ISBN 978-92-990073-5-8
3^{rd} Imeko TC13 Symposium on Measurements in Biology and Medicine
"New Frontiers in Biomedical Measurements"
April 17-18, 2014, Lecce, Italy

THRESHOLD ADAPTATION IN AUTOMATIC WAVELET-ICA FOR ELECTROENCEPHALOGRAPHIC ARTIFACT REMOVAL

Nadia Mammone[1], Aime' Lay-Ekuakille[2], Patrizia Vergallo[2] and Francesco C. Morabito[1]

[1]DICEAM Department, Mediterranean University of Reggio Calabria, Via Graziella, Feo di Vito, 89122 Reggio Calabria, nadia.mammone@unirc.it
[2]Dipartimento di Ingegneria dell'Innovazione, University of Salento

Abstract: Electroencephalography (EEG) is a well established methodology to record the electrical activity of the brain. We can be interested in monitoring the cerebral electrical activity for different purposes: studying the cognitive activity, interfacing the brain with the machine, extracting diagnostic information, etc. Artifacts are unwelcome signals, generated by electromagnetic sources not related to cerebral activity, that may overlap to the EEG signals and affect their processing. Whatever the goal of EEG processing, a preprocessing step consisting in artifact removal is normally required. Unfortunately, artifact removal is unavoidably a lossy procedure, therefore, the goal must be removing artifacts losing the minimum amount of useful information embedded in the EEG. To this purpose, Automatic Wavelet-ICA was recently proposed by the authors. The technique is multistep and parameter dependent, thus its performance may vary significantly with the parameter setting. The present paper shows the results of the optimization with respect to the threshold used for artifact detection.

Keywords: Automatic artifact rejection, Electroencephalography, Wavelet Transform, Independent Component Analysis, Entropy.

1. INTRODUCTION

Electroencephalography (EEG) is nowadays one of the key and most widespread technique used to have knowledge of the ongoing activity of the brain. The aims can be different: studying the cognitive cerebral activity, interfacing the brain with the machine (to allow for a mind-control of the machine itself), extracting diagnostic information, etc. Artifacts are unwelcome signals, generated by artifactual electromagnetic sources, whose field gets mixed to the bio-electromagnetic field generated by the brain during is activity, that is what we aim to collect via EEG recording [1], [2], [3]). In this way, the electrical activity of the brain might be partially or completely hidden and, consequently, EEG processing might provide incorrect results. Artifacts can be generated by different sources such as muscles, eye movements and blinks, sweating, breathing, heart beat, electrical line noise, etc. EEG might be totally obscured, for example by heavy artifact with muscular origin, or might be distorted, exhibiting shapes that are typical of pathological events even though nothing pathological happened. Whatever the goal of our analysis is, a preprocessing step of artifact rejection is normally required when dealing with EEG. Unfortunately, artifact removal is unavoidably a lossy procedure: we can either discard the entire artifactual epoch (but the real time continuous EEG processing is no longer possible) or try to reduce the effect of artifacts in different ways. Thus the goal must be reducing artifacts while losing the minimum amount of useful information embedded in the EEG.

Betta et al. [4] Proposed an automated analysis of REM sleep, which includes both a REMs detection algorithm and an ocular artifact removal system, the two steps based respectively on Wavelet Transform and adaptive filtering.

Adib et al. [5] Presented a method to remove artifacts in electroencephalography records during Galvanic Vestibular Stimulation (GVS), they combined time-series regression methods with wavelet decomposition methods.

Daly et al. [6] presented a comparative study of automatic methods for removing blink, electrocardiographic, and electromyographic artifacts from the EEG. Three methods were considered; wavelet, blind source separation (BSS), and multivariate singular spectrum analysis (MSSA)-based correction.

Daly et al. [7] also presented an algorithm for identifying clean EEG epochs by thresholding statistical properties of the EEG because lack of a clear analytical metric for identifying artifact free, clean EEG signals inhibits robust comparison of different artifact removal methods.

Zima et al. [8] introduced an automatic sequential procedure which is capable of removing short-duration, high-amplitude artifacts from long-term neonatal EEG recordings. The artifacts are removed sequentially in short-term signals using Independent Component Analysis (ICA) transformation and wavelet denoising.

