Automated Detection and Correction of Eye Blink and Muscular Artefacts in EEG Signal for Analysis of Autism Spectrum Disorder

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***Abstract*— Autism Spectrum Disorder (ASD) is a neural development disorder affecting the information processing capability of the brain by altering how nerve cells and their synapses interconnect and organize. Electroencephalograph or EEG signals records the electrical activity of the brain from the scalp which can be utilized to identify and investigate the brain wave pattern which are specific to individuals with ASD. Therefore, the analysis of ASD can be done by scrutinizing the specific bands (Theta, Mu and Beta) of the EEG signal. However, EEG signals are mainly contaminated by Ocular (Eye-blink) and Myogenic artefacts which pose problems in EEG interpretation. In this paper an automated real-time method for detection and removal of Ocular and Myogenic artefacts for multichannel EEG signal is proposed which would enhance the diagnostic accuracy. The proposed methodology has been validated against 20 subjects from Caltech, Physionet, Swartz Center for Computational Neuroscience and the computed average correlation and regression are 0.7574 and 0.6992 respectively.**

I. INTRODUCTION

Autism spectrum disorder (ASD) is one of the rare form of neurodevelopmental disorders based on the set of criteria including deficit in communication, impaired in social interaction, repetitive or stereotyped behaviour, lack of cognitive skills, language loss, atypical visual perception, and imaginative underdevelopment [1, 2]. Shortfall in motor coordination and communication can render an autistic patient to be dependent upon others and makes daily life more difficult [3, 4]. Research in genetics and genomics have identified a large number of synaptic dysfunction leading to multiple cognitive defects in children with ASD [5]. This is caused due to expansion of fragile X mental retardation1 (fmr1) gene, which diminishes the neuronal mRNA [6], suggesting synaptic dysfunction leading to cognitive and behavioural impairment. Neuroimaging studies have discovered the overgrowth of the cortical white matter and abnormal pattern in the frontal and temporal lobe during prenatal and postnatal brain evolution [2]. EEG is a non-invasive clinical tool for the examination of human neurology [7]. Since, ASDs are neural level disorder, EEG signals hint about how the disorder has affected the neurons and their synapses connectivity and functionality [2]. EEG helps identifying area of brain which is highly involved in particular function with unique variable characteristics [7, 8]. Brain connectivity graph obtained from EEG [8] has revealed that ASD group has less ability to form localised network distinguishing them from typical group.

Now, from the diagnostic front if EEG is analysed in a real life environment the prominent presence of artefacts especially, eye blink and muscle movement are found in the signals captured by EEG electrode from the scalp of the subject. Although, these artefacts are of non-interst from the diagnostic perspective, the experienced medical practitioners, through their visual observation of the electrode signals find it extremely diffcult to trace the EEG information amid these artefacts. In a conventional offline approach, since doctors rely on the visual inspection of the EEG signal, the channels containing artefacts are generally rejected. However, to diagnose ASD, a belief that all the information pertaining to EEG should be made available to the doctors which could enhance the diagnostic accuracy. Furthermore, if these offline diagnostic procedure is carried out in a online real time environment as a part of home care treatment and therapy it would be much more beneficial for the autistic patients, particularly children. However, the frequency range for the above artefacts overlap with the EEG spectrum including θ, μ and β bands making the artefacts removal extremely challenging task. Therefore, motivated by this aforementioned observations regarding the existing offline diagnostic procedure, in this paper we propose an automated detection and correction methodology of the eye blinks and muscular artefacts without loss of vital information from the mixed and discarded EEG channels in an online real time environment to treat ASD patients at home and formulate a personalised therapy. The paper is organised into following sections. Section II explains the theoretical background. Section III describes the algorithm. Section IV deals with experimental setup, results and discussion. Section V the conclusion.

