EFFECT OF SAMPLING FREQUENCY ON SNR IN THE REMOVAL OF OCULAR ARTIFACTS IN EEG SIGNALS USING WAVELETS

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ABSTRACT

This study investigates the relationship between sampling frequency and SNR of Electroencephalogram (EEG) signal. The EEG is a standard technique for investigating the electrical activity of brains in different psychological and pathological states. At the time of EEG recording, various artifacts such as muscle activity, eye blinks, eye movements and electrical noise corrupt the EEG signal. Normally, EEG signals fall in the frequency range of DC to 60 Hz and amplitude of 1-5 µv. Ocular artifacts have the similar statistical properties of EEG signals, and often interfere with EEG signal, making the analysis of EEG signals more complex. In this research paper, two different datasets were taken from Physionet data base. The sampling frequency of one dataset is 100Hz and the sampling frequency of another dataset is 250Hz. The research paper attempts to establish the relationship between sampling frequency and SNR of EEG signal. In this paper, the collected EEG signals are normalized and then mixed linearly with the normalized Electrooculography (EOG) signals, resulting in noisy EEG signals. Later soft and hard thresholding techniques were applied for detail coefficients and to estimate the SNR of the denoised EEG signals. This research paper concludes that signals with lower sampling rates provide better SNR than the signals with higher sampling rates. In addition to this, Haar wavelet provided better SNR compared to dB10 and Sym8 wavelets.

Keywords: Sampling Frequency, SNR, Wavelets, EEG, EOG.

INTRODUCTION

Electroencephalogram (EEG) is a standard technique to diagnose different disorders of the nervous system, such as epilepsy, classifying stages of sleep in patients, seizures and brain damage. EEG is the electrical activity recorded from the scalp surface, which is picked up by conductive media and electrodes (Arab et al., 2010; Niedermeyer & da Silva, 2005). EEG has been performing a vital role to investigate the brain activities in clinical application and scientific research for several years (Almubarak & Wong, 2011; Holmes & Lombroso, 1993; Murugavel & Ramakrishnan, 2012). The EEG signals can be contaminated by various artifacts, of which the major noise source is ocular artifact. Eye-movement and eye-blink artifacts are the major sources of ocular artifacts (Thakor et al., 1993). However, artifacts are the major enemies of high-class EEG signals. Mixing these ocular artifacts with the EEG signal at the time of recording causes problems in the precise estimation of EEG signal. These artifacts will plunge into either of the 2 categories namely, technical and physiological artifacts. Power line noise 50/60Hz falls into technical artifact category while the artifacts that crop up because of ocular (EOG), heart (ECG) and muscular activity (EMG) falls into physiological artifacts category respectively (Venkataramanan et al., 2005).

Regression in the time domain and frequency domain methods were proposed in removing eye blinks artifacts (Gratton et al., 1983; Jung et al., 2000; Schlögl et al., 2007). These methods require a reliable reference channel. This channel can be contaminated by EEG. So, EEG has to be removed from the reference channel by regression techniques. Hence, the regression methods are not the finest to remove EOG artifacts.

In this research paper, the number of levels of decomposition of EEG signal is explained. Once the number of levels of decomposition is estimated then the noisy EEG signal is decomposed to many levels using different wavelets. This decomposition gives low frequency and high frequency components of noisy Electro encephalogram signal. The high frequency components contain more noise information than low frequency components, and are processed with soft thresholding technique. After the thresholding, the denoised signal is constructed and estimated the SNR.

1. Materials and Methods

Two EEG signal datasets, having different sampling frequencies, which were collected from physionet data base (PhysioNet, n.d.) to estimate the effect of sampling rate on the SNR of denoised signal using denoised algorithm (Mathworks, n.d.).

To achieve the noisy EEG signal, the normalised Electroencephalogram signal is mixed with the Electrooculogram signal with noise variance of 0.4.

The noisy EEG signal can be modeled in the following manner:

$$y(n) = x(n) + \sigma e(n)$$

where, x(n) is the original Electroencephalogram signal, e(n) is the Electrooculogram signal, σ is the noise variance and y(n) is the noisy EEG signal.

