# Epileptic Event Detection Algorithm For Ambulatory Monitoring Platforms

F. Pinho[a], João Ferreira[b], Joana Reis[b,c], N.J. Sousa[b,c], J.J Cerqueira[b,c], J.H. Correia[a],N.S. Dias[b,c,d]

*a) Department of industrial Electronics, University of Minho, Guimarães, Portugal*

*b) Life and Health Sciences Research Institute, University of Minho, Braga, Portugal*

*c) ICVS/3B's, PT Government Associate Laboratory, University of Minho, Braga, Portugal*

*d) DIGARC, Polytechnic Institute of Cavado and Ave, Barcelos, Portugal*

*Abstract*— **Detecting epileptic electroencephalography (EEG) signals, both automatically and accurately, is significant in ambulatory long-term monitoring patients with epilepsy. In this study, it is presented a novel epileptic-like event detection algorithm based on a mixture of amplitude, frequency and spatial analysis with rule-based decision. In this work, EEG signals from 6 different subjects were searched for epileptic-like and normal data segments. The herein proposed algorithm detects putative epileptic EEG channels by comparing the RMS values of EEG activity with a hysteresis threshold, on a channel basis. The raw EEG signals are filtered with an artefact attenuation technique. The threshold is calculated on a reviewer-visually-selected baseline epoch, free of artefacts. Generalized epileptic activity detection is based on a spatial decision rule. Experimental results have shown detection rates as high as 95% with a false-negative rate as low as 1%. The algorithm seems to show a promising detection performance, even on artefact contaminated datasets. The proposed algorithm is intended to be used in real-time ambulatory monitoring of epileptic patients and features characteristics as subject personalization, small size window analysis, good artefact immunity and no need for classifier training.**

***Keywords—epilepsy; event detection; root mean square; ambulatory;***

## II. INTRODUCTION

Epilepsy has been described as a brain disorder characterized by an enduring predisposition to generate epileptic seizures and by the neurobiologic, cognitive, psychological, and social consequences of this condition [1]. Over the past decades, ambulatory monitoring of epilepsy through electroencephalography (EEG) has proven to be a useful cost-effective tool in the diagnosis of the pathology and certain non-epileptic paroxysmal disorders [2, 3]. The EEG recording of patients suffering from epilepsy show two categories of abnormal activity: inter-ictal, abnormal signals recorded between epileptic seizures; and ictal, the activity recorded during an epileptic seizure [4]. These two specific epileptic events have been well described by literature and its detection can be achieved by visual scanning of EEG recordings by an experienced neurophysiologist [4, 5]. Epileptic events have been described into four major groups: focal ictal patterns; focal inter-ictal patterns, generalized ictal patterns and generalized inter-ictal patterns. Focal ictal and inter-ictal events are more difficult to detect due to their high spatial, morphologic and inter-subject variability, these being the predominant factors to the poor inter-reviewer agreement [6].

Automated epileptic event detection has been studied with different approaches. Among the previously reported studies, some try to mimic human observers [7], others implement amplitude and frequency analysis [6, 8-10], frequency analysis with artificial neural networks[11], frequency and amplitude analysis through wavelets and machine learning algorithms [12, 13], and finally decisions systems based on rules [14].

One of the most implemented and commercially used epilepsy event detection methods is the Gotman's algorithm [14]. This is based on the decomposition of the EEG into elementary waves, and the application of thresholds to the amplitude, duration and rhythmicity of EEG signals.

Despite the fact that all of these studies have achieved good detection rates, the application in real-time epilepsy monitoring renders in a challenging detection paradigm.

Real-time epileptic event detection deals with tree major difficulties. First, EEG signals can be predominantly contaminated with artifacts due to muscle activity, pulse, eyes blink and flutter and even electromagnetic interference (EMI) [5]. Once artifacts may mislead the detection of the true epileptic events, some studies have already devoted their attention to the attenuation of artefact in the EEG signals [15-19].

The epoch size of data to be analysed has also been studied. If the epoch size is increased in order to get a smoother and less variant frequency spectrum, the events detection get delayed which might not be compatible online latency restrictions. On the other end, if the epoch is too short, the signal features might not be sensitive enough to differentiate epileptic-like from normal activity. A trade-off between these two scenarios must be pursued in order to produce the desired outcome from the detection algorithm [2, 3].

