventions of experts.**

Index Terms—**EEG, MVMD, eye blink, EOG, ICA**

I. Introduction

Electroencephalogram (EEG) is a non-invasive technique for recording the conglomeration of electric potential generated in neurons. Currently, this technique is being used for various medical and non-medical applications such as brain-computer interfaces [1]. However, EEG signals are easily contaminated by other signals like electromagnetic radiations or power line noise that creates inductive currents in the cables which are connected to the participant. With the knowledge of the signal characteristics, such noise can be easily eliminated [2]. Another major artifact source is the electrophysiological responses of other organs like eye, heart, muscles and so on. Presence of these artifacts degrades the performance of EEG-based applications and analysis. Eye-blinks and eye movements are the most problematic artifacts that affects EEG signals. Removal of blink artifacts is challenging as these are non-stationary and non-linearly mixed with EEG. In some cases, the electroocculography (EOG) signal has been used as the reference for detecting the blink artifacts in the EEG data. However, this requires a separate sensor for recording the horizontal and vertical eye movements. In this paper, we have proposed a novel approach for removing the eye blink related artifacts without using any EOG sensor. The proposed method is an extension of the multivariate variational mode decomposition (MVMD) [3] which aligns the decomposed signals with common frequencies across modes.

The techniques used for EEG blink removal can be broadly classified into regression-based, wavelet-based, filtering, blind source separation (BSS) and empirical mode decomposition (EMD)-based [4]. Various hybrid models involving fusion of these techniques have been explored [4]. Regression-based approaches are easier to use, however, the decision to chose appropriate model orders, reference channels, limits their usage. Wavelet-based methods fail in identifying the artifacts completely that gets overlapped with the spectral properties of the signal. Conventional filtering fails to effectively remove the undesired blink components from the EEG signal as they are oscillated with time-varying frequency and are non-linearly generated [5]. Most widely used BSS approach is independent component analysis (ICA) [6]. The method is well-suited for EEG data with large number of channels and samples. A major shortcoming here is the manual intervention required for identifying the noisy components. Approaches involving decomposition methods like EMD lack proper mathematical grounding and its performance gets degraded when the input is noisy [7]. Various multivariate extensions of mode decomposition algorithms have been used recently in [5], [2]. However, they fail to properly align the modes in terms of common frequencies across modes [3].

The authors in [3] have used MVMD to separate out the alpha rhythms (8-12 Hz) from a multi-channel EEG. The mode-alignment property of MVMD has been utilized for the said purpose. This motivated us to systematically extend this approach for detecting the low-frequency blink artifacts. Results show that the proposed approach can be used to detect blinks automatically and successfully. Hence, the main novelty lies in the automated detection and removal of blink artifacts from EEG signals based on the intrinsic mode functions (IMFs) generated by MVMD algorithm. The detection of blink related peaks using specific IMFs is found to be an advantage over directly detecting them from the raw EEG signals. Moreover, the EEG related information in the non-blink region is relatively unaffected as compared to ICA-based approach resulting in higher correlation between the raw and processed signals. The proposed method does not affect the important frequency bands in EEG signal after the blink removal, whereas ICA alters the signal in some places. Also, proposed method can be used on low resolution devices

