Efficient Filter for EEG Signal Using Non Local Mean Approach

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Abstract: *Non Local Mean (NLM) filter has attracted great attention within the images and signal processing field especially in the last ten years. The main contribution of this paper to the field of biomedical signals processing is introducing the straightforward application of the fast NLM filter to EEG signal contaminated with "Additive White Gaussian Noise" (AWGN). The performance of this filter is analysed by evaluating its optimal parameters. All the tests are conducted using actual EEG signal captured from human brain. The performance of this filter is determined using "Output Signal to Noise Ratio" (SNRo) and "Cross Correlation" (CC) criteria. The NLM filter exhibits excellent performance in rejection the AWGN from the EEG signal.*

Keyword: EEG signal, NLM filter, and AWGN.

1. Introduction

The process of measuring the "electrical action of the brain" is called "Electroencephalography (EEG)". It is widely used as a powerful tool for brain machine interfaces, medicine, and cognitive sciences [1]. The nature of information exchange with the nervous system is electrical. The information are processed by the brain neurons. These neurons can change the electrical currents flow across their membranes. These varying currents cause generation of electric and magnetic fields which can be measured using surface electrodes placed on the scalp. The recorded potentials between electrodes are amplified to form what is known as "Electroencephalography (EEG)". Therefore the EEG recordings give the overall knowledge about the activity of the brain neurons. The brain is the organ of human that responsible for controlling the nerves and muscles. The EEG is the most important noninvasive mean that used to evaluate the turmoil of the brain. It is also used to indicate the brain death and its other diseases [2]. EEG signals can be easily corrupted by noise because they have very small amplitude [3-4]. The EEG signal contaminated with different types of noise during its recording such as base line movements, electrode noise, and the noise generated from human body. These noises must be reduced as possible to perform accurate analyses for the EEG signal [5]. The nature of noise in EEG signal is "additive white gaussian" [6-7].Therefore, the proper filtering approaches are necessary to extract the clinical informations. The filtering methods are also involved in image processing field the main challenge here is how to keep the sharp edges. One of the modern methods of image filtering which offer the solution to this problem is the "Non Local Mean" filter presented by Buades et al. [8]. The filtering process is performed by taking the average of patches from various regions of the image which have the same spatial structure; depending on the basis that natural image consists of repeated patterns. This concept can be applied on several biomedical signals (EEG is a good example) which have a regular pattern that repeated with a little variation. Therefore, this signal is applicable to patch based filters. This work presents a brief description of the NLM filter and its implementation to EEG signal.

2. Filtering Methodology

The NLM filter deals with the problem of retrieving the true signal u from the noisy signal, v= u+n , n is "additive noise". The estimated $\overline{u(s)}$ of an arbitrary sample s is a weighted aggregate of values at different points t that are inside some "search neighborhood" N(s) and can be determined using Eq.(1) [9]:

$$\overline{u(s)} = \frac{1}{Z(s)} \sum_{t \in N(s)} w(s,t)\, v(t) \qquad (1)$$

where:

$$z(s)=\sum_{t} w(s,t) \qquad (2)$$

The weights can be calculated using Eq.(3) [10]:

$$w(s,t)= \exp\left(-\frac{\sum_{\delta\epsilon\Delta}\,[v(s+\delta)-v(t+\delta)]^2}{2L_\Delta\, \lambda^2}\right) = \exp\left(-\frac{d^2\,(s,t)}{2L_\Delta\, \lambda^2}\right) \qquad (3)$$

where:

λ: bandwidth parameter.

Δ: local patch of samples Enclosing s, consisting L_Δ samples; a patch of similar shape also encloses t.

The samples of the patch are centered on the interested points. In Eq.(3) the squared, summed point to point difference between samples of the patches is denoted by d^2. The samples in the patches are centered on s and t points. Each patch in Eq.(3) is submitted to self-averaging with the weight w(s,s)=1. A central patch corrector is applied to obtain smoother results as given in Eq.(4) [9]:

$$w(s,s) = \max_{t\,\epsilon N(s),t\neq s} w(s,t) \tag{4}$$

The innovation of NLM filter is that the weight w(s,t) relies on patch correlation, not on the distance between s and t points. The averaging process of the identical patches keeps edges, as opposed to the most common filters. By considering self-similarity expands along the signal, the N(s) is perfectly taken to be the complete signal, so the averaging operation is completely non-local [9]. In this research the fast NLM approach derived by Darbon et al [10] is applied to EEG (one dimension) signal. This method speeds up the NLM filter by avoiding the nested loops [10].

