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De-Noising Electroencephalogram (EEG) Signal Using Iterative Clipping Algorithm

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Signal de-noising has been a topic of great interest for a long period. EEG is used to detect the neurological diseases. In the process of EEG recording, signal is contaminated due to several factors. Hence, for analysis of EEG signal in order to detect the diseases, it is necessary that signal must be de-noised first. Here, de-noising of signal is expressed as an inverse problem with total variation. This is an optimization problem. The solution of this optimization problem is obtained by using the iterative clipping algorithm. In this article, iterative clipping algorithm is used for de-noising EEG signal. To measure the performance of method, signal to noise ratio(SNR) and root mean square error(RMSE) have been calculated. It has been observed that the approach used here, works well in de-noising the EEG signal.

Keywords: EEG; inverse problems; de-noising; total variation; iterative clipping algorithm.

Brain is one of the most important organs of human body which controls the coordination of muscles and nerves. Electroencephalogram (EEG) signal is a non-stationary biological signal and provides a lot of important information about different activities of the brain. It is the recording of electrical activity along the scalp with several electrodes placed on it over a short period of time. EEG is used to detect several neurological disorders[1],[2]. There are many factors which affect the recording and contaminate the EEG. Electrooculographic (EOG) is the most common physiological noise source that generates the EEG artefacts[3]. Therefore, denoising plays a vital role in analysis of the EEG signal.

The problem of de-noising a signal is simply the noise removal from that signal. During last few decades, many techniques have been used to denoise (remove artefacts) the EEG signals. Kalman filters[4], adaptive filters[5, 6]), blind source separation (BSS) method[7], independent component analysis (ICA) have been applied[8, 9, 10, 11] in artifact removing. Lagerlund *et al*[12] explored the applications of principal component analysis (PCA) in removing artefacts from EEG signals. Wavelet and its several variants have been widely used in artefact removing from EEG[13, 14]). Empirical Mode Decomposition [15, 16]) and ensemble empirical mode decomposition (EEMD) have been used in[17] and[18] to remove different artefacts present in EEG.

Another method proposed by Rudin et al. [19], total variation denoising is used in signal and image processing. Rodriguez & Wohlberg[20], Hu & Jacob[21] and Bredies et al[22] have applied it in image processing. In total variation regularization, minimization of a cost function produces the de-noising filter. All the algorithms that solve the optimization problem of de-noising can be used to implement the total variation regularization. So

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many methods are used to solve this problem. Selesnick and Bayram[23] have developed an algorithm based on[24] which has been used in this article.

Inverse problems deal with determining an input that produces an observed output, or determining an input that produces a desired output, often in presence of noise. Mathematically, let X and Y be spaces having appropriate structures such as Banach space, Hilbert space. Let *A : X ’!Y* be an operator which describes the relationship between the data y and the model parameter x. Direct problem: given the input x, find the output y; inverse problem: given an observed output y, find an input *x* that produces it. The solution minimizing

$$\|Ax - z\|_2^2 + \lambda \|Lx\|_1$$

is known as total variation regularized solution. Here L is a smoothing and *ë* is regularization parameter. Regularization parameter *ë* plays important role in solving an inverse problem[25, 26].

In this article, iterative clipping algorithms proposed in[23] have been used for de-noising EEG signal. Two performance measuring parameters, Signal to Noise Ratios (SNR) and Root Mean Square Errors (RMSE) have been calculated for different values of the regularization parameter *ë*. It has been observed that iterative clipping algorithm works well for de-noising the EEG signal.

MATERIAL AND METHODS

Material

Data used here is taken from research project of Kocaeli University, Turkey, taken by Dr. Huya K. Sevindir on applications of wavelets methods to EEG data collected at the Hospital of Kocaeli University[27].

Total Variation (TV) de-noising

The total variation of an N - point signal $x(n),\ 0 \le n \le N\text{-}1$ is defined as

$$TV(x) = \sum_{n=1}^{N-1} |\, x(n) - x(n-1) \,| = \|Dx\|_1$$

where D is an N-1 x N matrix.

Let $y(n)$ be the measured (noisy) data of the form

$$y(n) = x(n) + \varepsilon(n),\ n = 0, 1, 2, \ldots, N\text{-}1 \qquad \ldots(1)$$

where x(n) is (approximately) piecewise constant signal and å(n) is white Gaussian noise. Then the inverse problem is to estimate x(n) given the noisy data y(n). TV de-noising estimates the signal x(n) by solving the optimization problem

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

The regularization parameter *ë* controls the degree of smoothing[18].

