Automatic Artifact Correction of EEG Signals using Wavelet Transform

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***Abstract*: artifacts produced from non-cerebral origins such as ocular movements, Electromyogram activity and other electrical noises usually affect electroencephalographic data. It is needed to remove artifacts from electroencephalogram activity prior to information extraction and classification of Electroencephalographic activity. This work suggests an automated technique of artifact correction and noise suppression of scalp EEG data. The proposed technique helps in error-free classification of different electroencephalogram signals for implementation of a Brain-Computer interface and diagnosis of various diseases. This method uses independent component analysis for decomposition of EEG signals in independent components and Wavelet Transform denoising of the EEG signals. The identification of the artifactual independent component is done by the Fractal Sparsity criterion. The results of the methodology are validated by quantitative evaluation of the simulations performed for Electroencephalogram data. The results validate the efficacy of proposed artifact removal technique in correcting Electroencephalographic activity.**

***Index Terms*-- Electroencephalogram, Artifact correction, Independent Component Analysis, Wavelet Transform**

I. INTRODUCTION

Human brain generates electrical activity and recording of this electrical activity is done by placing electrode at different positions on the scalp. However, the recorded electrical activity is called Electroencephalogram (EEG) signals. EEG activity carry lots of information about the human subject, which is very difficult to understand simply by visual inspection [1]. With the advancement of the computer technology EEG signals analysis and identification can be done effectively without much training. EEG finds its applicability in the vast area of biomedical sciences. EEG signal evaluation can help in identification of various pathological conditions such as early detection of Alzheimer's disease, Parkinson's disease and epileptic seizures. Also, it makes possible the implementation of Brain Computer Interfaces (BCIs) for controlling assistive devices and applications [2]. A Brain Computer Interface is a pathway between human brain and external world. EEG is the most essential component of BCI, which establishes an artificial communication channel between human brain and external world and being used as an alternate method of communication by the patients of Amyotrophic Lateral Sclerosis (ALS), spinal injuries and cerebral palsy [3]. A set of sample EEG signals for the different first movements is given in Fig. 1.

The cortically generated EEG is often contaminated by non-cerebral artifact sources, which includes ocular movements, eye blinks, and Electromyogram (EMG) and Electrocardiogram (ECG) artifacts. Apart from these disturbances, other unknown sources noise such as instrumentation noise, electrical disturbances and external electromagnetic activity, have higher impact on EEG recordings in large extent. When such artifacts are strongly present with desirable EEG activity, it makes difficult the analysis and information extraction from EEG signals. Which causes in diminish of employability of EEG signals. Hence, it is essential to eliminate artifacts from EEG prior to any information extraction from EEGs.

In previous studies many techniques have been proposed to eliminate EEG artifacts. Most of the previously proposed techniques include three steps viz. obtaining the artifact sources from multichannel EEG recording using some signals separation schemes, followed by elimination of artifact sources and reconstruction of clean EEG. In early stages, only prevention steps were taken during the period of recording of EEG recording. This process lead to reduction in ocular and muscular artifacts by limiting ocular movements, ocular blinking and various body part movements. Some researchers excluded the artifact contaminated trials of EEG by employing the threshold criterion [4]. However, this technique requires more time and does not assure complete rejection of artifacts, as it is very difficult for any person to control ocular and muscular activities during EEG recording. In a different approach of artifact correction, the identification and rejection of contaminated EEG activity was performed by Electrooculogram (EOG) signal subtraction [5] and Independent Component Analysis (ICA) [6]. However, the limitation of this approach is that any inaccurate estimation of proportion of artifacts may lead to introduce distortion in the artifact corrected EEG. In addition, it is a lossy technique, since it loses certain amount of EEG activity picked up by EOG electrodes.

