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Artefact Removal from EEG Signals using Total Variation De-noising

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Abstract: Artefacts removing (de-noising) from EEG signals has been an important aspect for medical practitioners for diagnosis of health issues related to brain. Several methods have been used in last few decades. Wavelet and total variation based de-noising have attracted the attention of engineers and scientists due to their de-noising efficiency. In this article, EEG signals have been de-noised using total variation based method and results obtained have been compared with the results obtained from the celebrated wavelet based methods . The performance of methods is measured using two parameters: signal-to-noise ratio and root mean square error. It has been observed that total variation based de-noising methods produce better results than the wavelet based methods.

Keywords: Artefacts, EEG, optimization, regularizers, total variation de-noising, wavelets.

I. INTRODUCTION

The brain is one of the largest and most complex organs in the human body which is the central organ of the human nervous system. It controls most of the activities of the body, processing, integrating and coordinating the information it receives from the sense organs, and making decisions as to the instructions sent to the rest of the body. It is made up of more than 100 billion nerves that communicate in trillions of connections called synapses [18]. To determine the physical condition of a patient, measurement of physiological signals of the human body is the most important step. Therefore, the need of a system which could measure these signals properly and accurately, was essential. Electroencephalography (EEG) emerged as a tool to fulfill this requirement. It is an electrophysiological monitoring tool which records the electrical activity of the brain. It is non-invasive in which the electrical activities of brain are recorded by placing the electrodes along the scalp over a short period of time. This provides a lot of important information regarding different activities of the brain. In view of clinic, EEG indicates the recording of the spontaneous electrical activity of brain over a period of time [24]. EEG has played an important role in detecting neurological disorders such as Creutzfeldt-Jakob diseases (CJD), Alcoholic or vascular dementia, Alzheimers disease, Parkinson's disease, Huntingon's disease, Wilson's disease, motor neuron diseases, syphilis-related dementia, Schizophrenia [3, 17].

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EEG is also employed to diagnose depth of anaesthesia, brain death, encephalopathies, sleep disorders, coma, epilepsy, tumors. EEG has also been useful in development of many real time applications like neuro-feedback and brain-computer interface [4].

During the recording of EEG signals, several contaminates appear. Electrical signals of non-cerebral origin are called artefacts. In addition to instrumentation noise, there are two types of artefacts: biological and environmental. Electrooculographic (EOG), Electromyographic (EMG), respiratory and electrodermal response are the very often appearing biological noise sources that cause the emergence of EEG artefacts. Among these, EOG artefacts appear very often as it is not possible to prevent the eye movements and blinking during the EEG recording. Besides the artefacts caused by the body, many artefacts originate from outside the body. In presence of artefacts in EEG, accurate diagnosis of diseases is not possible. Therefore, efficient artefact removing techniques have been proved as of great significance in the scientific and technical community.

During last three decades, various techniques and algorithms to remove artefacts (de-noise) from EEG signals, have been attempted and utilized. Simple low pass, band pass or high pass filtering representation of EEG signals has been the early attempts to remove the artefacts. The drawback of this approach was that it could not work in case when the frequency band of the signal and interference overlap. In such situations, the different approaches like: Kalman filtering [12], adaptive filtering [9], blind source separation, Weiner filtering, empirical mode decomposition methods [10, 14, 23] and non-linear mode decomposition methods [5] have been applied. Several EEG de-noising techniques have been described in [21]. Last two decades have witnessed various techniques based on combination of different techniques: blind source separation and support machine vector, wavelets and independent component analysis, regression algorithm and independent component analysis [7], ICA and wavelet, CCA and EEMD [23].

Wavelets have been very useful in investigation of non-stationary signals like EEG. Several variants like: symlet, coif, haar, Db and bior wavelets have emerged in last decades and widely used. In wavelet method, signal is decomposed into a number of time shifted and scaled versions of a selected mother wavelet. In the process of de-noising the signals, first step is the decomposition of signals into different levels, second step is thresholding of the detail coefficients and third step is reconstruction of the signal from the filtered representation. Wavelets have been utilized largely in artefact removal from EEG [8, 11]. Recently, in [1], wavelets have been used in de-noising EEG signals.

Total variation de-noising method [16] which has attracted the attention of medical practitioners and engineers is another method broadly applied in signal and image processing. In total variation de-noising, the problem is expressed as a convex optimization problem having two parts. One is a data fidelity term which is normally quadratic and other one is a regularizer term (convex or non-convex). Several approaches have been proposed with the modifications in the regularizer term. The concept of total variation has been extended and generalized as well as employed in image processing widely [3]. Total variation has been applied as a regularizer in sparse signal and image processing. The idea of non-convex functions as a regularizer was proposed in [13]. In the optimization problem of total variation de-noising, in [20] a non-smooth convex regularizer have been replaced by a non-convex regularizer. In [6], the total variation method have been employed in removing the EOG artefact from EEG. Total variation de-noising with clipping algorithm has been applied in [25] in artefact removal from EEG signal.