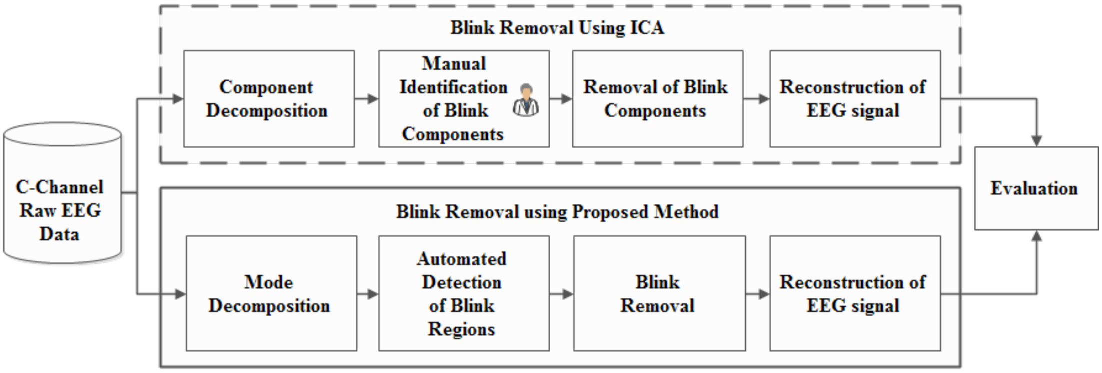

Fig. 1. Blink removal processing pipeline

and on any number of channels without compromising the performance unlike ICA which requires many channels to work effectively.

II. METHODOLOGY

Our proposed blink removal approach along with that using ICA (state of the art approach) has been depicted in Fig. 1. The raw EEG signal has been processed for:

1) **blink removal using ICA**: the steps involved are- *a*) decomposition of time series EEG signal into independent components using EEGLAB toolbox (https://sccn.ucsd.edu/eeglab/index.php; *b*) Identification of components corresponding to eye blinks. This is done manually by an EEG expert by analysing scalp topology plots and the corresponding power spectrum.
2) **blink removal using MVMD (Proposed approach)**: The steps involved in our proposed approach are: *a*) decomposition of time series EEG signal into intermediate modes/IMFs; *b*) detection of blink regions in the IMFs.

In case of ICA, the blink components are removed whereas in our proposed method, the detected blink regions are processed. Next the signal is reconstructed to get the blink-free EEG signal. Finally, we have compared the blink-free EEG signals obtained by our proposed method and that obtained using ICA.

A. Multivariate Variational Mode Decomposition

Multivariate Variational Mode Decomposition (MVMD) [3] is an extension of variational mode decomposition (VMD) [8] algorithm. In VMD, a one dimensional signal is decomposed into K number of modes $u_k(t)$ as, $x(t) = \sum_{k=1}^{K} u_k(t)$, so that, the sum of the bandwidths of all the modes is minimized and the signal gets reconstructed at least in least square sense or ideally fully, by summing up the K modes together. MVMD [3] extends this approach of VMD to multivariate data $x(t) = [x_1(t), x_2(t), x_3(t), ..., x_m(t)]$ by extracting K multivariate modulated oscillations $u_k(t)$ with $u_k(t) = [u_1(t), u_2(t), u_3(t), ..., u_m(t)]$. The resulting cost function is given by,

$$\underset{\{u_{k,m}\},\{\omega_{k,m}\}}{minimize} \{\sum_k \sum_m ||\partial_t [e^{j\omega_k t} u_+^{k,m}(t)]||_2^2\} \quad (1)$$

where $u_+^{k,m}$ is a complex valued signal with single frequency (ω_k) component across M channels, subject to the constraint that $\sum_k u_{k,m}(t) = x_m(t)$ with $m = 1, 2, 3, ..., M$. The algorithm is beneficial due to i) mode alignment property, ii) quasi-orthogonality across modes iii) separation of multivariate modulated oscillations inherent in the data and iv) robustness to noise.

Algorithm 1 Blink artifact removal using MVMD

Input: Raw EEG data: C channels each at sampling rate fs. Let each channel last from time-index $n = 0$ to $n = N - 1$.
Output: EEG data, $v_c[n], c \in \{0, \ldots, C-1\}$, of the same dimensions as input without blink artifacts
Procedure:

```
Decompose the given multi-channel EEG data into K IMFs using MVMD. Denote the c^th channel's k^th IMF by u_{k,c}[n].
b[n] ← 0, n ∈ {0, ..., N−1}
for k = 0 to K − 1 do
    if φ(u_{k,1}[·]) > δ and φ(u_{k,1}[·]) ≤ Δ then
        b[n] = u_{k,1}[n], n ∈ {0, ..., N−1}
        break
    end if
end for
Detect peaks and peak-widths in b[n]
I ← {}
for each detected peak (location p, width w) do
    I ← I ∪ {p − w, ..., p + w}
end for
for c = 0 to C − 1 do
    for k = 0 to K − 1 do
        if φ(u_{k,c}[·]) ≤ Δ then
            u_{k,c}[n], n ∈ I ← Data interpolated from u_{k,c}[n], n ∉ I
        end if
    end for
    v_c[n] = Σ_{k=0}^{K−1} u_{k,c}[n], n ∈ {0, ..., N−1}
end for
```