The high variability between subjects in the expression of the epileptic activity is also an event detection problem, and some studies have already reported methodologies to individually tune an algorithm [20, 21].

Finally, an algorithm that requires intensive processing may be expensive, in terms of power consumption, to the overall real-time detection platform. For long-term ambulatory monitoring, power consumption is one of the most important features [2, 3].

Besides the ability to perform online epileptic event detection, the devices developed for ambulatory monitoring of epilepsy should be wireless and wearable [2, 22]. Some studies have already addressed the development of such devices. While some developed platforms based on event detection through hardware [10], others rely in high-level processing algorithms that depend on high computational structures [20, 22-27].

Considering all of these problematic issues, this study describes an algorithm to be used locally in a wireless EEG acquisition platform for epilepsy long term monitoring.

## III. DATA

The classification methodology presented herein was applied to the *EEG Scalp CHB_MIT database*, as described by [28]. The complete database consists of 22 subjects from the Children's Hospital Boston. The individuals were monitored for several days with anti-seizure medication inhibition for a better signals characterization. The signals were acquired with a sampling frequency of 256 Samples-Per-Second and 16-bit resolution. The electrodes are arranged according to the standard 10-20, and has 23 bipolar channels with the following order: FP1-F7, F7-T7, T7-P7, P7-O1, FP1-F3, F3-C3, C3-P3, P3-O1, FP2-F4, F4-C4, C4-P4, P4-O2, FP2-F8, F8-T8, T8-P8, P8-O2, FZ-CZ, CZ-PZ, P7-T7, T7-FT9, FT9-FT10, FT10-T8 and T8-P8.

In this study several data files from 6 randomly selected subjects included in the entire database were used. The data were registered with two separate events: *Normal*, *and Epileptic-like* activity. The *epileptic-like* events (ictal and inter-ictal) were marked by visual inspection and included generalized inter-ictal and generalized ictal activities. The segments that did not show any type of the above described seizure events were regarded as normal (*Normal*).

For each individual, before the segments being marked with *Normal* or *Epileptic-like* labels, they were divided in 1 second epochs with 256 samples each. This time window was chosen as short as possible in order to maximize the real-time responsiveness of the detection algorithm.

## IV. METHODS

The developed algorithm is based on a time-varying amplitude analysis with spatial filtering and decision-making based on rules.

The detection algorithm takes into account the described morphology, spatial and temporal characteristics of the generalized epileptic-like activity regarding the possible generated artifacts.

To design the proposed algorithm, the most important signal characteristics that were taken into account were:

- Epileptic generalized ictal signals are described as events that evolve from a low-amplitude and fast-frequency to an increasing amplitude and decreasing frequency that disrupts the baseline activity [5];
- The generalized ictal pattern may also progress to an epileptiform burst pattern, which commonly accompanies clonic activity [5];
- Generalized ictal pattern is also identical to generalized inter-ictal spike and slow wave complex, except that it has a longer duration [6];
- Generalized inter-ictal patterns are characterized by less morphological variability then focal activity, and occur as a complex including a sharply contoured wave and a slow wave with a repetition frequency of 3 to 4 per second [5].
- Generalized ictal and inter-ictal patterns are also presented in almost all EEG channels on the opposite of focal events [5].

Despite the clear description of ictal and inter-ictal events, they still can be confused with some artifacts. Among all possible artifacts, the eyelid movement and flutter can simulate an inter-ictal event when the slow wave artifact of ocular flutter occurs in combination with faster frequency artifact from eyelid movement [5]. Although these specific artifact events may occur frequently, they can be distinguished from epileptic events because true events usually appear in states beyond drowsiness (which is the state for ocular flutter), and typically vary more in their amplitude and location [5]. Generalized muscular activity is also an artifact that must be taken into account because of its amplitude, frequency and time evolution which can be judged as belonging to inter-ictal activity [5].