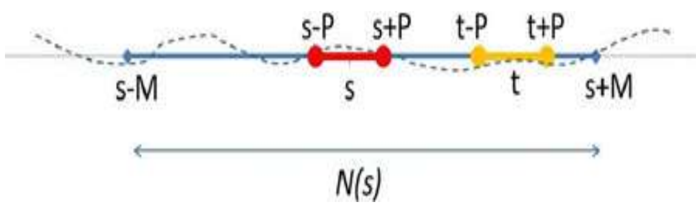

Figure 1: Representation of NLM parameters. The tiny patch centered on s is compared to patches centered on other points t in N(s) [9].

3. Performance Determination Metrics

To determine the robust of the NLM filter against the AWGN, an AWGN is added to the original EEG signal with SNR=5db (very high noise environment) then the filter is applied. Two determination metrics are used to quantitative the performance of this filter. The first metric is the SNRo given in Eq. (5) [11]. The second one is the CC which can be determined using Eq. (6) [12].

$$\text{SNRo (db)} = 10*\log_{10} \sum_{i=0}^{N-i} \frac{Ui^2}{[Ui-Vi]^2} \tag{5}$$

$$CC = \frac{\sum_{i=0}^{N-1} Ui.Vi}{\sqrt{\sum_{i=0}^{N-1} Ui^2 \sum_{i=0}^{N-i} Vi^2}} \tag{6}$$

where:

U: original EEG signal, V: filtered EEG signal.
N: Length of the EEG signal.

4. Results and Discussion

In this study the experiments are performed using actual EEG signals recorded in the brain-body dynamics lab at the University of Southern California. These signals are available in [13] for researchers. The original EEG signal is shown in figure 2 (a). The corrupted EEG signal with AWGN is illustrated in figure 2 (b). An examination for parameters selection of EEG NLM filter is done. This examination aims to evaluate the optimal parameters of the NLM filter which reject the noise efficiently. The most effective NLM parameters are the bandwidth (λ), the size of neighborhood search width N(s), and the length of the Patch Half Width (PHW). Figure 1 demonstrates the schematic geometric parameters of the one dimension patches centered on the points (s and t). The bandwidth (λ) governs the smoothing process of the signal. Kocher and Ville in [14] concluded that the (λ) must be scaled by the noise standard deviation (σ). They applied the NLM filter to different images corrupted with AWGN. They obtained good performance with λ=(0.5 σ). In this paper, several tests are conducted on the EEG signal to discover the optimum value of λ. The best results are achieved at λ=(0.7

σ) as illustrated in figures (3) and (4). The size of PHW must generally be the same as the size of features of interest. In fact the PHW determines the scale on which the patches are compared. The size of N(s) must be specified wisely. The small size of N(s) degrades the performance of filter, while the large size of N(s) requires more computations. Figures (5) and (6) show the performance of the NLM filter in term of both SNRo and CC respectively. These figures indicate the optimal values of PHW and N(s) are (PHW=3 and N(s) =2000). The detailed results are presented in tables (1-5). These tables illustrate the performance of the filter quantitatively. Figure 2 (c) demonstrates the filtered EEG signal after implementing the NLM filter with the optimum values of its parameters. For more visual comparison, four zoomed figures of figure 2 are presented in figures (7-10). These figures illustrate the great similarity between the original and the recovered signal and this indicates the high efficiency of the discussed filter.

5. Conclusion

This article offers the one dimensional implementation of the fast NLM filter. This filter is applied to the degraded EEG signal and its performance is analysed. A tuning for parameters selection is performed and the filter exhibited a robust performance in suppressing the AWGN from the EEG signal. This is evident from the quantitative and visual results that have been introduced in this paper. This lead to substantial conclusion that this filter efficient for filtering EEG signal and may be useful for filtering others biomedical signals.