The decomposition of noisy EEG signal is done for different levels based on the sampling frequency of collected EEG signal.

The number of levels of decomposition of noisy EEG signal can be estimated using the following formula:

$$\log 2^n = \log\left(\frac{\text{sampling frequency}}{\text{Approximation to what band of frequencies}}\right)$$

The sampling frequency of the dataset-1 is 100Hz and the approximation of frequencies is considered up to 3Hz. The EEG signal provides maximum frequency content, which resulted up to 3Hz.

$$\log 2^n = \log\frac{(100)}{3}$$

$$\log 2^n = \log (33.33)$$

$$2^n = 10*33.33$$

$$2^n = 333.3$$

Expressing 333.3 in terms of 2^n, we get,

$2^8 = 256$, this is less than 333.3

$2^9 = 512$, this is more than 333.3

Here "n" corresponds to number of levels of decomposition of EEG signal. The noisy EEG signal of dataset-1 was decomposed to level 9 using Daubechies, Sym8 and Haar wavelets with Heursure soft thresholding and estimated the SNR, as shown in Table 1.

The wave forms of Raw EEG and EOG signals, normalized EEG and EOG signals and denoised EEG signal of dataset-1 are provided in Figure 1.

Normalized EEG and EOG Signals and denoised EEG signal of dataset-1.

The nosiy EEG signal and denoised EEG signal of dataset-1 are provided in Figure 2.

The sampling frequency of the dataset-2 is 250Hz and the approximation of frequencies is considered up to 2Hz. The EEG signal provides maximum frequency content, which resulted up to 2Hz.

$$\log 2^n = \log\frac{(250)}{2}$$

$$\log 2^n = \log (125)$$

$$2^n = 10*125$$

$$2^n = 1250$$

Expressing 1250 in terms of 2^n, we get,

$2^{10} = 1024$, this is less than 1250

$2^{11} = 2048$, this is more than 1250

Here "n" corresponds to number of levels of decomposition of EEG signal. The noisy EEG signal of dataset-2 is decomposed to level 11 using Daubechies, Sym8 and Haar wavelets with Heursure soft thresholding (Kumar et al., 2016; Kumar, 2019) and estimated the SNR, as shown in Table 2. The wave forms of Raw EEG and EOG signals, Normalized EEG and EOG signals and denoised EEG signal of dataset-2 are provided in Figure 3