In this article, total variation based two methods have been used for artefacts removal from the EEG signals and results obtained have been compared with wavelet based methods. In total variation based method, clipping algorithm and non-convex regularizers have been applied. The comparison of methods is based on the resulting SNR and RMSE. Results show that total variation based methods perform better than wavelet based methods used here.

II. DATA AND METHODOLOGY

A. Data

Data used here is taken from research project of Kocaeli University, Turkey. The data was collected by Dr. Huya K. Sevindir at the Hospital of Kocaeli University [22]. We have used several samples to draw the conclusion. Samples are very large, so we have just taken the portion of sample to 3000 only to maintain the virtual visibility of the de-noised signal in figures.

B. Total Variation (TV) de-noising

Assume y(n) is the measured data having noise and is represented as

$$y(n) = x(n) + \varepsilon(n), \; n = 0, 1, 2, ..., N-1 \qquad (1)$$

Here, x(n) is the signal to be estimated and ε(n) is the white Gaussian noise.

One dimensional total variation de-noising is specified by minimization of the functional

$$\left\{ \frac{1}{2} \|y - x\|_2^2 + \lambda R \right\}$$

where $\lambda > 0$ is the regularization parameter and R is the regularizer (penalty) function. Selection of R depends on the method used and it may be chosen as convex or non-convex with certain conditions.

To use iterative clipping algorithm, R is selected as $\|Dx\|_1$ and to use non-convex regularizers, R is selected as $\sum_n \phi([Dx]_n)$

D is the (N-1) x N matrix given by:

$$D = \begin{bmatrix} -1 & 1 & & & & \\ & -1 & 1 & & & \\ & & & \ddots & & \\ & & & & -1 & 1 & \\ & & & & & -1 & 1 \end{bmatrix}$$

To solve the de-noising problem, solution of the following optimization problems are obtained:

For clipping algorithm:

$$\arg\min_{x \in R^n} \left\{ J(x) = \frac{1}{2} \|y - x\|_2^2 + \lambda \|Dx\|_1 \right\} \qquad (2)$$

And for using non-convex regularizers:

$$\arg\min_{x \in R^n} \left\{ J(x) = \frac{1}{2} \|y - x\|_2^2 + \lambda \sum_n \phi([Dx]_n) \right\} \qquad (3)$$

In (3), two regularizers have been used [20]:

The logarithmic regularizer

$$\phi(x; a) = \frac{1}{a} \log(1 + a|x|), \quad a > 0 \qquad (4)$$

and the arctangent regularizer

$$\phi(x; a) = \frac{2}{a\sqrt{3}} \left(\tan^{-1}\left(\frac{1 + 2a|x|}{\sqrt{3}} \right) - \frac{\pi}{6} \right), \quad a > 0 \quad (5)$$

C. Algorithm for TV de-noising

Problem (2) is solved by replacing D by A and formulating the dual by using an auxiliary vector z.

The iterative clipping algorithm for TV de-noising is given by:

$$\left. \begin{aligned} x^{(i+1)} &= y - \frac{\lambda}{2} A^t z^{(i)} \\ z^{(i+1)} &= clip\left(z^{(i)} + \frac{2}{\alpha\lambda} A x^{(i+1)}, 1 \right) \end{aligned} \right\} \qquad (6)$$

where $\alpha \geq \max eig(AA^t)$.

Problem (3) is solved by the algorithm in [20]. Iterations are given by

$$x^{(k+1)} = y - D^T \left(\frac{1}{\lambda} \left[W\left(Dx^{(k)} \right) \right]^{-1} + DD^T \right) Dy \qquad (7)$$

where W is a matrix given by

$$[W(Dv)]_{n,n} = \frac{\phi'([Dv]_n)}{[Dv]_n}.$$

III. NUMERICAL IMPLEMENTATION AND PERFORMANCE ANALYSIS

To implement wavelet based de-noising, MATLAB tools available in MATLAB 2018a have been used.

Total variation de-noising based on (6) is implemented by the MATLAB program discussed in [19].

Here α = 4 is set for de-noising. In the MATLAB program, *diff* command has been used to implement D.

Total variation de-noising based on (7) is implemented by the MATLAB programs demonstrated in [20]. Two non-convex regularizers: log and arctangent have been applied to de-noise the EEG signal.

Value of regularization parameter λ has been chosen as 2 and number of iterations is kept fixed at 100 in both algorithms.