The ICA based technique of artifact correction requires three steps to be carried out which includes decomposition of raw EEG signal in Independent Components (ICs), identification of noisy or artifactual ICs by visual inspection and rejection of such ICs [7]. However the limitation of the ICA based technique is that it requires visual inspection of ICs to eliminate artifactual components. This makes the technique more time-consuming and unsuitable for real-time applications. In few scenarios, the useful cerebral activity leaks with the artifact ICs and therefore the complete rejection of artifactual ICs may lead to loss of useful information and distortion in the extracted features. In addition, the efficiency of such techniques mostly relied on the quality of fragmentation of artifacts from EEG activity and identification of artifactual ICs. In recent times, many new Time Frequency Representation (TFR) based artifact correction methods have proposed. A Wavelet Transform (WT) based EEG denoising technique is introduced in [8] and its variants are proposed in [9]. In WT de- noising technique the artifacts are removed after thresholding of wavelet coefficients. The value of WT coefficients which are having magnitude less than the predefined threshold are set to zero [10]. Finally, the artifact eliminated EEG is recovered by performing inverse WT on the thresholded WT coefficients. However, the main limitation of this technique is to select an appropriate value of threshold, as an inappropriate threshold may yield distortion in the actual EEG activity. The limitations of ICA and TFR technique are eliminated in another proposed approach viz. Wavelet enhanced ICA (wICA) artifact suppression method. Wavelet enhanced ICA (wICA) was proposed by Castellanos and Makarov [11]. However, the limitation of this method is that it is not a fully automated online artifact removal method is still needed.

In present work, an automated artifact correction technique is proposed for ocular artifact elimination and noise suppression from EEG signals. The proposed technique relies on the joined application of ICA algorithm and WT. This study is based on the fact that the ocular artifacts contribute high amplitude to the WT coefficients, hence suppression of WT coefficients yield ocular artifact corrected signals. The proposed technique is performed on simulated EEG signals in order to explain the efficacy of technique effectively. The proposed technique is carried out by first separating multichannel EEGs into fundamental Independent Components (ICs) using MULTI-COMBI ICA algorithm. Once ICs of the EEG signals are obtained, the criterion of Fractal Sparsity is applied for automated detection of the artifactual ICs. Further, WT coefficients are calculated for the identified artifactual ICs and thresholding of calculated WT coefficients is performed using soft thresholding criterion. Thresholded WT coefficients are further processed by inverse WT to represent in time domain as clean ICs. Afterwards, inverse ICA algorithm is applied to the clean ICs to reconstruct ocular artifact free EEG signals. The methodology is validated on simulated EEG records of ocular artifact contaminated signals.

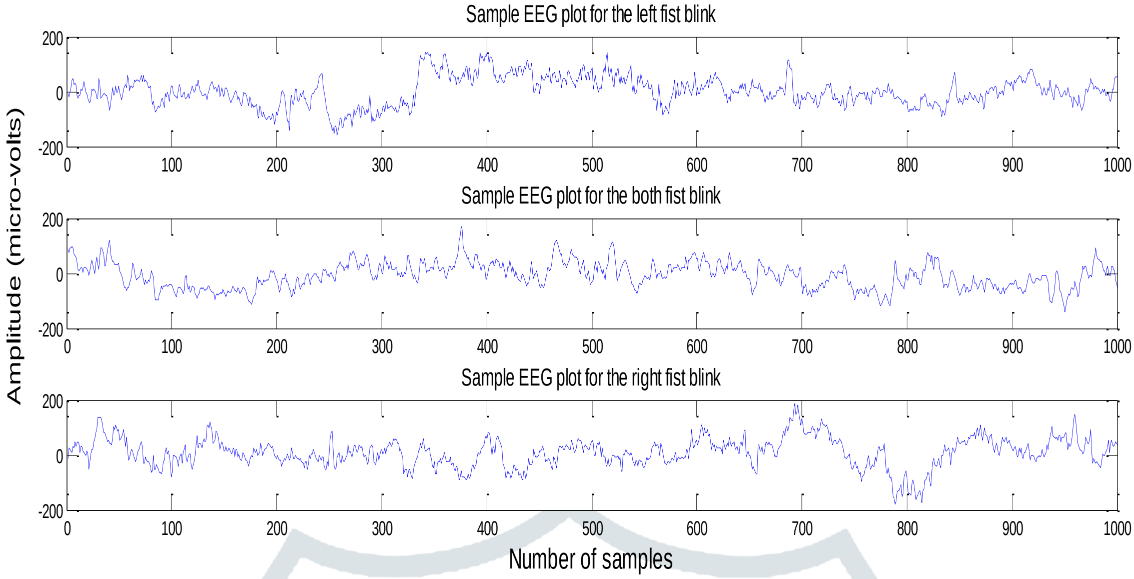

Fig. 1 Sample EEG plot for the different type of first movements

II. PROPOSED METHODOLOGY

In this subsection the basic ICA model and implementation is explained in first part. However, in the second part WT based artifact correction technique is briefly described.