In a clinical environment the subjects will be asked to stay as quiet and relaxed as possible to achieve a baseline signal segment of 30 seconds. In the data herein analyzed, a segment of 30 seconds free from artifacts and epileptic-like activity of the EEG files provided, was employed as baseline (*Fig. 1*).

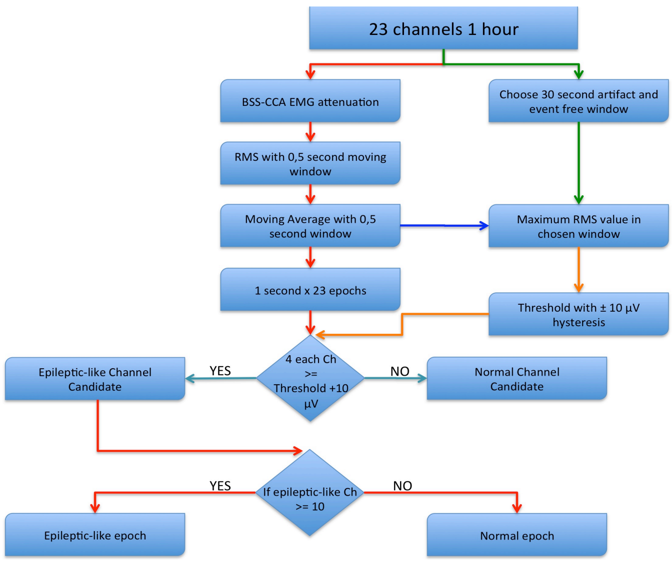


Fig. 1: Flowchart of the epileptic event detection algorithm.

This baseline is the basis of personalization for each subject and allows a specific combination for each subject/acquisition system.

After that the proposed algorithm applies a well documented muscular artifact attenuation based on the blind source separation-canonical correlation analysis technique (BSS-CCA) [29]. This technique has shown previously good results in epileptic EEG signals [30].

For BSS-CCA application, the Matlab™ Automatic Artifact Removal Toolbox (AAR) [31] and EEGLAB [32] were used and configured to 1 second window length, 1 second shift between correlative window, the sampling frequency set to 256 Hz and used the *emg_psd* criterion set to 10. This criterion considers to be EMG the components having 10 times (the established value) more average power spectrum than in the EEG spectrum.

After the BSS-CCA application, the algorithm calculates the root mean squared (RMS) value according to equation (1) in a sliding window of 128 points, in each channel.

RMS is a statistical measure of the magnitude of a varying quantity. The use of this measure has already been reported as the most effective feature to be used in an epileptic event detection algorithm [33]. RMS takes into account amplitude, in frequency and time domains as it reflects the DC, and AC components of a signal in a specific time window [34].

$$x_{rms} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \qquad (1)$$

The RMS window length was chosen to be 128 points long due to the fact that inter-ictal patterns show increased amplitude waves that repeat in a frequency of 3 to 4 cycles per second. The used dataset has a sampling frequency of 256 Hz thus, a RMS window length of 0.5 seconds was employed.

Then a moving average filter was also applied on each channel, again with 128 points regarding the same aspects of RMS. This filter was applied to decrease the RMS waves variability, in order to get more regular signals.

After these calculations for all epochs, the maximum RMS filtered value in the initially chosen 10 second baseline window between all channels determines the threshold for epileptic event detection.

To increase sensitivity it was applied a hysteresis of about ±10 µV. Tests were carried out on different threshold values in order to achieve the best detection rates. This pilot study was applied to 2 subject's signals that were not taken into account on final results.

Because eyelid may be detected above the threshold, the algorithm ignores 4 channels (FP1-F7, Fp1-F3, Fp2-F4, Fp2-F8) in respect to vertical and horizontal eye movements.

Then the RMS amplitude filtered on each channel is analyzed point-by-point in comparison to the established threshold and each epoch is marked as epileptic-like or normal candidate. Once the filtered RMS surpasses the hysteresis threshold, that epoch from that channel is considered an epileptic-like candidate.

After this, if in a certain time instant at least half the channels are epileptic-like candidates, that epoch is considered as an epileptic event.

## I. Results

The presented algorithm was applied to 3 hour-segments of 6 subjects.