Javidi et al. [9] introduced a new class of complex domain blind source extraction algorithms suitable for the extraction of both circular and non-circular complex signals is proposed. The performance is assessed through simulations on real-time artifact removal from EEG signals, verified using both qualitative and quantitative metrics.

Winkler et al. [10] proposed a universal classifier of independent components for the subject independent removal of artifacts from EEG data.

De Vos et al. [11] discussed the evaluation of algorithms

ISBN 978-92-990073-5-8

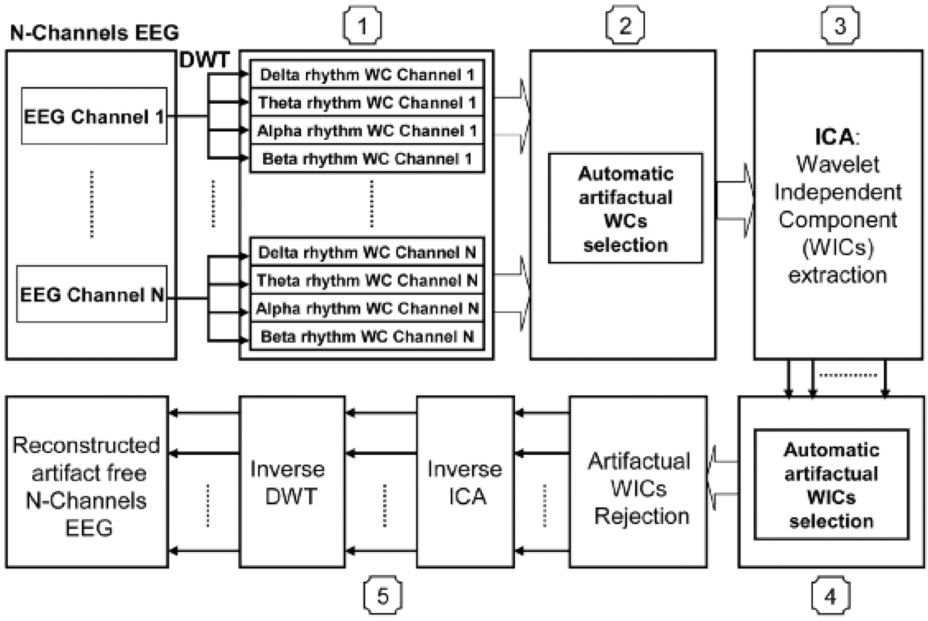

Fig. 1. Block diagram of Wavelet-ICA processing system for EEG artifact rejection. The EEG recording is first partitioned into the four major EEG rhythms. The artifact-linked wavelet components are then selected from the sub-tracings representing the rhythms and passed through ICA. The Wavelet-Independent Components of artifactual origin are selected and cancelled. Inverse ICA and Wavelet reconstruction are then performed in order to recover the clean EEG dataset. The blocks that are numerically labelled are discussed in detail in the corresponding subsections of Section 2.

using Independent Component Analysis for automatic removal of ECG, pulsation and respiration artifacts in neonatal EEG before automated seizure detection.

Bartels et al. [12] introduced an algorithm that removes artifacts from EEG based on blind source separation and support vector machine.

Gao et al. [13] introduced different algorithms for the removal of various artifacts from EEG signals using combined methods.

Removing artifacts while preserving the information content of the EEG requires a tool that is able to efficiently isolate the artifacts and an expert classifier that is able to discriminate between artifactual and useful content. So far, a lot of techniques have been proposed to isolate and reject the artifacts but most of them are not automatical, in other words they need an expert user to perform the classification and rejection steps. The issue of automatization is a key topic in EEG artifact rejection: a technique, to be considered fully automatic, must ensure that the user is not required to detect artifacts nor to interact with the procedure until the reconstructed clean EEG is produced.

The drawback of dealing with a non automatic procedure is twofold: realtime EEG processing is not possible (because the EEG should be preprocessed manually) and expert knowledge about EEG artifacts is required, whatever the purpose of EEG processing is. Of course, reaching good performance with an automatic rejection algorithm is more challenging than succeeding with a semi-automatic method that is supervised by an expert, this is why automatic methods should be compared against one another as well as semi-automatic or manual methods.