B. Proposed extension of MVMD

Algorithm 1 details the proposed blink artifact removal approach using MVMD. The algorithm uses two thresholds $\delta = 2$ Hz and $\Delta = 4$ Hz based on the observations made in Fig. 2. The function $\phi(u[\cdot])$ returns the dominant frequency of a signal (or IMF), $u[\cdot]$. The square brackets indicate that the algorithm is applied on digital signals.

Our proposed Algorithm 1 works as follows. First, the EEG signals are decomposed into K IMFs per channel using MVMD. The length of each IMF is equal to the original signal length N. The number of IMFs should be large enough so that each IMF occupies only a small band of frequencies and consequently blink detection becomes easier. Empirically, we found that 10 IMFs are sufficient (although 20 also yields similar results). Normally, ocular artifacts like eye blinks and eye movements are represented as low frequency (below 4Hz) signals [9]. Hence a straightforward approach would be to reject all IMFs having dominant frequency below that. However, this would also remove some low frequency and slow-varying useful components of the EEG signal. Thus, we have tried to identify the blink regions from IMFs. Eye blinks have higher amplitude compared to normal EEG signal but conventional peak-detection algorithm on the raw EEG signal produces many false alarms. However, the IMFs that correspond to blinks are smoother due to the band-limited spectral content. As a result, peak-detection works better on these IMFs. Due to the mode-alignment property of MVMD, the dominant frequency for a given IMF is similar across channels and hence it is sufficient to consider the first channel's IMFs. Fig. 2 shows a raw EEG data along with few example IMFs. We note that IMFs having lower dominant frequency are smoother than the original signal, hence, peak-detection algorithms works better in this case. It is evident from Fig. 2 that blinks are most prominent in IMFs having dominant frequency closer to 4 Hz (i.e. Fig. 2 (c)). Thus, we propose that IMFs that have the dominant frequency in the range $(\delta = 2, \Delta]$ are chosen for peak detection. In our implementation, the `findpeaks` function in Matlab is used to detect peaks and their widths. This procedure is explained in Steps 2 to 9 in Algorithm 1. For each detected peak, the corresponding width is used to determine the duration of the blink region as explained in steps 10 to 13 in Algorithm 1. All IMFs that have the dominant frequency below Δ Hz are modified as follows: samples outside the blink regions are linearly interpolated to replace the samples inside the blink regions. The reconstructed blink free EEG signal is obtained by adding the modified IMFs with unmodified ones. This procedure is explained in Steps 14 to 21 in Algorithm 1.

C. Datasets used

We have used 3 different datasets in our present work.

1) Synthetically generated EEG data: We generated synthetic EEG signal using the tools provided in [10]. First a clean EEG data is generated and then blinks are added at known locations. 10 such 4-channel EEG data is created with a sampling frequency of 220 Hz and various SNR values. Thus, in this dataset, we have information about blink start and end locations. This effectively helps in the validation of blink removal algorithms.

2) High end EEG: Covert Shift Dataset: This dataset [11] aims to study whether visual attention shifts in different pairs of directions can be differentiated via alpha wave activity in the brain. 8 healthy subjects were asked to fixate and covertly shift attention alternately. A 60-channel actiCAP EEG device is used to record brain activations at a sampling rate of 1000 Hz, along with 2-channel EOG. We have used this dataset to compare the performance of the proposed method for blink removal taking EOG channels as ground truth for blink positions.