2.1 INDEPENDENT COMPONENT ANALYSIS (ICA)

The purpose of ICA is to separate mixed signals to set of fundamental signals. It is assumed that the EEG sources are mixed following linear instantaneous mixing [13]. The EEG data is assumed to be generated as per the following model [14]:

$$\boldsymbol{x}(t) = \boldsymbol{A}\boldsymbol{s}(t) + \boldsymbol{n}(t) \quad (1)$$

where $\boldsymbol{x}(t) = [x_1(t), x_2(t), \dots\dots, x_I(t)]^T$is a linear mixture of J sources $\boldsymbol{s}(t) = [s_1(t), s_2(t), \dots, s_J(t)]^T$, $\boldsymbol{A}$ is a $I \times J$ mixing matrix, and $\boldsymbol{n}(t) = [n_1(t), n_2(t), \dots, n_I(t)]^T$is additive noise picked up by the EEG electrodes [13].

With Eq. (1), the aim of ICA is to obtain the de-mixing matrix $\boldsymbol{W}$ to estimate sources as,

$$\boldsymbol{s}(t) = \boldsymbol{W}\boldsymbol{x}(t) \quad (2)$$

Once $\boldsymbol{W}$ is obtained, $\boldsymbol{A}$ can be estimated as $\boldsymbol{A} = \boldsymbol{W}^{-1}$. ICA is based on following assumptions about data and process: (i) the raw experimental EEG data $\boldsymbol{x}(t)$ registered at EEG electrodes, is a spatially stable mixture of the activities of temporarily independent cerebral and artifactual sources, (ii) the mixing of potentials arising from different parts of the brain, scalp, and body is linear at the EEG electrodes, (iii) the number of sources is no bigger than the number of electrodes [13].

In present work, we consider the number of electrodes are equal to number of sources i.e. M=N. For Blind Source Separation purpose, the MULTI-COMBI ICA algorithm have been proposed in this work. The signals reconstruction ability of MULTI-COMBI ICA algorithm is evaluated by visually comparing the simulated ICs obtained after ICA algorithm with the original independent EEG sources. For ease of understanding, the ICA algorithms have been implemented on simulated EEG data in this work. EEG-like activity is generated in MATLAB using functions developed by Yeung et al. [15]. To generate EEG-like activity noise.m function is used. Further, in order to generate eye-blink-like activity peak.m function is used in MATLAB. To estimate the performance of ICA algorithm, 10 sets of six EEG sources with 256 Hz sampling frequency are generated. Thereafter, six EEG channels are realized by mixing of these independent EEG source signals.