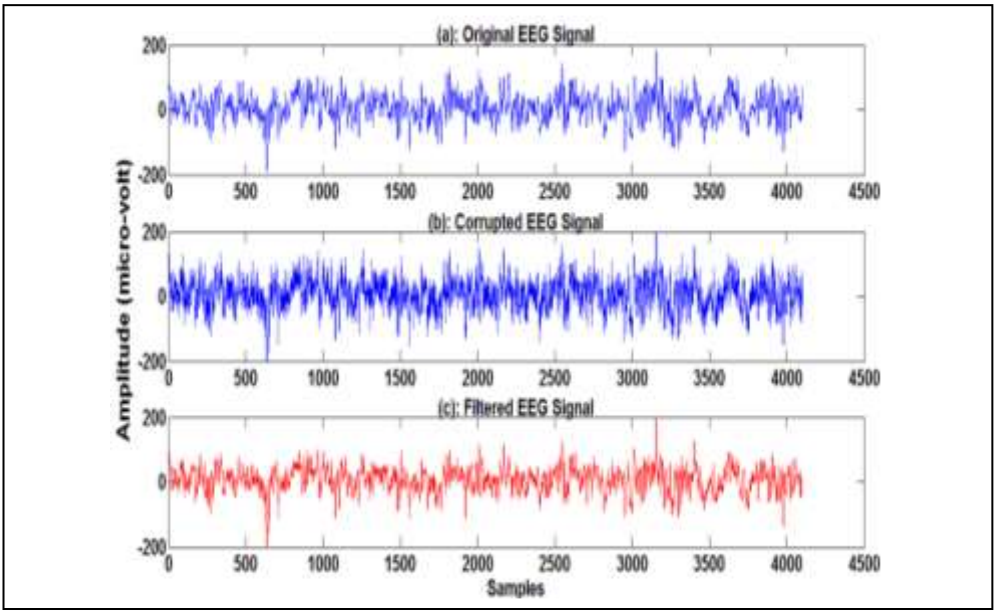

Figure 2: Visual comparison between original, corrupted, and filtered EEG signal.

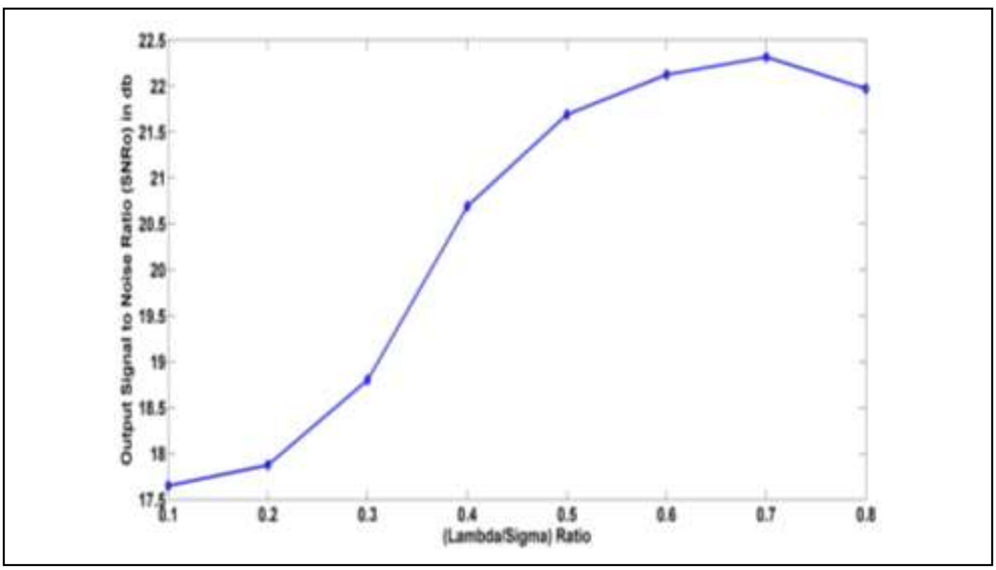

Figure 3: Optimal value of λ in term of SNRo.