3) CogBeacon Dataset: CogBeacon[1] is a publicly available multimodal dataset [12] consisting of 76 sessions of EEG data collected from 19 male and female users performing different versions of the Wisconsin Card Sorting Test (WCST) [13], [14] for testing the ability to display flexibility in thinking. The system provides feedback on whether a particular match is right or wrong. The matching rule changes frequently, and the user has to figure out the rule based on the feedback given. Researchers also created two modified versions (V1 and V2), based on the number of available options for the user to choose the cards, in each turn of this game, so as to increase the computational demands of the task. The *raw EEG data* was captured using a consumer grade Muse headset [2], sampled at a frequency of 220 Hz; from 4 EEG electrodes placed at locations `AF7`, `AF8`, `TP9`, and `TP10` respectively, as per the International Standard 10-20 system of EEG electrode scalp locations. This is accompanied by *fatigue self report* - indicated by a push button placed in front of the subject while performing the task. The dataset also contains facial key-points captured using a camera and user performance statistics during the task. Authors used these information to classify the `FATIGUE` and `NO-FATIGUE` states of a subject with fatigue self-report taken as ground truth. We have used our proposed approach on this dataset to remove blink and compare the overall classification accuracy afterwards.

D. Evaluation metrics

We have used following metrics for quantitative evaluation of our proposed approach with respect to ICA-based approach. **Signal-to-error ratio (SER)** [15]: SER is a measure of how much the non-blink EEG regions are getting altered by the noise cleaning technique and is expressed as,

$$SER = \frac{1}{M}\sum_{i=1}^{M} p_i \times 10\log_{10}\frac{E\{(x_i^2)\}}{E\{(\hat{d}_i^2)\}} \tag{2}$$

where M denotes the number of EEG channels, x is the raw EEG data and $\hat{d}$ is the error in processed EEG data in the non-blink region given by $\hat{d}$ = (raw EEG - filtered EEG). Ideally, in the non-blink regions, the processed EEG should be same

[1] https://github.com/MikeMpapa/CogBeacon-MultiModal_Dataset_for_Cognitive_Fatigue

[2] https://choosemuse.com/what-it-measures/

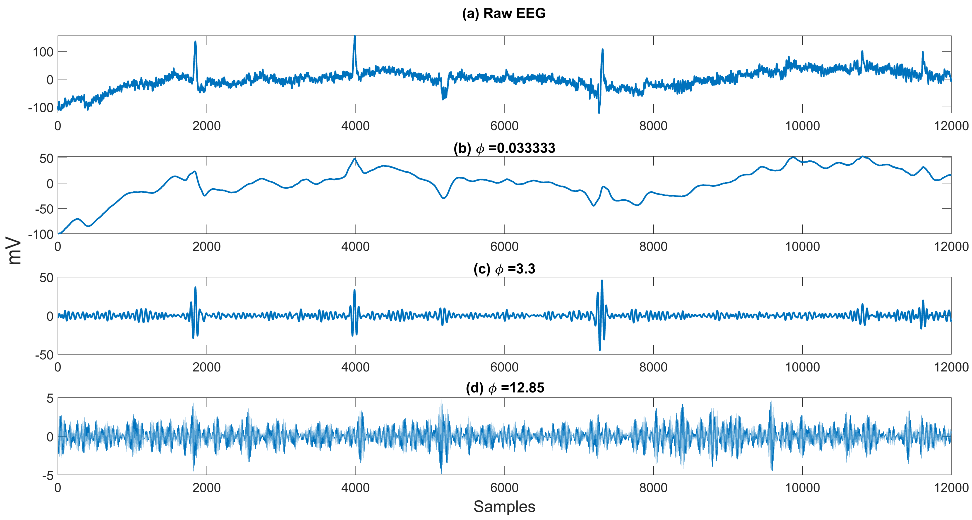

Fig. 2. (a) Original EEG signal for channel AF3, and example IMFs with different dominant frequencies (ϕ): (b) to (d)

as the raw EEG giving a value of $\hat{d}$ = 0. $E\{\cdot\}$ is the power of the signal and p is the weight obtained from each channel defined as,

$$p_i = E\{(x_i^2)\}|_{corruptedsegments} - E(x_i^2)|_{cleansegments} \quad (3)$$

Higher values of SER indicates better noise cleaning performance.