In *Fig. 2,* the application of the algorithm and the comparison between an inter-ictal event and an eye blink artifact can be observed. The two events differ spatially, as well as in amplitude and frequency.

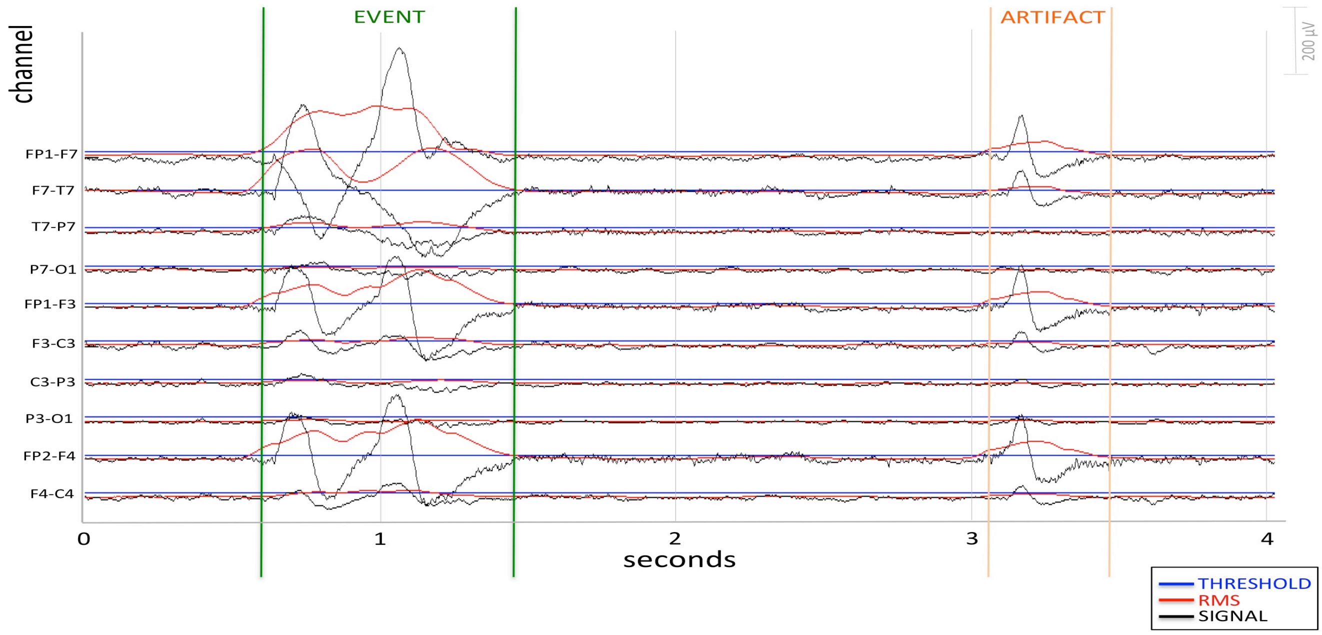


Fig. 2: 10 channel demonstration of algorithm application. The blink artifact data points only surpass the threshold in 4 channels (3 of them discarded from analysis) while in inter-ictal event all channels surpass the threshold.

It was analyzed an overall of 18 hours EEG, with an average false positive detection rate of 5.0%, a false negative rate of 0.8% and 5.7% total detection error rate.
The final results are shown in Table I with the individual and overall percentages.

TABLE I. OVERALL DETECTION RESULTS

| Subject | False Positive | False Negative | Detection Error | Threshold (µV) | Total Number of epochs |
|---|---|---|---|---|---|
| 1 | 7,1% | 0,3% | 7,4% | 33,8 | 10800 |
| 2 | 4,8% | 0,7% | 5,5% | 35,4 | 10800 |
| 3 | 6,3% | 1,9% | 8,2% | 20,5 | 10800 |
| 4 | 4,0% | 0,4% | 4,4% | 68,2 | 10800 |
| 5 | 4,3% | 1,0% | 5,3% | 40,7 | 10800 |
| 6 | 3,4% | 0,2% | 3,6% | 72,3 | 10800 |
| Average | 5,0% | 0,8% | 5,7% | 45,2 | 10800 |

On Table II, the misdetection rates for both ictal and inter-ictal events identified on 1-hour data segments of the same subjects are presented.