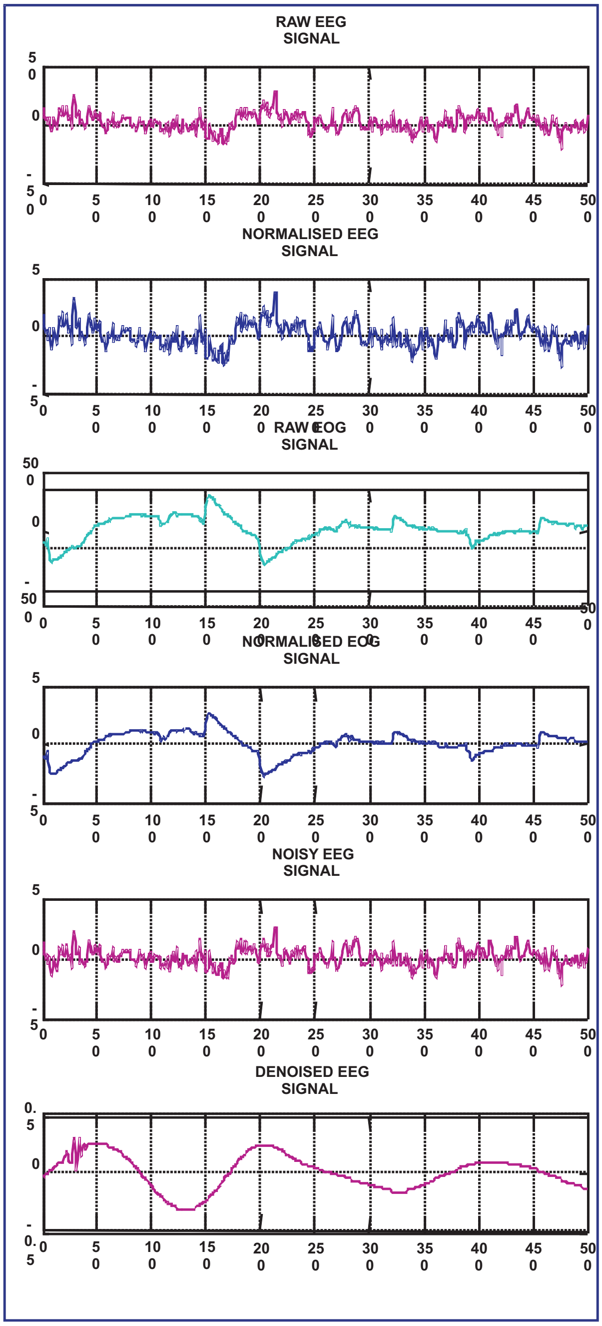

Figure 1. Raw EEG and EOG Signals, Normalized EEG and EOG Signals and Denoised EEG Signal of Dataset-1

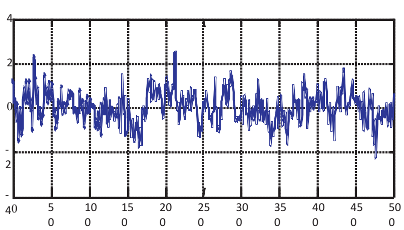

Figure 2. Noisy and Denoised EEG signal of dataset -1

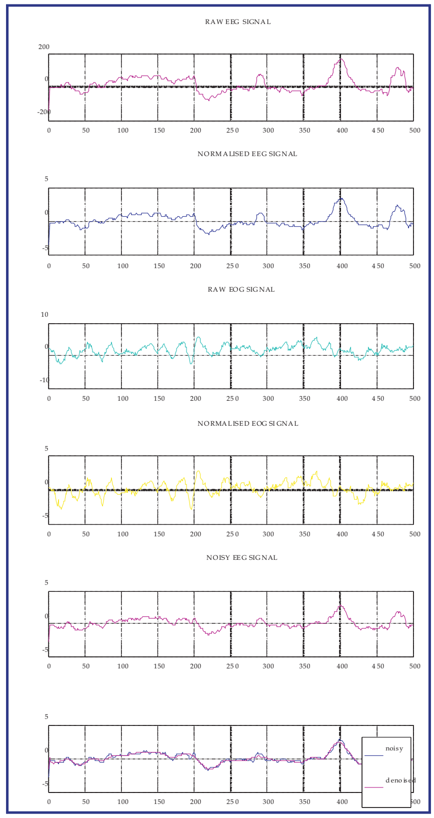

Figure 3. Raw EEG and EOG Signals, Normalized EEG and EOG Signals and Denoised EEG Signal of Dataset-2

Levels of Decomposition	SNR in dB dB10	Sym8	Haar
Level 4	4.0764	3.7540	3.9063
Level 5	4.8649	4.7653	6.5434
Level 6	7.6227	5.1869	7.6856
Level 7	9.2693	5.7833	16.5956
Level 8	11.9001	5.9238	17.5997
Level 9	11.9225	5.9095	17.5997

Table 1. Comparison of SNR with Different Wavelets and Different Levels of Decomposition of Dataset-1 (100Hz Sampling Frequency)

Levels of Decomposition	SNR in dB dB10	Sym8	Haar
Level 4	0.4623	0.6051	1.0264
Level 5	1.8117	1.7215	2.0966
Level 6	2.3803	1.9254	3.3609
Level 7	2.6521	2.2572	6.7465
Level 8	2.7760	2.9138	7.6775
Level 9	2.7889	2.8942	7.6775
Level 10	2.8103	2.9163	7.6775
Level 11	2.8295	2.9196	7.6775
Level 12	2.8455	2.9286	7.6775

Table 2. Comparison of SNR using Different Wavelets with Different Levels of Decomposition of Dataset-2 (250 Sampling Frequency).

2. Results

The results obtained from the denoising of EEG algorithm are provided in Table 1 and Table 2.