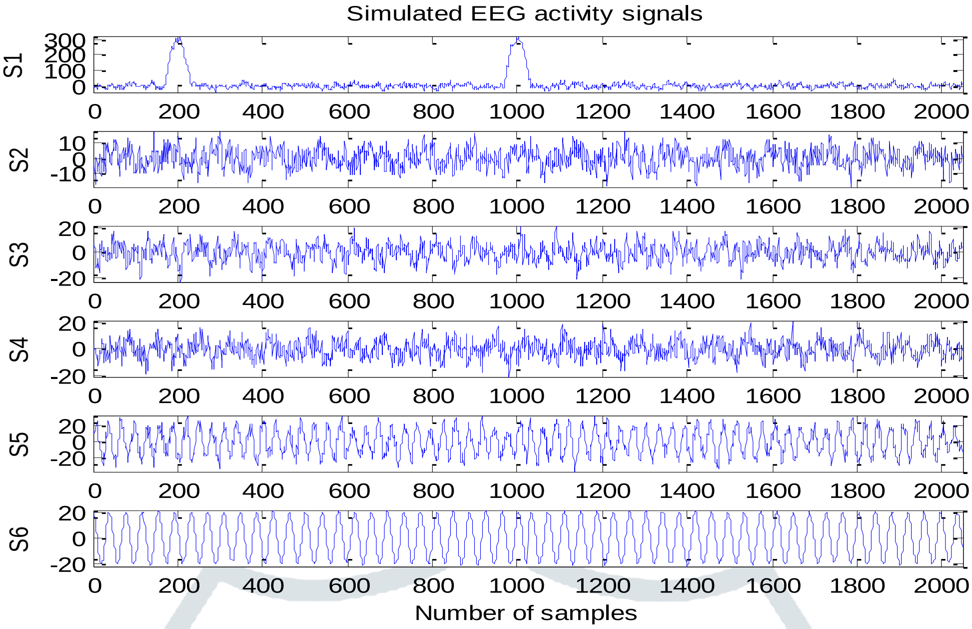

Fig. 2 A set of six simulated EEG sources resembling real human neural activity

Fig.2 shows a typical set of six simulated EEG sources resembling real human neural activity. In Fig.2, source S1 represents cerebral activity with two eye-blink artifacts, sources S2, S3 and S4 represents random cerebral activity, and sources S5 and S6 represents rhythmic cerebral activity of *13 Hz* and *30 Hz* respectively. Furthermore, the set of six channel EEG activity obtained after mixing of simulated EEG sources is presented in Fig.3. The set of six channel EEG activity is generated by multiplying separate EEG sources with a 6×6 radom matrix ***A***. The random mixing matrix is generated by randn.m function in MATLAB.

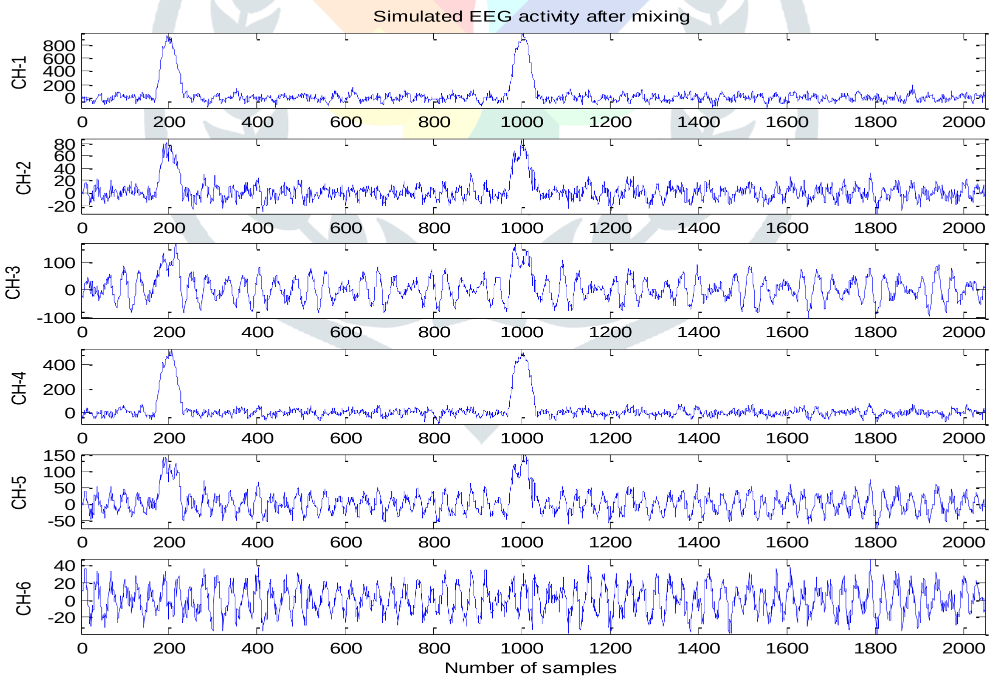

Fig. 3 A set of six channel EEG activity obtained after mixing of simulated EEG sources