TABLE II. ICTAL AND INTER-ICTAL DETECTION

| Subject | Ictal epochs | Ictal undetected epochs | Inter-Ictal epochs | Inter-ictal undetected epochs | Total Number of epochs |
|---|---|---|---|---|---|
| 1 | 40 | 0 | 1394 | 9 (0.6%) | 3600 |
| 2 | 82 | 0 | 293 | 11 (3.8%) | 3600 |
| 3 | 52 | 0 | 1252 | 15 (1.2%) | 3600 |
| 4 | 115 | 0 | 1792 | 7 (0.4%) | 3600 |
| 5 | 171 | 0 | 419 | 18 (4.3%) | 3600 |
| 6 | 22 | 0 | 259 | 16 (6.2%) | 3600 |

## II. DISCUSSION AND CONCLUSION

The proposed algorithm achieved a good performance with reduced rates of false positives and false negatives.
The false positive percentage is overdue to generalized muscular activity that was not totally inhibited by BSS-CCA method, some eyelid movements, intense alfa rhythm experienced in some subjects and some focal inter-ictal patterns.
The good performance results in ictal activity detection, agrees with the description of these events that evolve from a low-amplitude-high-frequency to high-amplitude low-frequency in a long lasting time [5]. These two characteristics had an increased impact in RMS that lead to their detection through the established threshold.
Although ictal activity detection provided excellent results, the main difficulties are faced on generalizing inter-ictal pattern detection to several subjects. Frequently, generalized inter-ictal activity presents the same characteristics of generalized ictal pattern but with shorter periods [6]. The established threshold was tuned to achieve very high sensitivity in respect to the time characteristics of inter-ictal patterns. An established rule was that if in a certain time point, the signal surpasses the threshold, it was considered as an epileptic-like candidate channel on that specific epoch. Due to the threshold's high sensitivity to achieve the best performance in inter-ictal event detection, sometimes false-positive detections (specially muscular and eyelid movement artifacts that can increase RMS in a short time) were generated.
Two subjects presented high levels of alfa rhythm in a wide extension of the signals. Regarding the already described characteristics of the threshold, an intense alfa rhythm has also generated some false positives. Alfa rhythm is normally associated with drowsiness and pre-sleeping states. Because the presented algorithm is not intended to be used in epilepsy sleeping studies, the alfa rhythm detection will probably not be a future problem.
Some false positives were also generated due to focal inter-ictal activity. One of the basic principles of this algorithm is to detect generalized epileptic-like activity. Focal inter-ictal activity can be expressed in many and different ways. These events are the hardest to detect and are usually restricted to a specific group of channels [5]. While focal epileptic-like activity was not the goal of this algorithm, it can be tuned to give a higher weight to a specific set of channels.
Although the developed algorithm doesn't directly analyse frequency features as in Gotham's algorithm, it must be taken into account that the signals frequency variation influence directly the RMS value. Gotham's algorithm applies amplitude thresholds to identify possible event-related epochs, and then analyses frequency features in a 2 seconds window (minimum length) [14]. On the other end, the proposed algorithm does not analyse the power spectrum of an event-related candidate epoch. The foundation rules that were taken into account say that generalized ictal and inter-ictal patterns increase the amplitude and decrease the frequency of the background activity [5]. These two changes in the signals promote an increase in RMS that surpasses the established threshold and thereby mark that epoch as epileptic-like candidate. Because this algorithm is intended to be used on an ambulatory scenario with a minimum detection delay requirement, a 1 second window was chosen. Epileptic-like pattern characteristic frequency features are harder to detect on short epochs (1 second) than on larger windows such as those employed in Gothman's (2 to 10 seconds) [14].In order to clearly distinguish the power spectra from epileptic-like and normal signals, the window length to analyse must be wide enough [34]. This reason leads some studies to analyse only the ictal events, because of the long lasting feature of these pattern [4, 7, 11, 13, 20, 26, 35-37].Once this algorithm analyses a small time window, it does not discriminate ictal from inter-ictal events in epileptic-like patterns.
Artifacts are the biggest generators of false-positives in a detection scenario [4]. Because artifacts can simulate some epileptic-like activity features, the algorithms must be sensitive enough to select the artefact-free epileptic-related activity. By eliminating artifacts, the problem of distinguishing epileptic-like from normal activity is greatly reduced.
If an algorithm ignores the artifacts and uses a long time window to analyse the signals, it is usually not intended to be used on ambulatory and real-time scenarios.