II. THEORETICAL BACKGROUND

A. *Discrete Wavelet Transform*

Discrete Wavelet Transform (DWT) is computed by passing the signal through low pass filter with impulse response **'g'** resulting in approximate coefficient C_a (1) and high pass filter **'h'** resulting detailed coefficient C_d (2) and then down sampled. At each decomposition level, each output filter has half the frequency band of the input, so the frequency resolution has doubled. Haar transform [9] is used, as it is implemented using only addition and subtraction, and is

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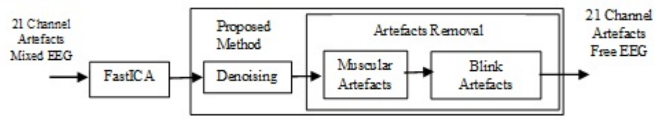

Fig. 1. Block Diagram of Proposed Methodology

found to be computationally efficient.

$$Y(low) = \sum_{k=-\infty}^{k=\infty} x(k) * g(2*n-k) \tag{1}$$

$$Y(high) = \sum_{k=-\infty}^{k=\infty} x(k) * h(2*n-k) \tag{2}$$

The EEG signal was mixed with artifacts in some ratio, then passed through FastICA [10] thereby obtaining independent components. Considering A=mixing matrix, S=source matrix, X=input mixed matrix, FastICA works on $X = A*S$ and estimates $Y = W*X$ where $Y \approx S$, W=Unmixing matrix and Y= estimated independent component matrix.

III. PROPOSED METHODOLOGY

A. Denoising

The FastICA outputs as presented in the previous section and shown in Fig. 1, are corrupted with noise frequency ranging from 50 to 60 Hz shown in Fig. 2. Wavelet based denoising removes the noise present in the signal without affecting its characteristics. Wavelet transform is applied to the signal, which produces the wavelet coefficients to the level where noise is distinguished. Soft thresholding method [11] is applied as a pre-processing step for Denoising. The denoised signal is shown in Fig. 3.
The method for removal of muscular and blink artefacts from EEG signal is proposed below and shown in Fig. 1.

B. Proposed Detection and Removal Methodology of Muscular Artefacts

Muscular or myogenic artefacts arise from the activity of different head muscle groups which influence the EEG recordings [12]. Myogenic artefacts lie in frequency range greater than Beta band (β) i.e. 16-31 Hz [13] and have high power spectral density [14] than the normal EEG as shown in Fig. 4. First (C_{d1}) and second (C_{d2}) detailed coefficients are computed using (2). Muscular artefacts overlap in C_{d1} and C_{d2} region hence, both the coefficients are analysed here. As described in section II.A, after wavelet transform decomposition, the length of C_{d1} is twice as that of C_{d2}. Hence, alternate zero padding is done making C_{d1} and C_{d2} equal. If sampling frequency is **'F'** Hz and the signal is observed for **'T'** sec then **'FT'** number of samples are accumulated and divided into **'x'** equal frames. Please note that 'FT' needs to be stored, thereby higher 'FT' indicates more memory requirement. However, if 'FT' is high, the performance of the proposed methodology would be precise.

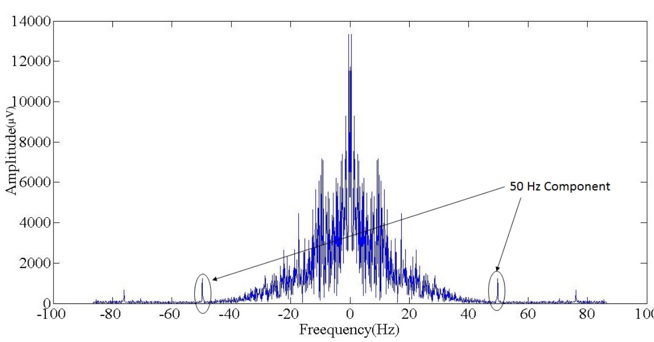

Fig. 2. Amplitude vs Frequency plot of EEG signal with 50Hz line frequency noise.

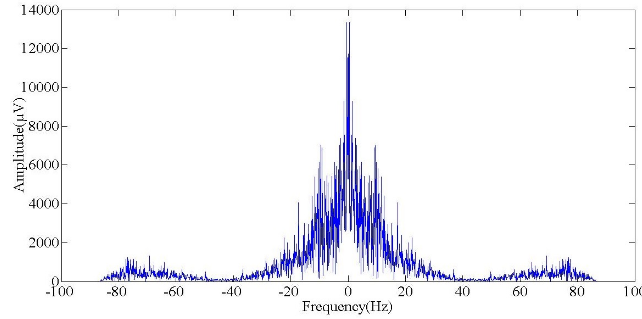

Fig. 3. Amplitude vs Frequency plot of EEG signal after Denoising.