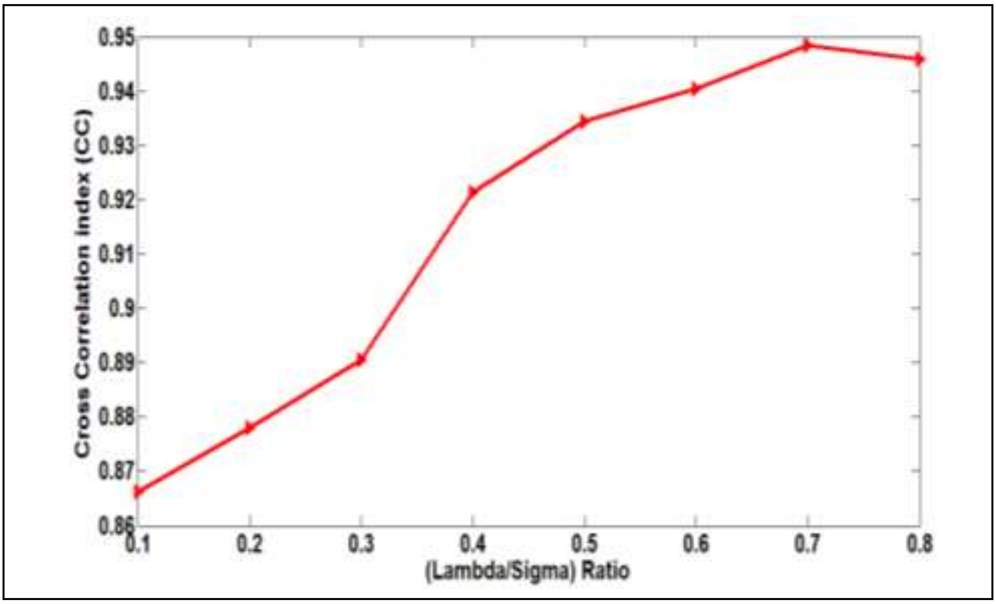

Figure 4: Optimal value of λ in term of CC.

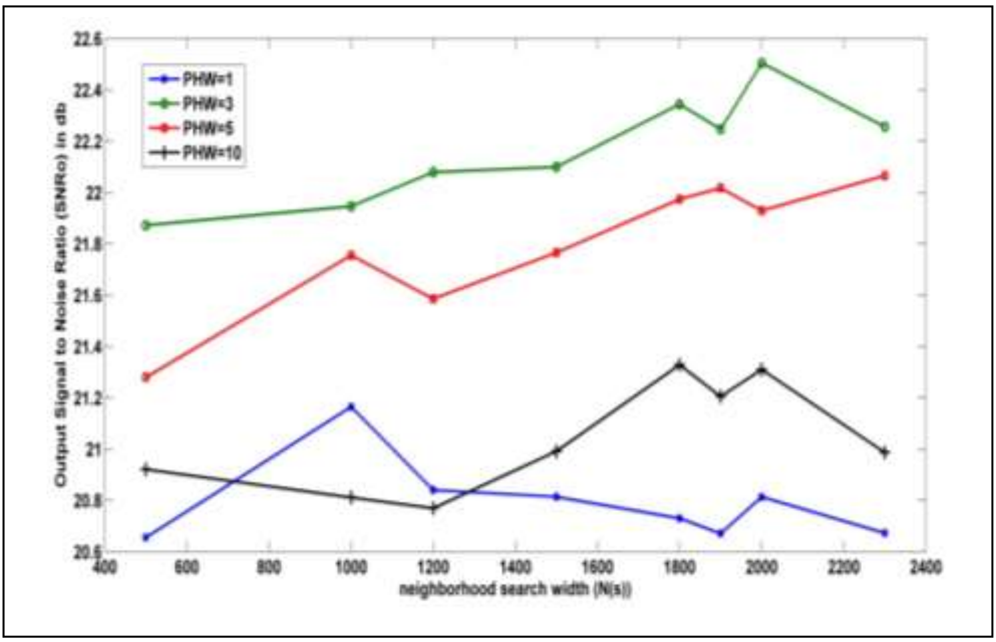

Figure 5: Performance of NLM filter in term of SNRo at different sizes of PHW and N(s).