Correlation: the correlation between the raw EEG and the processed EEG in both blink and blink-free segments are also considered as a metric.

Variance-based metric (V): it is defined as the ratio of variance in the processed blink segment to the variance in the blink segment. Lesser the value of V, better is the performance of the noise cleaning approach.

Percentage change in band power: this is calculated for theta, alpha and beta bands. Theoretically, these bands are devoid of blink artifacts and hence, any blink removal approach should not alter these band powers.

Classification accuracy: finally we computed the classification accuracy of detecting fatigue and non-fatigue states using CogBeacon dataset. This helps to establish the importance of blink removal and its contribution in the overall assessment of cognitive states from EEG signal.

III. Results and Discussions

This section details the outcomes of our proposed approach on various datasets.

A. Performance on simulated dataset

In synthetically generated EEG signal, the exact blink start and end locations are known. Hence, certain metrics defined in section II-D can only be calculated on synthetic EEG data. Fig. 3 shows a sample plot of a raw EEG signal and the corresponding blink-free signals obtained by ICA and proposed method. It is observed that the signal obtained by our method correlates well with the raw signal. Kindly note in the figure that the ICA constructed signal alters the non-blink portions, whereas, the proposed method corrects only the blink portions. Similar plots are obtained for all the datasets and are avoided for the sake of brevity.

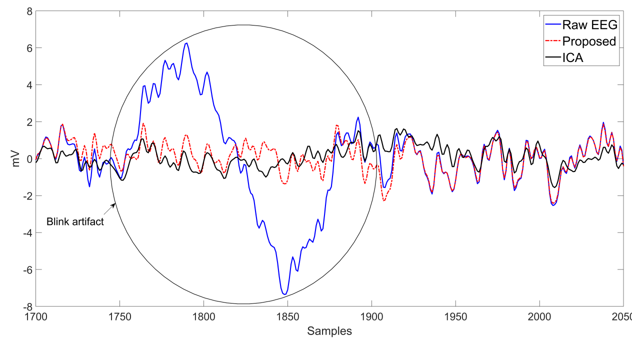

Fig. 3. Raw and processed EEG signals after removing blink artifacts by proposed approach and ICA. The blink region is circled

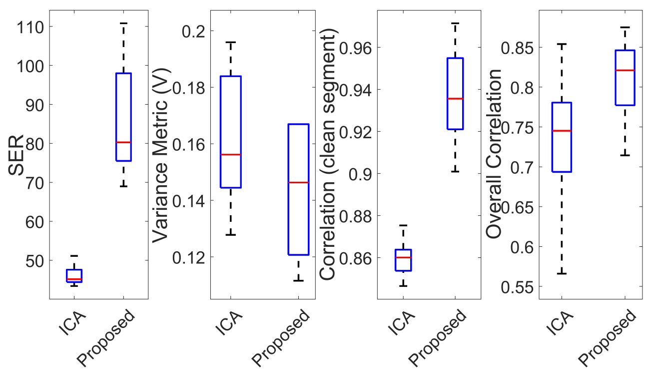

Fig. 4. Performance metrics for the proposed approach on synthetic data

Fig. 4 and 5 show various evaluation metrics calculated on the simulated data. SER is high for our proposed method compared to ICA which indicates better performance of our