Since our method is targeted towards proposing automated real time environment and on-chip implementation, we will keep 'T' as low as 10sec and show that the performance of the proposed method is favourably comparable to those of the existing methodology. Wavelet power spectral density (WPS) can be computed as: $S_{1j} = \sum_{i=1}^{n}(Cd_1^2)_{ji}$ & $S_{2j} = \sum_{i=1}^{n}(Cd_2^2)_{ji}$. Where, *n*=number of samples in each frame, *i*=sample number, *j*= frame number ranging from 1 to x, S_{1j} = WPS of frame in C_{d1}, S_{2j} =WPS of frame in C_{d2}.

Frame by frame comparison of S_{1j} & S_{2j} as shown in Fig. 5 is done to find out the maximum. Assume m_j denote the maximum after comparison and P_k be the mean. The average of the calculated maxima of each time frame is found using $P_k = \frac{\sum_{j=1}^{x} m_{jk}}{x}$ Where, *k*= number of independent signal component, x=number of frames in C_{d1} & C_{d2}. The mean P_k is compared with S_{1jk} & S_{2jk}. If $S_{1jk} > P_k$ then all the samples in that frame are made zero i.e. $(C_{d1})_{jk}$=0. Similar procedure is applied for second detailed coefficient and $(C_{d2})_{jk}$ is made zero. The signal reconstruction is carried out using the inverse wavelet transform [9]. The result is

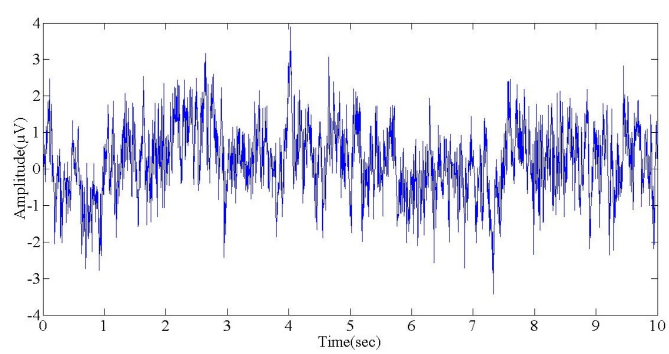

Fig. 4. Amplitude vs Time plot for EEG signal mixed with Muscular Artefacts.

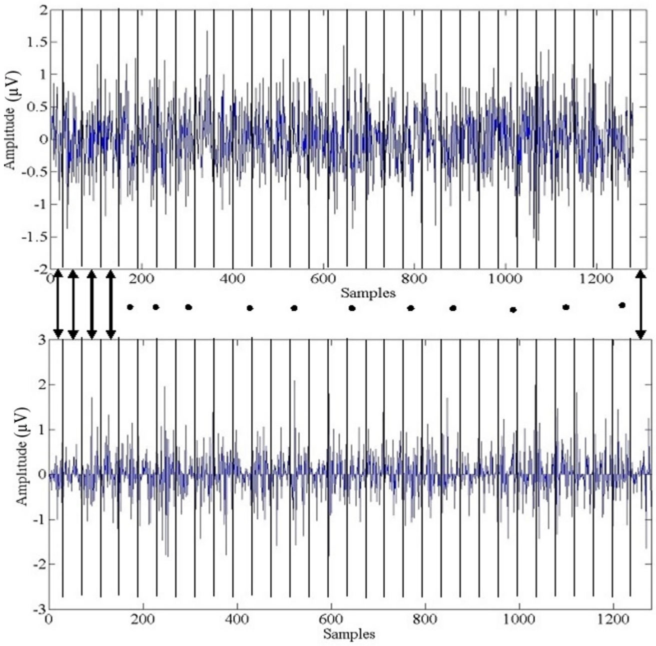

Fig. 5. Frame comparison of S_{1j} (top) & S_{2j} (bottom) for Muscular Artefacts

plotted in Fig. 6.