Another delicate issue is the method evaluation. Artifact rejection methods should be first tested on simulated artifactual EEG (artifact-free EEG recording where simulated artifacts are mixed artificially) in order to be able to compare the original artifact-free EEG with the EEG reconstructed after artifact rejection. Often, the algorithms are tested over real EEG and their performance is evaluated only visually.

In order to deal with all these issues, a technique was recently proposed by the authors ([14], [15], [16], [17], [18], [19]) that performs automatic artifact rejection while not discarding any epoch of the EEG recording. Very encouraging results were obtained, however, in order to make the technique more efficient and reliable, further improvement is required to minimize the EEG information loss. AWICA technique is multistep and parametrical: the present paper shows the results of parameter optimization with respect to different kind of artifact. The paper is organized as follows: Section 2. shortly illustrates AWICA technique and highlights which parameters of the procedure are tuned to be optimized, Section 4. reports the results and Section 5. discusses the conclusions.

ISBN 978-92-990073-5-8

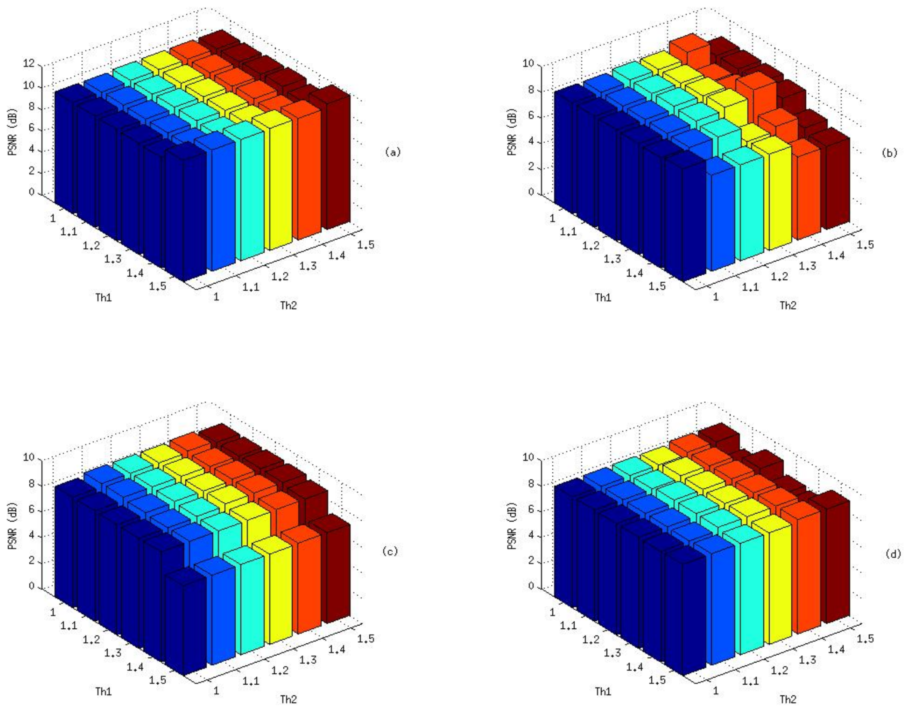

Fig. 2. Comparison of the quality of artifact rejection for different threshold1 and threshold2 settings and different artifacts: (a) eye blink; (b) muscular activity; (c) electrical shift; (d) linear trend. The original artifact-free EEG is compared with the EEG reconstructed after artifact rejection. The metric used for the comparison is the Peak Signal to Noise Ratio (PSNR). X- and Y- axes account for Threshold 1 and Threshold 2, on the Z-axis, PSNR values are reported as 3D bars.

2. METHODOLOGY: AUTOMATIC WAVELET-ICA

AWICA description:

The technique presented in [14] is a fully automatized method based on the joint use of Wavelet Transform and Independent Component Analysis. The method is here just shortly summarized, for a full, complete description, please refer to [14]. The block diagram of AWICA is depicted in Figure 1: the first step consists in partitioning each EEG channel into the four major bands of brain activity (delta, theta, alpha and beta); therefore each EEG time series is split into four time series and is accounted by a Wavelet Component (WC).