Considering these constraints, the ability to perform detection without classifier training and personalization, the herein proposed algorithm can be characterized as a simple and promising method for epileptic activity detection to be used in ambulatory monitoring of epileptic patients.

## ACKNOWLEDGMENT

This work is supported by FEDER funds through the Programa Operacional Fatores de Competitividade – COMPETE and National Funds through FCT – Fundação para a Ciência e Tecnologia with the reference Project: FCOMP-01-0124-FEDER-022674.

This work is also supported by ADI Project "DoIT - Desenvolvimento e Operacionalização da Investigação de Translação" (project nº 13853, PPS4-MyHealth), funded by Fundo Europeu de Desenvolvimento Regional (FEDER) through the Programa Operacional Factores de Competitividade (POFC).

## REFERENCES

[1] R. S. Fisher, W. v. E. Boas, W. Blume, C. Elger, P. Genton, P. Lee, *et al.*, "Epileptic seizures and epilepsy: definitions proposed by the International League Against Epilepsy (ILAE) and the International Bureau for Epilepsy (IBE)," *Epilepsia,* vol. 46, pp. 470-472, 2005.

[2] U. Seneviratne, A. Mohamed, M. Cook, and W. D'Souza, "The utility of ambulatory electroencephalography in routine clinical practice: A critical review," *Epilepsy research,* 2013.

[3] H. J. Faulkner, H. Arima, and A. Mohamed, "The utility of prolonged outpatient ambulatory EEG," *Seizure,* vol. 21, pp. 491-495, 2012.

[4] A. T. Tzallas, M. G. Tsipouras, D. G. Tsalikakis, E. C. Karvounis, L. Astrakas, S. Konitsiotis, *et al.*, "Automated epileptic seizure detection methods: a review study," *Epilepsy-histological, electroencephalographic and psychological aspects, edited by D. Stevanovic,* pp. 75-98, 2012.

[5] J. M. Stern and J. Engel, *Atlas of EEG patterns*: Wolters Kluwer Health, 2005.

[6] D. T. Barkmeier, A. K. Shah, D. Flanagan, M. D. Atkinson, R. Agarwal, D. R. Fuerst, *et al.*, "High inter-reviewer variability of spike detection on intracranial EEG addressed by an automated multi-channel algorithm," *Clinical Neurophysiology,* vol. 123, pp. 1088-1095, 2012.

[7] W. Deburchgraeve, P. J. Cherian, M. De Vos, R. M. Swarte, J. H. Blok, G. H. Visser, *et al.*, "Automated neonatal seizure detection mimicking a human observer reading EEG," *Clinical Neurophysiology,* vol. 119, pp. 2447-2454, 2008.

[8] R. Yadav, R. Agarwal, and M. N. S. Swamy, "A novel morphology-based classifier for automatic detection of epileptic seizures," in *Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE*, 2010, pp. 5545-5548.

[9] M. C. Toet, F. Groenendaal, D. Osredkar, A. C. van Huffelen, and L. S. de Vries, "Postneonatal epilepsy following amplitude-integrated EEG-detected neonatal seizures," *Pediatric neurology,* vol. 32, pp. 241-247, 2005.

[10] S. Raghunathan, S. K. Gupta, M. P. Ward, R. M. Worth, K. Roy, and P. P. Irazoqui, "The design and hardware implementation of a low-power real-time seizure detection algorithm," *Journal of neural engineering,* vol. 6, p. 056005, 2009.

[11] L. Guo, D. Rivero, J. Dorado, J. R. Rabunal, and A. Pazos, "Automatic epileptic seizure detection in EEGs based on line length feature and artificial neural networks," *Journal of neuroscience methods,* vol. 191, pp. 101-109, 2010.