Algorithm for TV de-noising

Problem (2) is solved by replacing D by A and formulating the dual by using an auxiliary vector z[5].

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

$$\begin{aligned} x^{(i+1)} &= y - \frac{\lambda}{2} A^t z^{(i)} \\ z^{(i+1)} &= clip\left(z^{(i)} + \frac{2}{\alpha\lambda} A x^{(i+1)}, 1 \right) \end{aligned} \qquad \ldots(3)$$

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

Numerical implementation and performance analysis

Total variation de-noising based on (3) is implemented by the MATLAB program described in[23]. Here á = 4 is set for de-noising. In the MATLAB program, D is implemented with the *diff* command. Number of iterations is kept fixed at 100 in algorithm.

To evaluate the performance, Signal to Noise Ratio (SNR) and Root Mean Square Error (RMSE) have been calculated for different values of regularization parameter *ë* in table1.

Figure1 shows the original data while Figure2, Figure3, Figure4 and Figure5 show the de-noised data.

RESULTS AND DISCUSSION

In this article, de-noising of EEG signal is modeled as an inverse problem with total variation and is expressed as the minimization of a non-differentiable cost function. Minimization of a non-differentiable cost function is a complex problem.

It is minimized using the iterative clipping algorithm. It has been used for de-noising the EEG signal. More SNR implies more de-noising and on the contrary, more RMSE implies lesser de-noising. Table1 shows the values of SNR and RMSE for different values of ë. From the result obtained, we observe that iterative clipping algorithm works well for de-noising the EEG signal. We also observe that as ë increases, SNR decreases and RMSE increases. Figure1 represents the original data. Figure2 represents the de-noised data with SNR = 29.0011& RMSE = 0.1756for ë = 0.5, Figure3 represents the de-noised data with SNR = 24.5130& RMSE = 0.2918 for ë = 1.0, Figure4 represents the de-noised data with SNR = 22.0242 & RMSE = 0.3853 for ë = 1.5 and Figure5 represents the de-noised data with SNR = 20.2630 & RMSE = 0.4680 for ë = 2.0. Thus, through de-noising, the quality of EEG signal is enhanced.

Table1. Calculation of SNR and RMSE

Values of λ	SNR	RMSE
0.5	29.0011	0.1756
1.0	24.5130	0.2918
1.5	22.0242	0.3853
2.0	20.2630	0.4680

CONCLUSIONS

Increased values of signal to noise ratio for different values of regularization parameter show that iterative clipping algorithm is suitable for de-noising the EEG signal. As the values of regularization parameter increase, the signal to noise ratio decreases and root mean square error increases. This shows that de-noising depends on the values of the regularization parameter. This

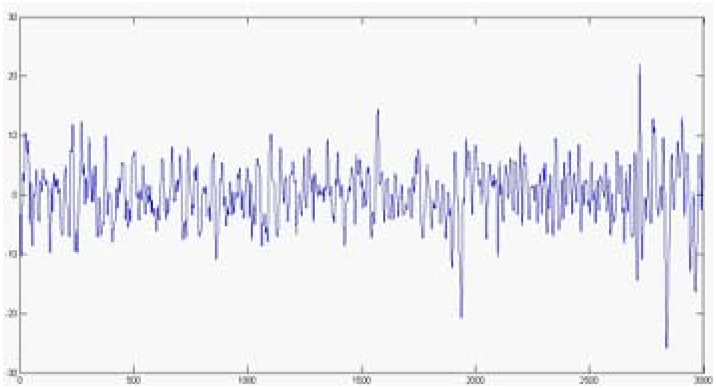

Fig. 1. Original signal

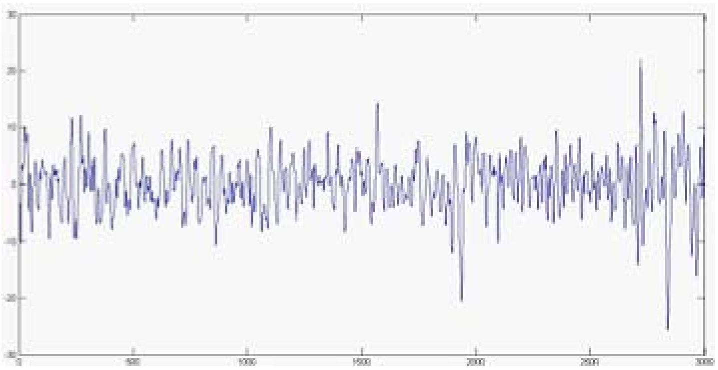

Fig. 2. Total variation de-noising using iterative clipping algorithm for regularization parameter λ = 0.5 (SNR = 29.0011, RMSE = 0.1756)