The next step is to automatically identify the WCs linked to artifactual events quantifying their degree of artifactuality through some markers (kurtosis and entropy) [20], [14], [21]. The next step is passing the artifactual WCs through ICA in order to extract the artifactual content and concentrate it in a few independent components (ICs). Then, the artifactual Wavelet Independent Components are automatically selected and rejected. Finally, the EEG is reconstructed in three steps: inverse ICA (to reconstruct the artifact-free WICs) and inverse DWT (to reconstruct the artifact-free WCs), in the end, the overall artifact-free EEG dataset is reconstructed.

EEG data description:

EEG data are from a database available online (ftp://ftp.ieee.org/uploads/press/rangayyan/) which consists of an eight-channel artifact-free EEG. The sampling rate is 100Hz and the time duration is 7.5 sec. The electrode montage and the EEG recording are shown in [16].

According to [22], four types of artifacts were synthesized: eye blink, muscular activity, electrical shift, linear trend. We modelled electrical shift artifacts by implementing discontinuities, linear trends with a slope of $100\mu V$ per second, temporal muscle artifacts using random noise band-pass filtered (FIR) between 20 and 60 Hz and eye blinks by random noise band-pass filtered (FIR) between 1 and 3 Hz.

In order to simulate a real artifactual EEG, we mixed one by one the synthesized artifacts to the central or frontal electrodes of the EEG (with a 0 dB signal-to-noise-noise

ISBN 978-92-990073-5-8

ratio). Thus, we obtained four EEG dataset where two channels are corrupted by artifacts [14].

3. METHOD OPTIMIZATION

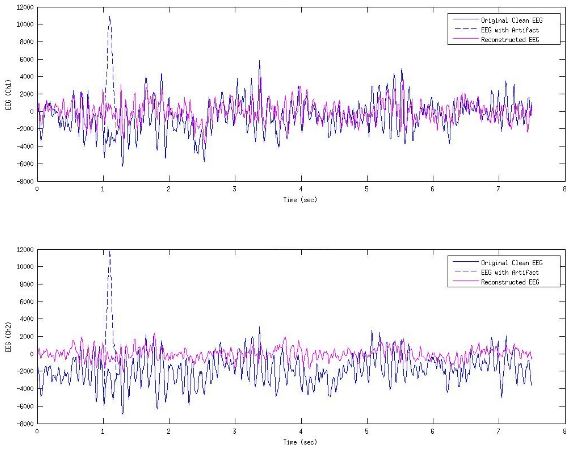

Fig. 3. Results of blink artifact rejection. This figure shows the original artifact-free EEG, the EEG with the simulated blink artifact and the EEG reconstructed after artifact rejection with threshold1=1.5 and Threshold2=1.5.

As discussed in the Introduction, the goal of the present paper is to investigate the possibility of AWICA optimization. Since AWICA is multistep and parametrical, in order to optimize it we have to analyze how its performance depends on the involved parameters. In particular, the present paper focuses on the dependence on the two threshold that are used for artifactual WCs and artifactual WICs detection: *Th1* (Section 2.) and *Th2* (Section 2.), respectively. To this purpose, the four simulated artifactual EEG were proccesed by AWICA with *Th1* and *Th2* running from 1 to 1.5 with a 0.1 step: therefore we have 6 possible values for either Th1 and Th2 and, globally, 36 different parameter setting for AWICA.

Each of the four EEG dataset was processed by AWICA in every possible parameter setting, therefore, 144 test were carried out.

The goal of the test was to compare the similarity between the original artifact-free EEG and the EEG reconstructed by AWICA after the artifacts that were artificially mixed were rejected. The measure we chose to compare the original and the reconstructed time series is the Peak Signal to Noise Ratio (PSNR). PSNR is a measure of the peak error and is expressed in decibels. PSNR is here used to measure the quality of lossy reconstruction. The signal in this case is the original artifact-free EEG and the noise is the error due to signal reconstruction after artifact rejection. The higher the PSNR the better the reconstruction. The higher the PSNR, the better is the quality of the reconstructed signal data.