Evaluation of performance of methods has been done on two performance measure parameters: SNR and RMSE. Calculated values of SNR and RMSE are presented in Table1.

Table1. Computation of SNR and RMSE

Method	Type	SNR	RMSE
Wavelet	Coif3	15.2143	0.8213
	Db3	15.4795	0.8110
Total variation (Non-convex regularizers)	Arctangent	16.4336	0.7165
	Logarithmic	16.5356	0.7056
Total variation	Iterative Clipping Algorithm	20.2630	0.4680

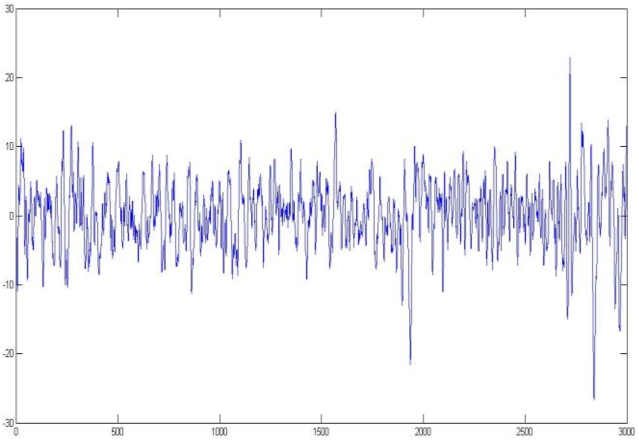

Figure 1. Original Data

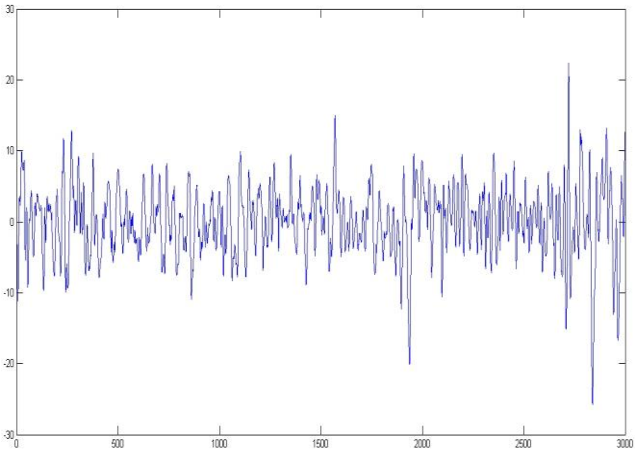

Figure 2 De-noised signal using Wavelet (Coif3)

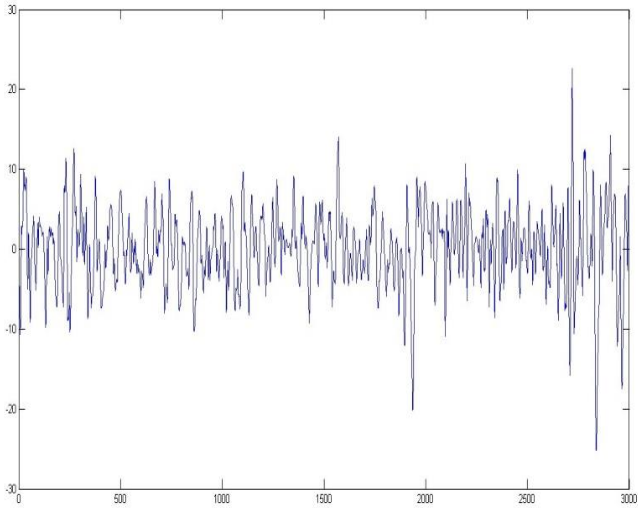

Figure 3 De-noised signal using wavelet (db3)