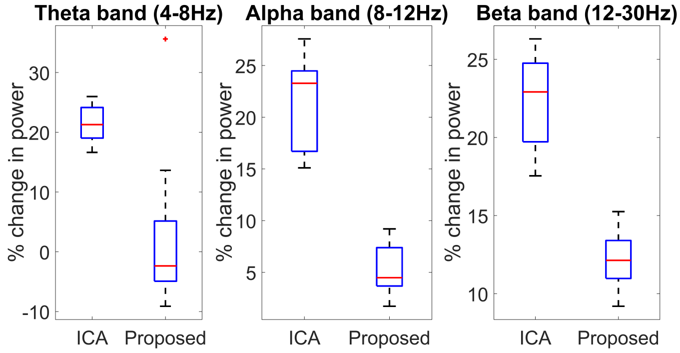

Fig. 5. Percentage change in powers from blink-free EEG to the processed EEG

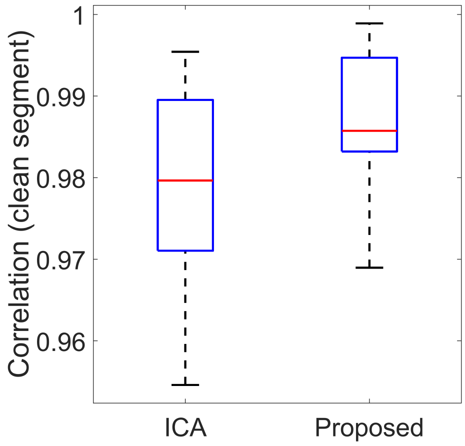

Fig. 6. Correlation in the non-blink regions for high-end EEG

approach. The correlation values obtained for both blink and non-blink regions are also shown in Fig. 4. It is to be noted that for both the regions, correlation is higher in case of our approach compared to that in ICA-based method. Lesser value of variance-based metric (V) in Fig. 4 for the proposed method is indicative of better performance in comparison to ICA.

The percentage change in the powers of theta, alpha and beta bands from raw EEG and the filtered EEG in the non-blink regions using the proposed and the ICA methods is depicted in Fig. 5. It is observed that the change is less in the proposed method in comparison to ICA. This can be attributed to the fact that ICA rejects the whole component identified as blink component and hence leads to loss of valuable data in the frequency bins outside of the blinks also.

B. Performance on high end EEG dataset

Fig. 6 shows the boxplot of correlation values (across participants) obtained in the non-blink EEG segments using ICA and proposed method. The correlation values are averaged over 57 channels. The blink regions are identified using the vertical EOG data. As the EOG data is affected by other surface EMG signals and EEG, the exact start and end positions of blink portions cannot be determined using EOG. Hence, in this case, we have evaluated the blink removal approach using correlation coefficient metric only. It is seen that the correlation obtained is good in both the cases; however, the proposed technique performs slightly better than ICA (ICA: 0.9788 ($\pm$0.0133) Max: 0.9954, Min: 0.9546 and Proposed: 0.9869 ($\pm$0.0094) Max: 0.9989, Min: 0.9690).

C. Performance on CogBeacon dataset

The raw EEG data is processed using our method and ICA separately. The raw EEG data consists of 4 channels, with average duration (mm:ss) 04:53 $\pm$ 01:43, giving 4 independent components using ICA. Hence, we have decided to remove a maximum of 2 components to avoid loss of valuable data during the reconstruction phase. In the proposed method IMFs are calculated and peaks are detected as explained in Algorithm 1. Post reconstruction of the blink-free signal, non-overlapping windows of duration 2 seconds is used to compute a total of 80 features (20 features per channel). These features consisted of 9 morphological features such as 5 EEG band powers (delta, theta, alpha, beta and gamma) along with 4 band power ratios of alpha, beta and theta bands. Remaining 11 are statistical features such as mean, variance, standard deviation, kurtosis, skewness, maximum, minimum and three Hjorth parameters [16]. In total 4749 `NO-FATIGUE` and 2193 `FATIGUE` instances were obtained. A total of 3 such feature sets were generated using 3 different processing pipeline i.e. *a*) Without blink removal method; *b*) Blink removal using ICA; *c*) Blink removal using proposed approach. It is to be noted that ICA method is applied on the whole dataset for blink removal and then it is divided into windows for feature extraction. Class imbalance is then handled using *Synthetic Minority Over-sampling Technique* (SMOTE) [17] on the whole dataset prior to cross-validation. After performing SMOTE, the new feature set consisted of 9135 instances of which 4386 are `FATIGUE` instances (about 48% of total instances). This feature set is then used to learn a Random Forest classifier and different metrics are calculated for performance evaluation. Table I reports the classification accuracy and f-score obtained using various approaches, using a 10-fold cross validation technique averaged over 10 times. The upper half of the table corresponds to the original, unbalanced dataset and the bottom half to the balanced dataset obtained through SMOTE algorithm. Without any blink removal, we obtain a classification accuracy of 84.94%, which is quite high compared to that reported in the state of the art [12] (i.e. 67%). One major difference is that the authors in [12] have used band power values provided by MUSE device itself, whereas, we have derived beta, delta and gamma band powers from the raw EEG. From Table I it is evident that blink removal using ICA performs well in all cases, where as our proposed method is also at par in all respects. The precision/recall values are in the same range as the corresponding accuracy values and hence, we have reported only the f-score.