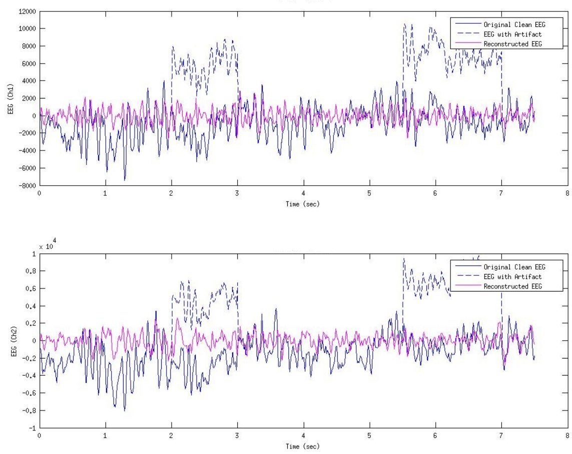

Fig. 4. Results of electrical shift artifact rejection. This figure shows the original artifact-free EEG, the EEG with the simulated electrical shift artifact and the EEG reconstructed after artifact rejection with threshold1=1 and Threshold2=1.4.

$$PNSR = 20\log_{10}\frac{\max_{i=1}^{N} x(i)}{\sqrt{\frac{\sum_{i=1}^{N}(x(i)-x_{rec}(i))^2}{N}}}$$

4. RESULTS

The technique AWICA was implemented in MATLAB® and was applied to the synthesized artifactual dataset [1].

Since the frequency range of the EEG was 0-50 Hz, a $N=4$ levels wavelet decomposition was sufficient to partition the frequency range of interest into the sub-bands corresponding to the major EEG rhythms (delta: 0-4 Hz, theta: 4-8 Hz, alpha: 8-12 Hz, beta: above 12 Hz).

Figures 2 shows the comparison of the quality of EEG artifact rejection for different threshold1 and threshold2 setting and different kind of artifact. Each sub-figure is associated to a different simulated artifactual EEG: EEG with blink (Figure 2.a), muscle activity (Figure 2.b), electrical shift (Figure 2.c), linear trend (Figure 2.d). Each sub-plot shows a 3D bar diagram representing the different PSNR values obtained applying AWICA with different Th1-Th2 parameter setting. The original artifact-free EEG is compared with the EEG reconstructed after artifact rejection, in other words each artifact-free EEG time series is compared with the corresponding reconstructed EEG

[1]The toolbox is open source and available, if interested, please send an email to the corresponding author: *nadia.mammone@unirc.it*

ISBN 978-92-990073-5-8

time series, then the average PSNR is estimated over the 8 time series (8 EEG channels). Since the higher the PSNR, the better the reconstruction, we can infer that the optimal threshold setting depends on the nature of the artifact: for blink artifact (Figure 2.a) the best setting is Th1=1.5 and Th2=1.5, for muscular activity artifact (Figure 2.b) the best setting was Th1=1.3 and Th2=1.4, for electrical shift artifact (Figure 2.c) the best setting was Th1=1 and Th2=1.4 or Th1=1.3 and Th2=1.4, for linear trend artifact (Figure 2.d) the best setting was Th1=1 or 1.2 or 1.5 and Th2=1.5.

This means that threshold setting should be tuned according to the kind of artifact that occurred and that a pre-processing step of artifact classification would improve the performance.

Figures 3-6 show the visual comparison between the original artifact-free EEG, the simulated artifactual EEG and the EEG reconstructed by AWICA when the best threshold setting is selected according to PSNR.

Figure 3 shows the comparison for blink, Figure 5) for muscular activity, Figure 4 for the electrical shift and Figure 6 for the linear trend.

The best performance were achieved for blink and muscular activity suppression. Looking at Figures 4 and 6, we can see that artifacts were reduced but the EEG was partially distorted also in the artifact-free segments. Future investigations should be focused on minimizing the distortion, especially in those segments that are not affected by artifacts and that should be mostly preserved.