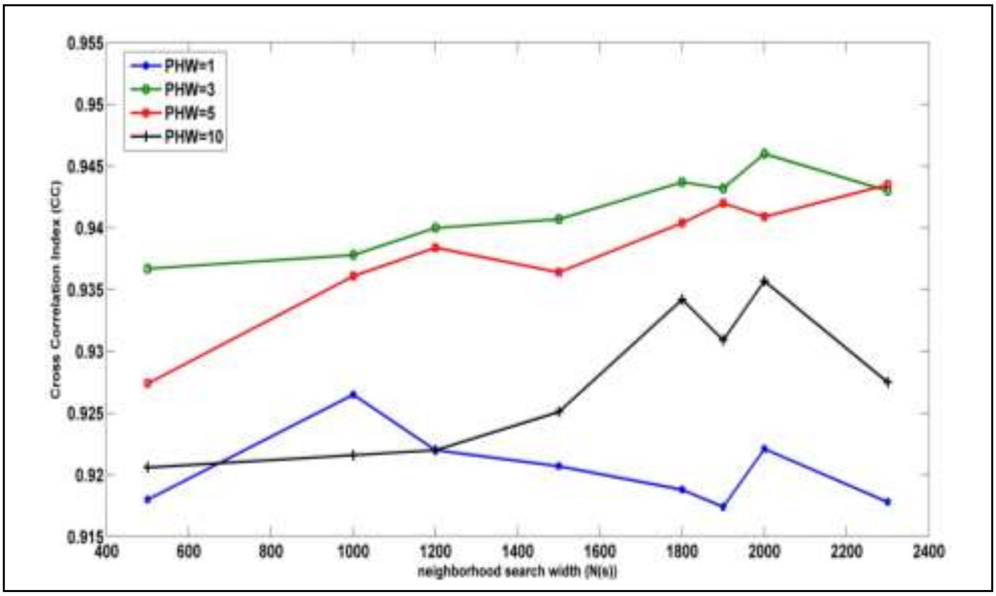

Figure 6: Performance of NLM filter in term of CC at different sizes of PHW and N(s).

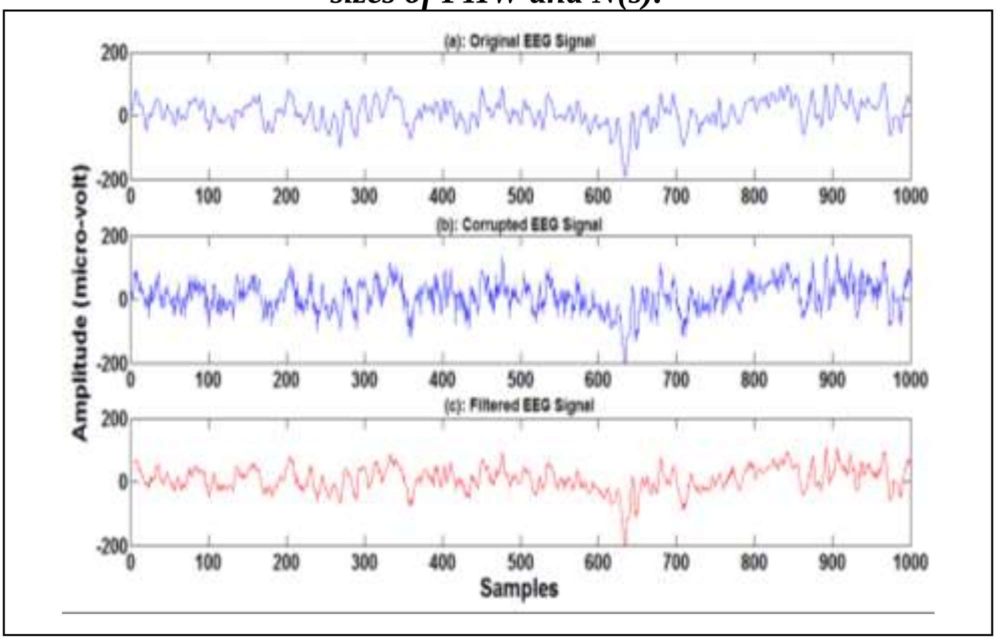

Figure 7: Zooming on figure 2 for the first 1000 samples.