D. Discussions

Results show that our proposed approach is able to successfully clean the eye blinks from the raw EEG data. Our ap-

TABLE I
COMPARATIVE CLASSIFICATION ACCURACY ON COGBEACON DATASET

Approach	Accuracy	f-score
Without Blink Removal	84.94±0.95	0.89±0.01
Blink Removal using ICA	89.94±0.92	0.93±0.01
Blink Removal using proposed approach	87.92±0.96	0.91±0.01
Without Blink Removal	87.93±0.89	0.88±0.01
Blink Removal using ICA	91.97±0.85	0.92±0.01
Blink Removal using proposed approach	90.12±0.76	0.90±0.01

proach outperforms the state of the art ICA-based approach on synthetically generated EEG dataset and low resolution EEG dataset. The classification accuracy obtained on the publicly available CogBeacon dataset is comparable with that obtained using state of the art approach (ICA). However, our approach is preferable over the ICA-based method for the following reasons: i) the major concern in the ICA-based method is that, once the independent components are obtained, it requires manual intervention of an expert to identify the blink-related components. Our approach can automatically detect blinks from IMFs and hence, manual intervention is not required; ii) Since the number of independent components that contribute to form a complete EEG signal is not known, the number of distinct components obtained post ICA is typically set as the number of input EEG channels. Hence, for low resolution EEG devices having small number of input channels (for example 4-channel MUSE device), the number of components is small. In such a scenario, it is difficult to correctly identify the artifact components and hence ICA does not perform well for such devices; iii) ICA rejects the whole artifact component which might contain other useful EEG components as well. Removal of such components leads to removal of the accompanied EEG data as evident from Fig. 3 and Fig. 5. In our approach, we are only detecting the blink regions and reconstructing the EEG signal after removing it. Hence, other useful information contained in alpha, beta or theta bands are not affected. Lastly; iv) ICA is a source separation-based algorithm, hence, requires the spatial locations of the electrodes (i.e. spatial distribution of the individual signal sources) as well a large number of channels to perform well. On the other hand, our approach is not restricted to any such constraint and can be applied to a variety of EEG devices available in the market.

IV. CONCLUSIONS AND FUTURE SCOPE

In this paper, we have proposed a novel blink removal approach to be applied on EEG signal. Presence of eye blinks and other eye movement related artifacts in the EEG signal degrades the overall performance of any EEG-based applications. We have decomposed the raw EEG signal into a number of intermediate frequency components using MVMD technique and then removed blinks from these components. The study also throws light on the advantages of using certain IMFs for detecting the blink portions over the raw EEG signals. The reconstructed blink-free EEG signal so obtained has been evaluated using various metrics. The proposed approach has been applied on synthetically generated EEG signal as well as on two publicly available EEG datasets. Results show good correlation between raw and processed EEG signal. We have also compared our approach with state of the art ICA algorithm used for blink removal. The classification accuracy obtained for CogBeacon dataset (90%) is comparable with that obtained using ICA (91%). However, ICA needs manual intervention for blink removal whereas our approach can automatically detect the blinks. Moreover, unlike ICA, our proposed approach can be applied successfully on low resolution as well as on high resolution multi channel EEG signals. In addition, the proposed approach does not affect other EEG bands like alpha, beta, theta and hence, it is more suitable for EEG-based cognitive analysis. In future, we would like to apply this for various BCI or EEG-based applications and analysis for improving overall system performance.

V. ACKNOWLEDGMENTS

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