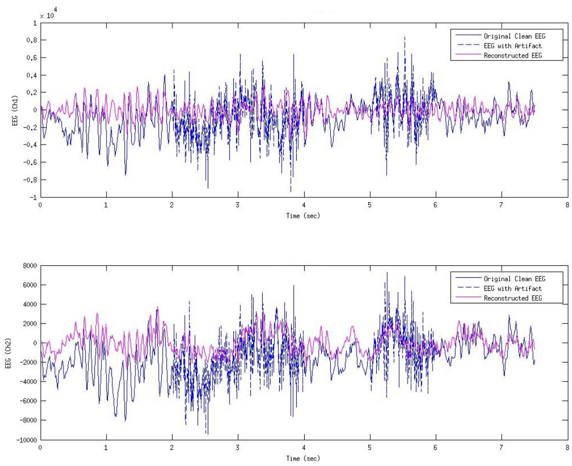

Fig. 5. Results of muscle artifact rejection. This figure shows the original artifact-free EEG, the EEG with the simulated muscular artifact and the EEG reconstructed after artifact rejection with threshold1=1.3 and Threshold2=1.4.

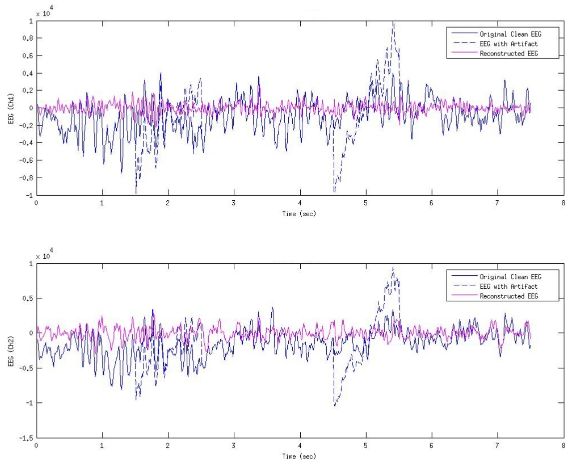

Fig. 6. Results of linear trend artifact rejection. This figure shows the original artifact-free EEG, the EEG with the simulated linear trend artifact and the EEG reconstructed after artifact rejection with threshold1=1.5 and Threshold2=1.5.

5. CONCLUSIONS

In this paper, the importance of Electroencephalography (EEG) artifact removal was addressed. Since EEG is one of the key and most widespread technique used to have knowledge of the ongoing activity of the brain and artifacts are unwelcome signals that may overlap to the electrical activity of the brain and can affect EEG processing, artifact removal is a necessary pre-processing step, whatever the purpose of our EEG analysis. Unfortunately, artifact removal is unavoidably a lossy procedure, thus the goal must be reducing artifacts while losing the minimum amount of useful information embedded in the EEG. To this purpose, in this paper we investigate the optimization of Automatic Wavelet-ICA (AWICA), a multi-step and parametrical technique recently proposed by the authors. The present paper shows the results of parameter optimization with respect to different kind of artifacts: ocular blink, muscular activity, electrical shift and linear trend. The results show that each artifact is better reduced with a specific parameter setting, therefore, future research will be focused on classifying artifacts together with their detection for optimal parameter setting.

REFERENCES

[1] P. Vergallo and A. Lay-Ekuakille. Brain source localization: A new method based on music algorithm and spatial sparsity. *Rev. Sci. Instrum.*, 84:085117, 2013.

[2] P.Vergallo, A. Lay-Ekuakille, N.I. Giannoccaro, A., Trabacca, D. Labate, F. C. Morabito, S.Urooj, and V. Bhateja. Identification of visual evoked potentials in eeg detection by empirical mode decomposition.

IEEE SSD'2014, Barcelona, 2014.

[3] A. Lay-Ekuakille, P. Vergallo, D. Caratelli, F. Conversano, S. Casciaro, and A. Trabacca. Multispectrum approach in quantitative eeg: Accuracy and physical effort. *IEEE Sensors Journal*, 13(9):3331 ? 3340, 2013.

[4] M. Betta, A. Gemignani, A. Landi, M. Laurino, P. Piaggi, and D. Menicucci. Detection and removal of ocular artifacts from EEG signals for an automated REM sleep analysis. *Conf Proc IEEE Eng Med Biol Soc*, pages 5079–82, 2013.

[5] M. Adib and E. Cretu. Wavelet-based artifact identification and separation technique for EEG signals during galvanic vestibular stimulation. *Comput Math Methods Med*, 2013:167069:Epub, 2013.