C. Detection and Removal of Eye Blink Artefacts

After successful removal of muscular artefacts as described in section III.A, further processing of eye blink artefacts is carried out. An eye blink can lasts up to 400ms [15] and lie in Theta (θ) i.e. 4-7Hz and Mu (μ) i.e. 8-12Hz frequency range of the EEG spectrum [13]. These have a magnitude 10 times higher than the brain electrical signal [15]. It occurs as a large dip on the frontal channels FP1-F3, FP2-F4, FP1-F7 and FP2-F8, [13, 16, 17] (according to the International 10-20 System of Electrode Placement) because these channels are located nearest to eyes. The eyeball acts as a dipole, with cornea as positive pole with respect to the retina. When eye goes from open to close the electrode sense a downward reflection. Similarly, when eye goes from close to open an upward reflection occurs at the electrode. This results a high amplitude negative peak in EEG [15, 17, 18].

Assume C_{a1} to be the first level approximate coefficient obtained using (1). Similarly, decomposition is done up to fourth level to obtain C_{a4} which corresponds to theta band.

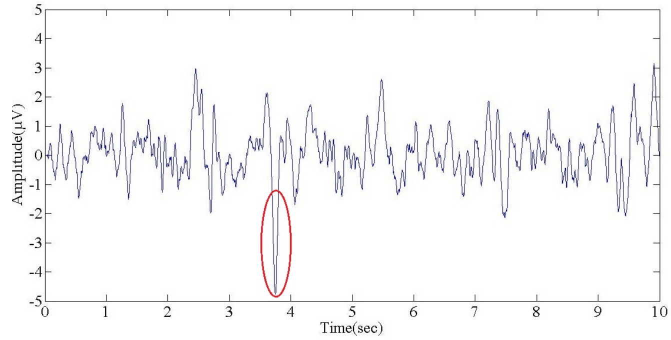

Fig. 7. Amplitude vs Time plot for EEG signal mixed with Blink Artefacts

Further, the time domain mapping of all the negative peaks in C_{a4} is carried out and stored in Y_{tp} where p is the selected negative peaks in C_{a4}. In frequency domain, theta band is reached and corresponding time domain mapping is done to extract artefacts in that band only.

For each of the selected negative sample after mapping in time domain, a window is taken to effectively select the blink and the maximum negative peak is obtained. This process is repeated for the entire range of the signal. The red circle in Fig. 7 indicates the highest detected negative peak.

The mean of negative peaks is computed and used as threshold, calculated as $Mean = \frac{\sum_{p=1}^{l} Y_{tp}}{l}$ Where, l is the number of negative peaks, which corresponds eye blink. If Mean$<Y_{tp}$, then Y_{tp}=0.

Fig. 8 is obtained after removing all the eye blinks from the EEG signal.

IV. Results & Discussion

EEG signals were obtained from Caltech, Physionet and Swartz Center for Computational Neuroscience [19]. These EEG signals were recorded from different patients and were presented in Matlab readable format. Following cases are demonstrated with addition of different artefacts externally. The signals were sampled at the rate of 173Hz [19] and observed for 10sec. In Case I (Table-I), first seven signal are left clean and hence a high value of Correlation Coefficient as expected, is experimentally determined along with Regression. Case II (Table-I), having both the artefacts, a low value of correlation coefficient is observed. Case III (Table-I), from signal 9 to 12 only blink artefacts are removed. Case