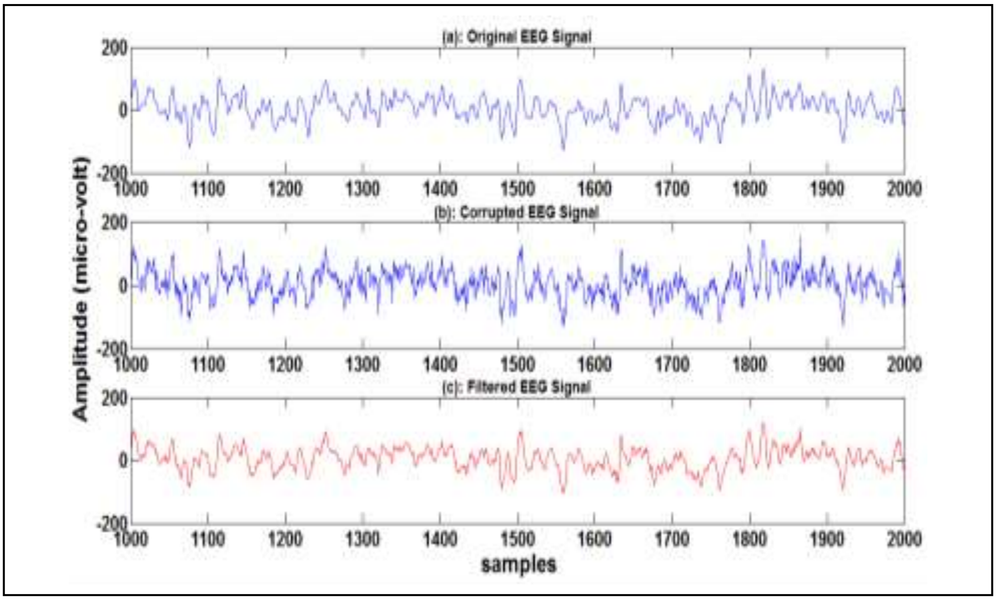

Figure 8: Zooming on figure 2 for the second 1000 samples.

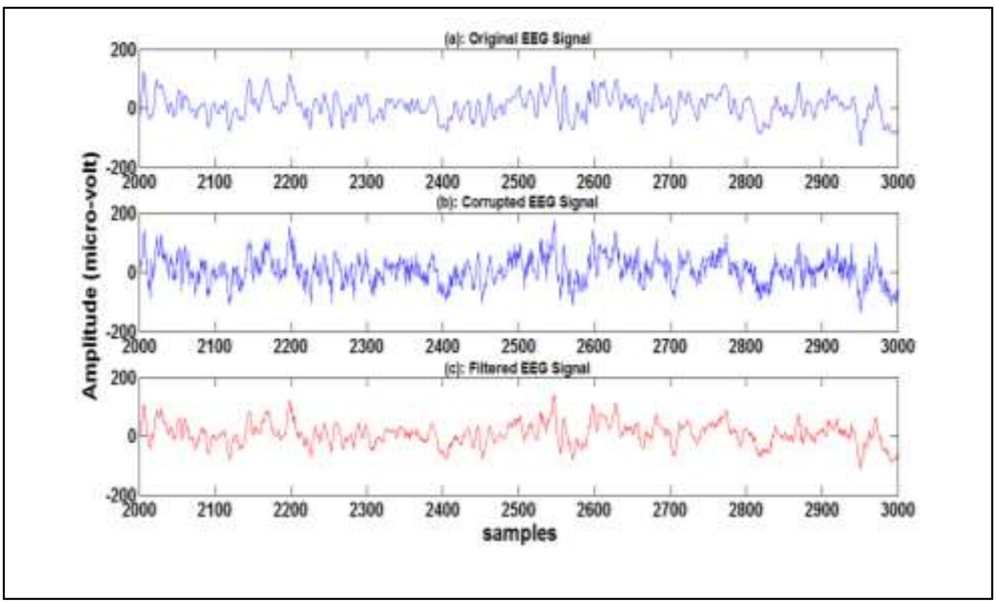

Figure 9: Zooming on figure 2 for the third 1000 samples.