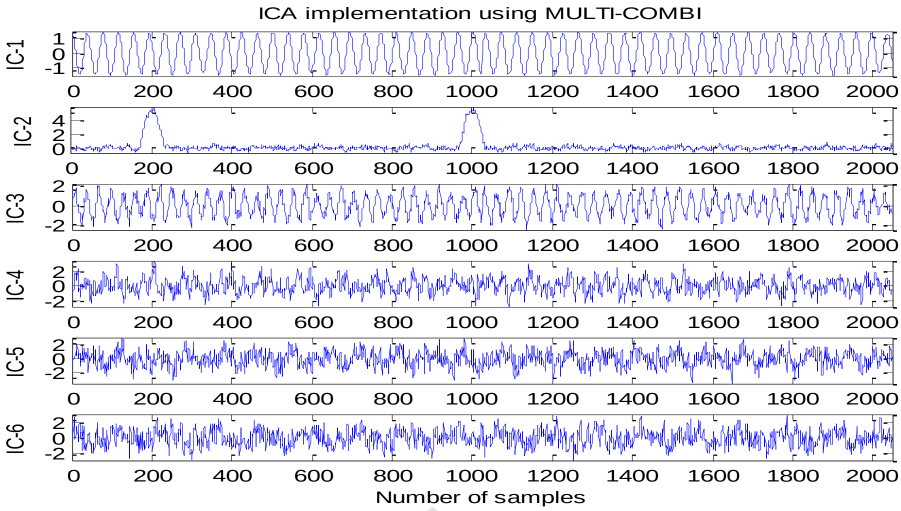

Fig. 4 Separated ICs obtained using MULTI-COMBI ICA algorithms

Fig.4 represents the separated Independent Components (ICs) obtained using MULTI-COMBI ICA algorithm, when mixed EEG signals presented in Fig.3 are given as the input. On comparing Fig.2 and Fig.4, it is observed that MULTI-COMBI ICA algorithm successfully estimated eye blink artifact IC, rhythmic EEG activity and other cerebral EEG activity successfully from mixed EEG signals.

2.2 WAVELET TRANSFORM (WT)

Stationary signals maintain same frequency component for all time intervals. For such signals Fourier Transform (FT) gives sufficient information about frequency spectra, as frequency does not change with time. However for Non-Stationary or chirp signals FT is not sufficient. As FT does not provide information to distinguish between two different Non-Stationary signals which contain same frequency component at different time interval [16]. WT over comes this sort coming of FT and provides time-frequency information of a non-stationary signal. Continuous Wavelet Transform (CWT) is given by

$$\text{CWT}(\tau, s) = \frac{1}{\sqrt{|s|}} \int f(t).\varphi^*\left(\frac{t-\tau}{s}\right) dt \qquad (3)$$

Here, φ is a Mother Wavelet function. Meyer Wavelet function in frequency domain is given as

$$\varphi(\omega)=(2\pi)^{-1/2}.e^{i\omega/2}.sin\left(\frac{\pi}{2}.\vartheta\left(\frac{3}{2\pi}.|\omega|-1\right)\right), \qquad \frac{2\pi}{3} \leq |\omega| \leq \frac{4\pi}{3} \qquad (4)$$

In present work Meyer Wavelet is considered as the mother wavelet function for calculation of the wavelet coefficients.

III. RESULTS AND DISCUSSION

3.1 AUTOMATIC IDENTIFICATION OF ARTIFACT IC

In order to automatically identify the artifactual ICs after performing ICA algorithm, the criterion of Fractal Sparsity is used in present work. The criterion of Fractal Sparsity was originally proposed by Upadhyay et al. for automatic identification of artifactual ICs [17]. As per the Fractal Sparsity criterion, the ICs which has value of Fractal Sparsity greater than the value of mean of Fractal Sparsity calculated from all ICs, are considered as the artifactual. Table 1 shows the Fractal Sparsity value of the ICs presented in Fig. 4. The mean of the Fractal Sparsity value calculated for ICs shown in Fig. 4 is 4.07. It is clear from Table 1 that only second ICs is having value of Fractal Sparsity greater than the mean of all Fractal Sparsity values. Thus only second IC is identified as artifactual using Fractal Sparsity criterion. Which is true for the present set of simulated EEG signals. It is evident from Fig. 4 and Table 1 that the automatic identification of artifactual ICs can be done effectively.