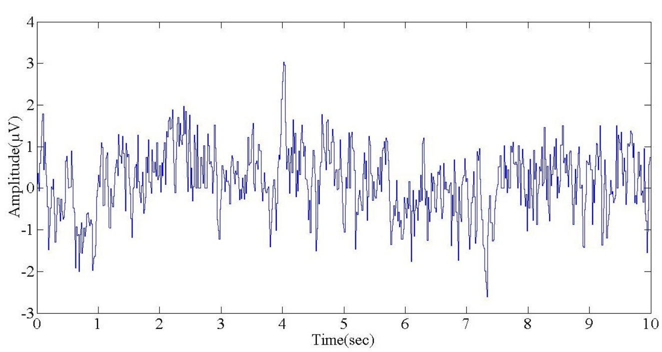

Fig. 6. Amplitude vs Time plot for EEG signal after removing Muscular Artefacts

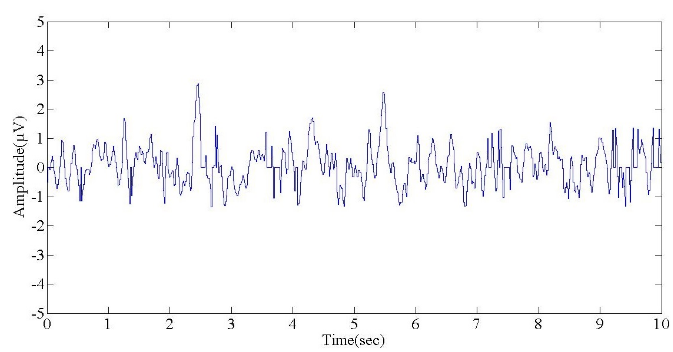

Fig. 8. Amplitude vs Time plot for EEG signal after removing Eye Blink Artefacts

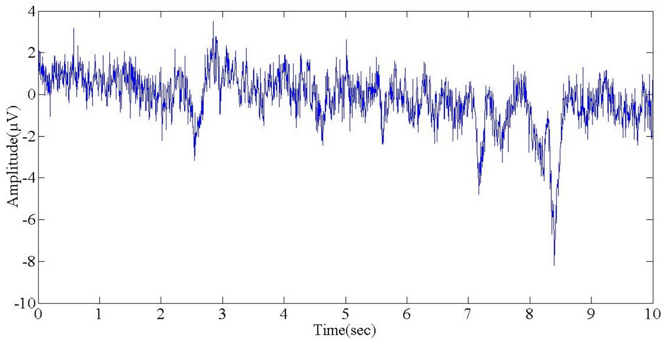

Fig. 9. Amplitude vs Time plot for EEG signal mixed with both the Artefacts

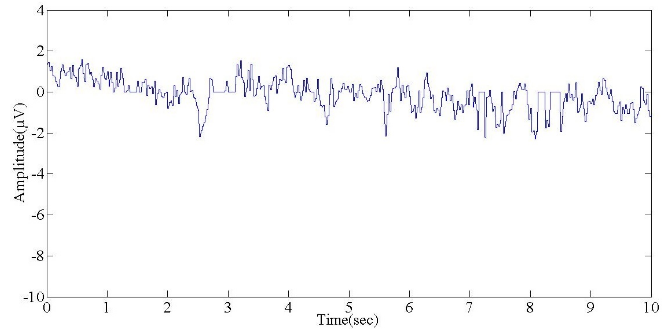

Fig. 10. Amplitude vs Time plot for EEG signal free from Artefacts

IV and Case V (Table-I), muscular artefacts are detected and removed.

In Case VI (Table-I), the EEG signals of various subjects sampled at 256Hz were observed for 10sec. No external artefacts are added to these signals. These are detected with artefacts and removed.

The results of the experiment are shown in table 1 with various performance metrics. Fig. 9 & 10 shows the mixed artefact EEG signal before and after applying the algorithm respectively.

TABLE I

PERFORMANCE METRICS

Case	**EEG Signal**	**Artefacts**		**Average Correlation Coefficient**	**Regression**
		Muscular Artefacts	*Blink Artefacts*		
Case I	Signal 1-7	No	No	0.9416	0.8124
Case II	Signal 8	Random Manner	Alternate	0.5649	0.6555
Case III	Signal 9-12	No	Yes	0.8894	0.4667
Case IV	Signal 13-16	Alternate Frames	No	0.7078	0.7300
Case V	Signal 17-21	Random Manner	No	0.6275	0.7828
Case VI	Other EEG Signal 1	Random	Random	0.8307	0.6680
	Other EEG Signal 2	Random	Random	0.7350	0.7791

V. CONCLUSIONS

This work introduces an evaluation method for EEG signals. The proposed algorithm is able to detect and significantly remove eye blink and myogenic artefacts from the signal. This algorithm has been validated for EEG signals obtained from various sources and the corresponding average correlation coefficient and regression are 0.7574 and 0.6992 respectively indicating an acceptable performance. This method can be implemented in real-time environment, which can be adopted to assist doctors in analysing and diagnosis of ASD.

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