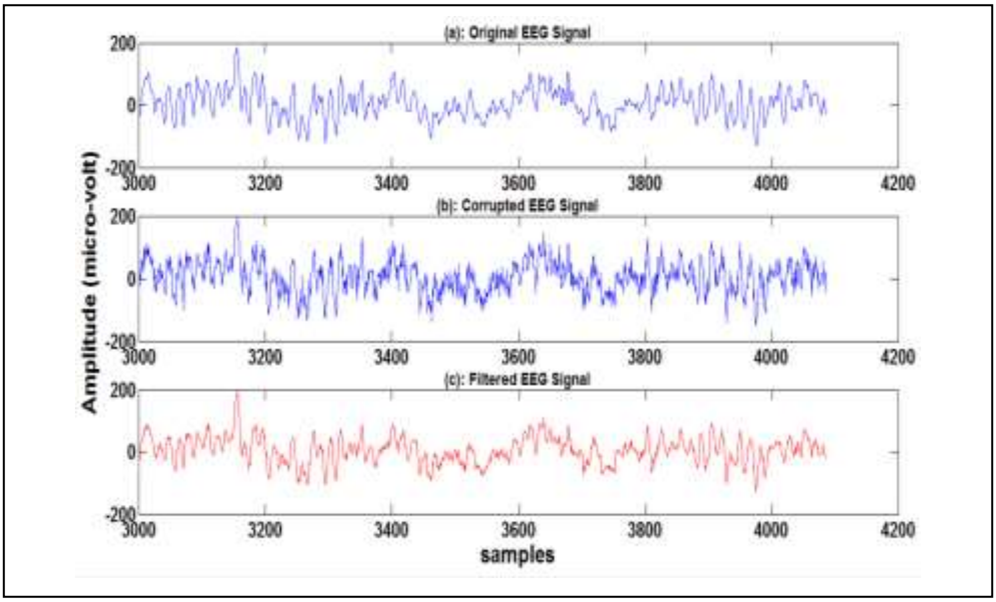

Figure 10: Zooming on figure 2 for the last 1086 samples.

Table (1): Performance of filter in response to tuning N(s) at PHW=10 and λ=0.7σ.

Neighborhood search width N(s)	500	1000	1200	1500	1800	1900	2000	2300
Output Signal to Noise Ratio (SNRo) in db	20.9213	20.8115	20.7697	20.9919	21.3291	21.2056	21.3102	20.9871
Cross Correlation (CC)	0.9206	0.9216	0.9220	0.9251	0.9342	0.9309	0.9357	0.9275

Table (2): Performance of filter in response to tuning N(s) at PHW=5 and λ=0.7σ.

Neighborhood search width N(s)	500	1000	1200	1500	1800	1900	2000	2300
Output Signal to Noise Ratio (SNRo) in db	21.2797	21.7558	21.5858	21.7662	21.9742	22.0178	21.9298	22.0661
Cross Correlation (CC)	0.9274	0.9361	0.9384	0.9364	0.9404	0.9420	0.9409	0.9435

Table (3): Performance of filter in response to tuning N(s) at PHW=3 and λ=0.7σ.

Neighborhood search width N(s)	500	1000	1200	1500	1800	1900	2000	2300
Output Signal to Noise Ratio (SNRo) in db	21.8725	21.9468	22.0794	22.0999	22.3443	22.2472	22.5051	22.2564
Cross Correlation (CC)	0.9367	0.9378	0.9400	0.9407	0.9437	0.9432	0.9460	0.9430

Table (4): Performance of filter in response to tuning N(s) at PHW=1 and λ=0.7σ.

Neighborhood search width N(s)	500	1000	1200	1500	1800	1900	2000	2300
Output Signal to Noise Ratio (SNRo) in db	20.6557	21.1652	20.8405	20.8145	20.7308	20.6713	20.8140	20.6732
Cross Correlation (CC)	0.9180	0.9265	0.9220	0.9207	0.9188	0.9174	0.9221	0.9178

Table (5): Performance of filter in response to tuning λ at PHW=3 and N(s)=2000.

Band Width (λ)	0.1σ	0.2σ	0.3σ	0.4σ	0.5σ	0.6σ	0.7σ	0.8σ
Output Signal to Noise Ratio (SNRo) in db	17.6493	17.8750	18.8011	20.6905	21.6905	22.1255	22.3160	21.9713
Cross Correlation (CC)	0.8662	0.8781	0.8905	0.9214	0.9345	0.9405	0.9485	0.9459

References

[1] H. Maki, T. Toda, S. Sakti, G. Neubig, and S. Nakamura, "EEG signal enhancement using multi-channel weiner filter with a spatial correlation prior", Conference paper, (ICASSP), IEEE, pp. 2639-2643, April, 2015.