[6] I. Daly, N. Nicolaou N, S. J. Nasuto, and K. Warwick. Automated artifact removal from the electroencephalogram: a comparative study. *Clin* EEG *Neurosci*, 44(4):291–306, 2013.

[7] I. Daly, F. Pichiorri, J. Faller, V. Kaiser, A. Kreilinger, R. Scherer, and G. Müller-Putz. What does clean EEG look like? *Conf Proc IEEE Eng Med Biol Soc*, pages 3963–6, 2012.

[8] M. Zima, P. Tichavský, K. Paul, and V. Kraja. Robust removal of short-duration artifacts in long neonatal EEG recordings using wavelet-enhanced ICA and adaptive combining of tentative reconstructions. *Physiol Meas*, 33(8):39–49, 2012.

[9] S. Javidi, D. P. Mandic, C. C. Took, and A. Cichocki. Kurtosis-based blind source extraction of complex non-circular signals with application in EEG artifact removal in real-time. *Front Neurosci*, 5:105:eCollection 2001, 2011.

[10] I. Winkler, S. Haufe, and M. Tangermann. Automatic classification of artifactual ICA-components for artifact removal in EEG signals. *Behav Brain Funct*, 7:30, 2011.

[11] M. De Vos, W. Deburchgraeve, P. J. Cherian, V. Matic, R. M. Swarte, P. Govaert, G. H. Visser, and S. Van Huffel. Automated artifact removal as preprocessing refines neonatal seizure detection. *Clin Neurophysiol*, 122(12):2345–54, 2011.

[12] G. Bartels, L. C. Shi, and B. L. Lu. Automatic artifact removal from EEG - a mixed approach based on double blind source separation and support vector machine. *Conf Proc IEEE Eng Med Biol Soc*, doi:10.1109/IEMBS.2010.5626481:5383–6, 2010.

[13] J. Gao, Y. Yang, J. Sun, and G. Yu. Automatic removal of various artifacts from EEG signals using combined methods. In *J Clin Neurophysiol, 27(5):312-20, 2010*.

[14] N. Mammone, F. La Foresta, and F. C. Morabito. Automatic artifact rejection from multichannel scalp EEG by wavelet ICA. In *Sensors Journal IEEE, 12(3):533-42, 2012*.

[15] N. Mammone and F. C. Morabito. Enhanced automatic artifact detection based on Independent Component Analysis and Renyi's entropy. *Neural Networks*, 21(7):1029–1040, 2008.

[16] Inuso G., La Foresta F., Mammone N., and Morabito F. C. Wavelet-ICA methodology for efficient artifact removal from electroencephalographic recordings. In *Proc. of International Joint Conference on Neural Networks (IJCNN 2007)*, Orlando, Florida, USA.

[17] Inuso G., La Foresta F., Mammone N., and Morabito F. C. Brain activity investigation by EEG processing: Wavelet analysis, kurtosis and renyi's entropy for artifact detection. In *Proc. of IEEE ICIA 2007 Conference*, Jeju Island, South Korea.

[18] N. Mammone, G. Inuso, F. La Foresta, and F.C. Morabito. Multiresolution ica for artifact identification from electroencephalographic recordings. *Lecture Notes in Artificial Intelligence*, 4692:680–687, 2007.

[19] Mammone N. and Morabito F. C. Independent Component Analysis and high-order statistics for automatic artifact rejection. In *2005 International Joint Conference on Neural Networks*, pages 2447–2452, Montréal, Canada, 2005.

[20] D. Labate, F. La Foresta, G. Occhiuto, F.C. Morabito, A. Lay-Ekuakille, and P. Vergallo. Empirical mode decomposition vs. wavelet decomposition for the extraction of respiratory signal from single-channel ecg: a comparison. *IEEE Sensors Journal*, 13(7):2666–2674, 2013.

[21] N. Mammone, D. Labate, and F. C. Morabito A. Lay-Ekuakille. Analysis of absence seizure generation using eeg spatial-temporal regularity measures. *International Journal of Neural Systems*, 22(6), 2012.

[22] Makeig S. Delorme A., Sejnowski T. Enhanced detection of artifacts in EEG data using higher-order statistics and Independent Component Analysis. *Neuroimage*, 34:1443–1449, 2007.