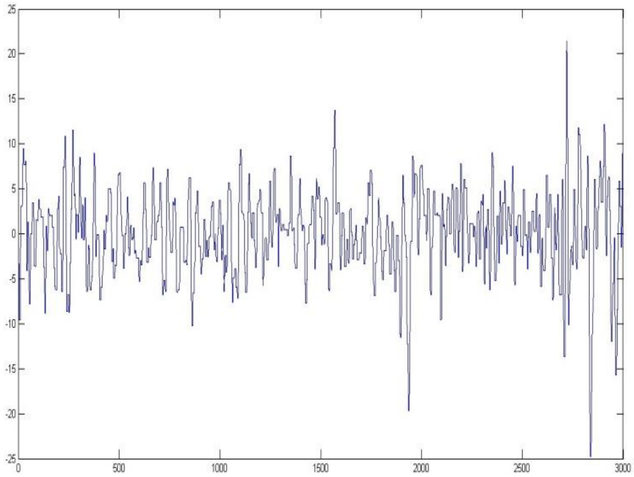

Figure 4 De-noised signal using arctangent regularizer

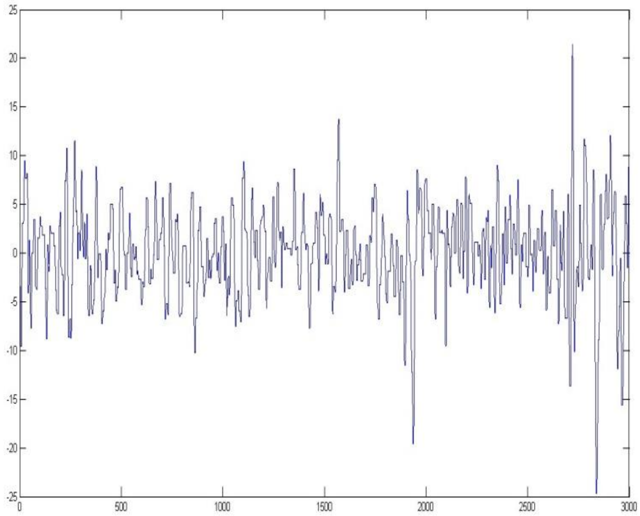

Figure 5 De-noised signal using logarithmic regularizer

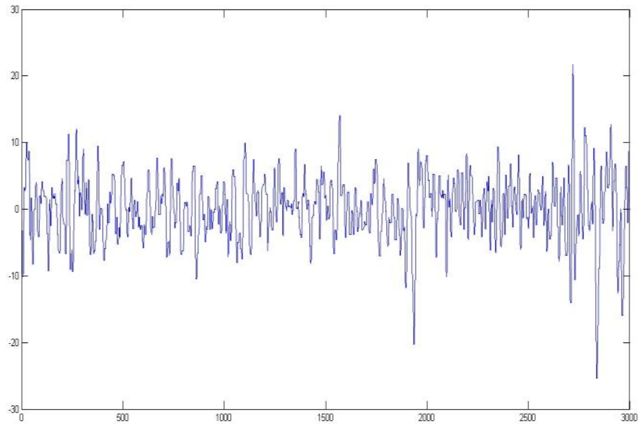

Figure 6 De-noised signal using Clipping Algorithm

Figure 1 shows the original data while Figure 2, Figure 3, Figure 4, Figure 5 and Figure 6 show the de-noised signals.

IV. RESULTS AND DISCUSSION

SNR and RMSE have been calculated to measure the performance of methods used here. Higher the values of SNR, better the performance of de-noising method. On the contrary, lower the values of RMSE, better the performance of de-noising method. It has been observed from Table1 that for wavelet (Coif3), value of SNR is 15.2143 (Figure 2), for wavelet (Db3), value of SNR is 15.4795 (Figure 3), for arctangent regularizer, value of SNR is 16.4336, (Figure 4); for logarithmic regularizer, value of SNR is 16.5356 (Figure 5) and for iterative clipping algorithm, value of SNR is 20.2630 (Figure 6). Thus, the values of SNR for total variation based methods are higher than the values of SNR for Wavelet based methods used here. This shows the efficiently of methods for de-noising the signals and better performance of total variation based methods than wavelet based methods. Similarly, we see that for wavelet (Coif3), value of RMSE is 0.8213 (Figure 2), for wavelet (Db3), value of RMSE is 0.8110 (Figure 3), for arctangent regularizer, value of RMSE is 0.7165, (Figure 4); for logarithmic regularizer, value of RMSE is 0.7056 (Figure 5) and for iterative clipping algorithm, value of RMSE is 0.4680 (Figure 6). Thus, the values of RMSE for total variation based methods are lower than the value of RMSE for wavelet based methods. Again, this shows better performance of total variation based methods than wavelet based methods. Also, it is observed that iterative clipping algorithm produces best result.

Figure 1 shows the original data. Figure 2 shows the de-noised signal using Coif3, Figure 3 shows the de-noised signal using Db3, Figure 4 shows the de-noised signal using arctangent regularizer, Figure 5 shows the de-noised signal using logarithmic regularizer and Figure 6 shows the de-noised signal using iterative clipping algorithm. Comparing these figures, we see that Figure 6 reflects most de-noised signal.

V. CONCLUSION

It has been observed that both the wavelet based and total variation based de-noising methods are efficiently applicable in removing artefacts from EEG signals. At the same time, it is observed that Db3 works better than Coif3. Iterative clipping method works better than the non-convex regularizers (arctangent and logarithmic). Also, total variation based methods have produced better results than wavelet based methods.

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