Table 1. Fractal Sparsity value computed from ICs presented in Fig. 4.

ICs	1	2	3	4	5	6
FS value	0.0015	16.98	0.55	2.34	2.48	2.06

3.2 INTERACTIONS BETWEEN ICA AND WT

This subsection studies the interaction between the two processing steps i.e. ICA based ICs estimation and WT based artifact correction. Once ICs are obtained from mixture of EEG signals using MULTI-COMBI algorithms, the identification of artifactual ICs is done be Fractal Sparsity criterion. By Fractal Sparsity criterion, it is observed that second represents the artifactual IC. However, rest of the ICs are artifact free and contain some kind cerebral activities. Once artifactual ICs are obtained, WT based artifact correction is performed on such ICs.

In order to suppress ocular artifacts, soft thresholding is performed on WT coefficients. This is derived from approach defined in [17]. The WT coefficients which has amplitude greater than $A \times (m(c) + s(c)) \leq$, is referred as coefficient of artifactual activity, where $m(c)$ denotes mean value of amplitude of WT coefficients, $s(c)$ is the standard deviation of amplitude and A is a gain applied to adjust the artifact amplitude. In order to suppress artifactual activity, the thresholding is applied to WT coefficients as follows

$$T(n) = \begin{cases} A \times T(n) & if\ T(n) > (A \times (m(c) + s(c))) \\ T(n) & else \end{cases}$$

Once thresholding is done, inverse WT is performed to reconstruct ICs in time domain. The ICs obtained after inverse WT are artifact free basically. The artifact free ICs reconstructed from artifactual ICs shown in Fig. 4 are given by Fig. 5 as IC_f-1 to IC_f-6. It can be observed from Fig.5 that only second IC is treated for the artifact correction and is completely free from artifact after treatment. However, other ICs are unaffected in this processing step as these ICs were already artifact free. Once artifact free ICs are obtained, the artifact free EEG activity is reconstructed by performing inverse MULTI-COMBI ICA algorithm on artifact free ICs. Fig.6 shows the artifact free EEG activity (represented as Sig_f-1 to Sig_f-6) obtained after performing inverse MULTI-COMBI ICA on IC_f-1 to IC_f-6.