Conclusion

The results presented in Tables 1 and 2, clearly conclude that signals having lower sampling rates will provide better SNR than the signals having higher sampling rates.

The number of levels of decomposition of the noisy EEG signal using wavelets depends on sampling frequency of the signal and approximation to what band of frequencies of EEG signal.

In addition to this, Haar wavelet provides better SNR compared to dB10 and Sym8 wavelets.

References

[1]. **Almubarak, S., & Wong, P. K. (2011).** Long-term clinical outcome of neonatal EEG findings. *Journal of Clinical Neurophysiology,* 28(2), 185-189. http://doi.org/10.1097/WNP.0b013e3182121731

[2]. **Arab, M. R., Suratgar, A. A., Martínez-Hernández, V. M., & Rezaei Ashtiani, A. (2010).** Electroencephalogram signals processing for the diagnosis of petit mal and grand mal epilepsies using an artificial neural network. *Journal of Applied Research and Technology,* 8(1), 120-128.

[3]. **Gratton, G., Coles, M. G., & Donchin, E. (1983).** A new method for off-line removal of ocular artifact. *Electroencephalography and Clinical Neurophysiology*, 55(4), 468-484. https://doi.org/10.1016/0013-4694(83)90135-9

[4]. **Holmes, G. L., & Lombroso, C. T. (1993).** Prognostic value of background patterns in the neonatal EEG. *Journal of Clinical Neurophysiology,* 10, 323-323.

[5]. **Jung, T. P., Makeig, S., Humphries, C., Lee, T. W., Mckeown, M. J., Iragui, V., & Sejnowski, T. J. (2000).** Removing electroen cephalographic artifacts by blind source separation. *Psychophysiology,* 37(2), 163-178. https://doi.org/10.1111/1469-8986.3720163

[6]. **Kumar, B. K. (2019).** Denoising of EEG signals using wavelets and various thresholding techniques. *International Journal of Electronics Engineering,* 11(2), 261-269.

[7]. **Kumar, B. K., Prasad, K. V. S. V. R., & Alekhya, D. (2016, August).** Performance comparision of various thresholding techniques on the removal of ocular artifacts in the EEG signals. In 2016 *International Conference on Inventive Computation Technologies (ICICT)* (Vol. 3, pp. 1-5). IEEE. https://doi.org/10.1109/INVENTIVE.2016.7830179

[8]. **Mathworks. (n.d.).** *MATLAB for Artificial Intelligence.* Retrieved from https://www.mathworks.com/

[9]. **Murugavel, A. M., & Ramakrishnan, S. (2012).** Tree based wavelet transform and DAG SVM for seizure detection. *Signal & Image Processing*, 3(1), 115-125.

[10]. **Niedermeyer, E., & da Silva, F. L. (2005).** *Electroencephalography: Basic Principles, Clinical Applications, and Related Fields.* Lippincott Williams & Wilkins.

[11]. **PhysioNet. (n.d.).** *The Research Resource for Complex Physiologic Signals.* Retrieved from https://www.physionet.org/

[12]. **Schlögl, A., Keinrath, C., Zimmermann, D., Scherer, R., Leeb, R., & Pfurtscheller, G. (2007).** A fully automated correction method of EOG artifacts in EEG recordings. *Clinical Neurophysiology,* 118(1), 98-104. https://doi.org/10.1016/j.clinph.2006.09.003

[13]. **Thakor, N. V., Xin-Rong, G., Yi-Chun, S., & Hanley, D. F. (1993).** Multiresolution wavelet analysis of evoked potentials. *IEEE Transactions on Biomedical Engineering,* 40(11), 1085-1094. http://doi.org/10.1109/10.245625

[14]. **Venkataramanan, S., Prabhat, P., Choudhury, S. R., Nemade, H. B., & Sahambi, J. S. (2005, January).** Biomedical instrumentation based on electrooculogram (EOG) signal processing and application to a hospital alarm system. In *Proceedings of 2005 International Conference on Intelligent Sensing and Information Processing* (pp. 535-540). IEEE. http://doi.org/10.1109/ICISIP.2005.1529512

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