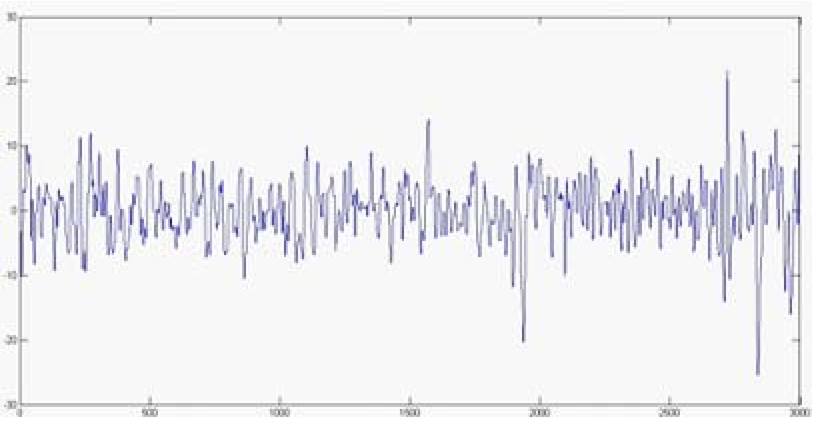

Fig. 3. Total variation de-noising using iterative clipping algorithm for regularization parameter λ = 1(SNR = 24.5130, RMSE = 0.2918)

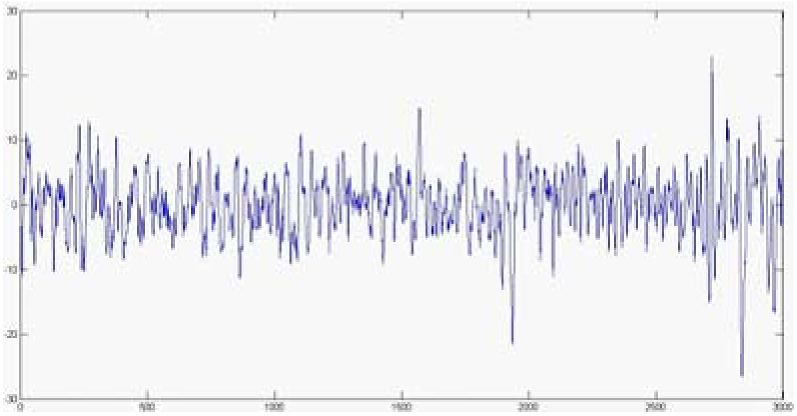

Fig. 4. Total variation de-noising using iterative clipping algorithm for regularization parameter λ = 1.5 (SNR = 22.0242, RMSE = 0.3853)

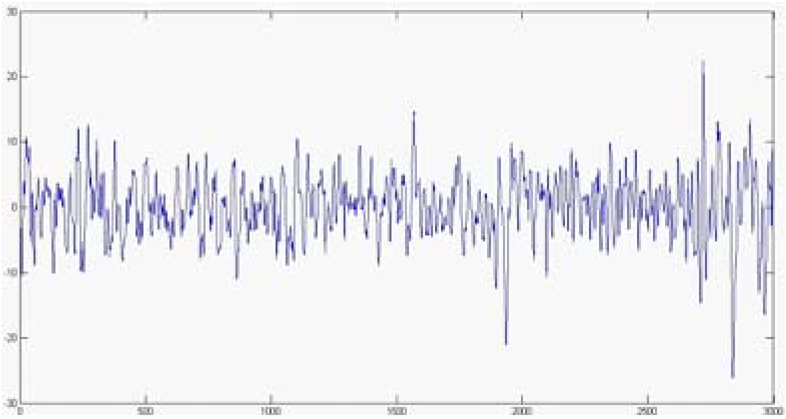

Fig. 5. Total variation de-noising using iterative clipping algorithm for regularization parameter λ = 2.0 (SNR = 20.2630, RMSE = 0.4680)

is reflected from table1. The calculated SNR and RMSE for different values of regularization parameter show a satisfactory result.

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