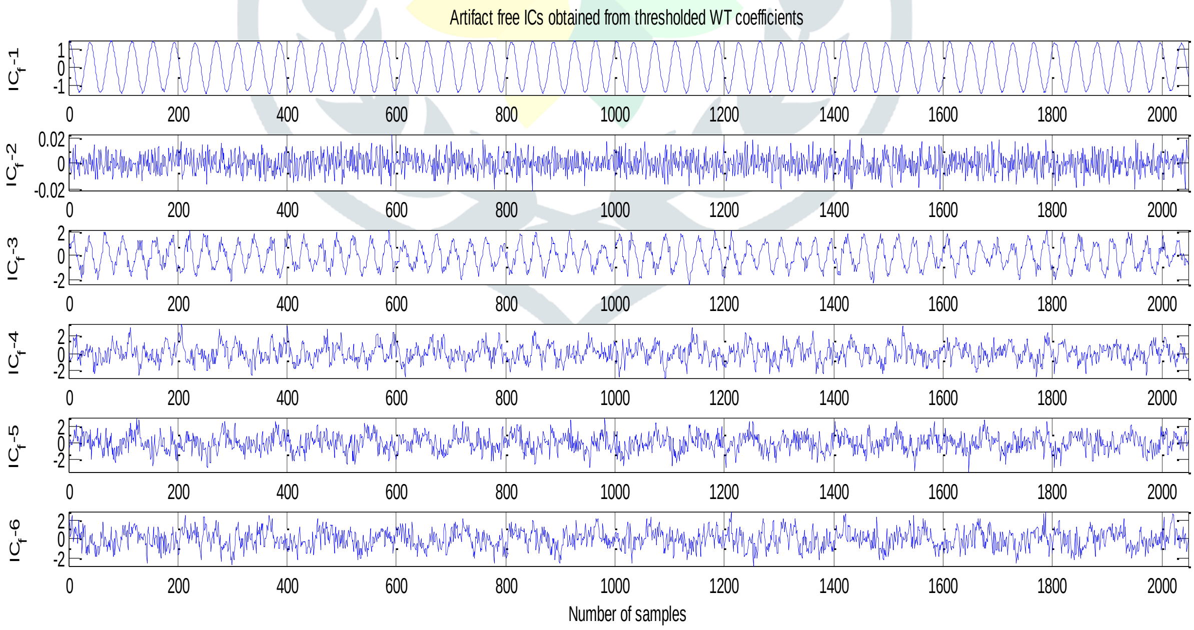

Fig. 5 Artifact free ICs obtained after performing inverse WT on thresholded coefficients

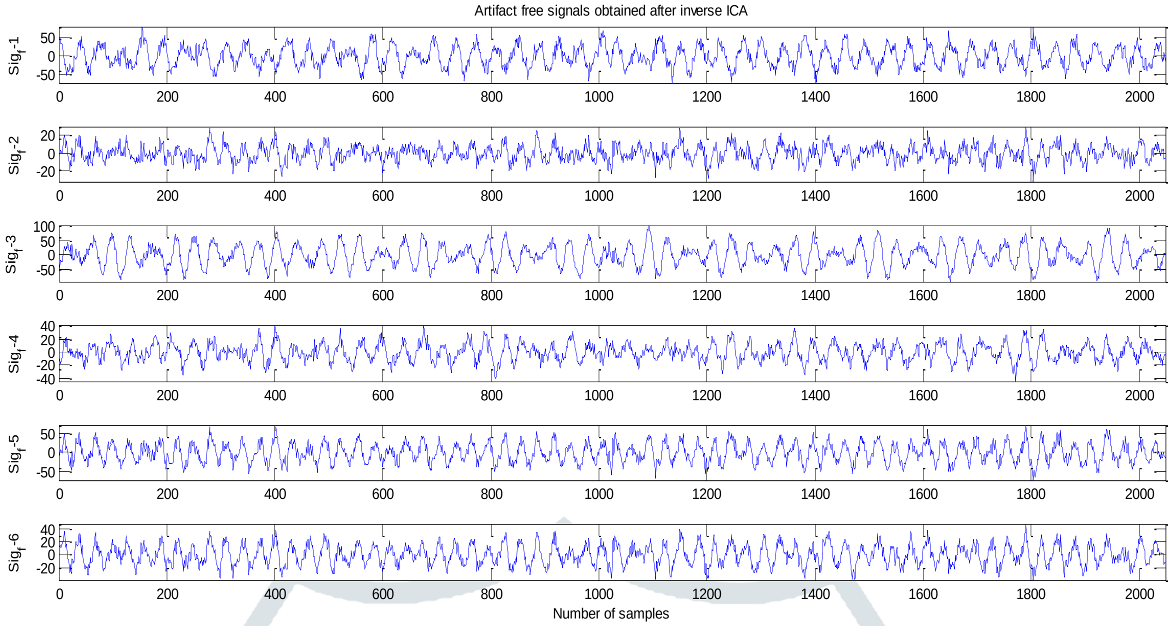

Fig. 6 Artifact free ICs obtained after performing inverse MULTI-COMBI ICA on IC$_f$-1 to IC$_f$-6

IV. CONCLUSION

In this paper a novel automated method of automated artifact removal of EEG data using Independent Component Analysis (ICA) and Wavelet Transform (WT) is proposed. The proposed technique helps in improving classification efficiency of the EEG signals in brain-computer interface application. The technique uses Fractal Sparsity criterion for automatic identification of artifactual ICs. The efficacy of the technique is validated on simulated artifactual EEG signals. It is observed that criterion of Fractal Sparsity efficiently identified for the artifactual IC. The WT thresholding is capable of removing artifacts from the ICs. The simulated results of the methodology have shown the potential of proposed technique in ocular artifact removal.

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