[2] G. Inuso, L. Foresta, N. Mammone, and C. Morabita, "Wavelet-ICA methodology for efficient artifact removal from Electroencephalographic recordings", conference paper, (IJCNN), IEEE, August, 2007.

[3] V. Colhoun, T. Adah, and J. Liu, "A feature-based approach to combine functional MRI, structural MRI and EEG brain imaging data", conference paper, (EMBS), IEEE, pp. 3672-3675, August, 2006.

[4] D. Kang, and L. Zhizeng,"A Method of Denoising Multi-channel EEG Signals Fast Based on PCA and DEBSS Algorithm", Conference Paper, (ICCSEE), IEEE, Vol.3, pp.322-326, March, 2012.

[5] L. Yu, "EEG De-Noising Based on Wavelet Transformation", Conference Paper, (ICBBE), IEEE, pp. 4-7, July, 2009.

[6] V. Prasad, P. Siddaiah, and B. prabhakara, "Denoising of Biological Signals Using Different Wavelet Based Methods and Their Comparison", Medwell Journal, pp. 146-149, Vol.7, Issue. 4, June, 2008.

[7] A. Mert, and A. Akan, "EEG Denoising Based on Empirical Mode Decomposition and Mutual Information", conference paper, (IFMBE), Springer, Vol. 41, pp. 631-634, September, 2014.

[8] A. Buades, B. Coll, and M. Morel, "A Review of Image Denoising Algorithms, with a New One", SIAM Journal, Vol. 4, No. 2, pp. 490-530, January, 2005.

[9] H. Tracy, L. Miller, "Nonlocal Means Denoising of ECG Signals", Transaction, IEEE, Vol. 95, No. 9, September, 2012.

[10] J. Darbon, A. Cunha, F. Chan, S. Osher, and G. Gensen, "Fast Non Local Filtering Applied to Electron Cryomicroscopy", conference paper, IEEE, pp. 1331-1334, June, 2008.

[11] M. Assam, K. Chafaa, M. Ghanai, and L. Moreno, "ECG denoising using Extended Kalman Filter", conference paper, (ICCAT), IEEE, pp. 1-6, May, 2013.

[12] A. Fallah, and S. Abbaspour, "Removing ECG Artifact from the Surface EMG Signal Using Adaptive Subtraction Technique", Journal of Biomedical Physics and Engineering, Vol. 4, No.1, pp. 33-38, March, 2013.

[13] Francisco Valero-Cuevas, "Brain-Body Dynamics Lab"

http://bbdl.usc.edu/Valero-Cuevas-Lab.php,

Date of downloading data: May, 2016.

[14] V. Ville, and M. Kocher, "SURE based non-local means" , Letter, IEEE, Vol. 16, Issue. 11, pp. 973-976, July, 2009.

مصفي كفوء لأشارة التخطيط الكهربائي للدماغ باستخدام طريقة الوسط غير المحلي

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المستخلص

جذب مصفي الوسط غير المحلي (Non Local Mean Filter) اهتماما كبيرا في العشر سنوات الأخيرة في مجال معالجة الصور والأشارة الرقمية. يقدم هذا البحث مساهمة لمجال معالجة الاشارات الطبية الحيوية لتناوله التطبيق الدقيق لمصفي الوسط غير المحلي السريع على اشارة التخطيط الكهربائي للدماغ الملوثة بضوضاء كاوس البيضاء (AWGN). تم تحليل اداء هذا المصفي عن طريق ايجاد امثل قيم لمتغيراته. اجريت كل الاختبارات باستخدام اشارات تخطيط كهربائي للدماغ حقيقية ملتقطة من دماغ بشري. استخدمت معايير نسبة الاشارة الى الضوضاء الخارجة (SNRo) و التطابق (CC) لقياس اداء هذا المصفي. ابدى المصفي اداء ممتاز في حجب الضوضاء من اشارة التخطيط الكهربائي للدماغ.

الكلمات الرئيسية: إشارة التخطيط الكهربائي للدماغ، مصفي الوسط غير المحلي، ضوضاء كاوس البيضاء.