[12] Y. Peng and B.-L. Lu, "Immune clonal algorithm based feature selection for epileptic EEG signal classification," in *Information Science, Signal Processing and their Applications (ISSPA), 2012 11th International Conference on*, 2012, pp. 848-853.

[13] Z. Zainuddin, L. K. Huong, and O. Pauline, "Reliable epileptic seizure detection using an improved wavelet neural network," *The Australasian medical journal,* vol. 6, p. 308, 2013.

[14] J. Gotman, "Automatic recognition of epileptic seizures in the EEG," *Electroencephalography and clinical Neurophysiology,* vol. 54, pp. 530-540, 1982.

[15] M. De Vos, W. Deburchgraeve, P. J. Cherian, V. Matic, R. M. Swarte, P. Govaert, *et al.*, "Automated artifact removal as preprocessing refines neonatal seizure detection," *Clinical Neurophysiology,* vol. 122, pp. 2345-2354, 2011.

[16] V. Krishnaveni, S. Jayaraman, S. Aravind, V. Hariharasudhan, and K. Ramadoss, "Automatic identification and Removal of ocular artifacts from EEG using Wavelet transform," *Measurement Science Review,* vol. 6, pp. 45-57, 2006.

[17] J. Karhunen, T. Hao, and J. Ylipaavalniemi, "A canonical correlation analysis based method for improving BSS of two related data sets," in *Latent Variable Analysis and Signal Separation*, ed: Springer, 2012, pp. 91-98.

[18] J. T. Gwin, K. Gramann, S. Makeig, and D. P. Ferris, "Removal of movement artifact from high-density EEG recorded during walking and running," *Journal of neurophysiology,* vol. 103, pp. 3526-3534, 2010.

[19] D. Safieddine, A. Kachenoura, L. Albera, G. Birot, A. Karfoul, A. Pasnicu, *et al.*, "Removal of muscle artifact from EEG data: comparison between stochastic (ICA and CCA) and deterministic (EMD and wavelet-based) approaches," *EURASIP Journal on Advances in Signal Processing,* vol. 2012, pp. 1-15, 2012.

[20] D. Chandler, J. Bisasky, J. L. V. M. Stanislaus, and T. Mohsenin, "Real-time multi-channel seizure detection and analysis hardware," in *Biomedical Circuits and Systems Conference (BioCAS), 2011 IEEE*, 2011, pp. 41-44.

[21] S. M. Haas, M. G. Frei, and I. Osorio, "Strategies for adapting automated seizure detection algorithms," *Medical engineering & physics,* vol. 29, pp. 895-909, 2007.

[22] A. Bastani, H. Kayyali, R. N. Schmidt, R. Qadir, and P. Manthena, "Wireless brain monitoring in the emergency department," in *Engineering in Medicine and Biology Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference of the*, 2006, pp. 2502-2505.

[23] S.-F. Liang, F.-Z. Shaw, C.-P. Young, D.-W. Chang, and Y.-C. Liao, "A closed-loop brain computer interface for real-time seizure detection and control," in *Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE*, 2010, pp. 4950-4953.

[24] C.-P. Young, C.-H. Hsieh, and H.-C. Wang, "A low-cost real-time closed-loop epileptic seizure monitor and controller," in *Instrumentation and Measurement Technology Conference, 2009. I2MTC'09. IEEE*, 2009, pp. 1768-1772.

[25] N. Verma, A. Shoeb, J. Bohorquez, J. Dawson, J. Guttag, and A. P. Chandrakasan, "A micro-power EEG acquisition SoC with integrated feature extraction processor for a chronic seizure detection system," *Solid-State Circuits, IEEE Journal of,* vol. 45, pp. 804-816, 2010.

[26] R. P. McEvoy, S. Faul, and W. P. Marnane, "Ambulatory REACT: real-time seizure detection with a DSP microprocessor," in *Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE*, 2010, pp. 2443-2446.

[27] B. Huyghe, J. Vanfleteren, and J. Doutreloigne, "Design of flexible, low-power and wireless sensor nodes for human posture tracking aiding epileptic seizure detection," in *Sensors, 2009 IEEE*, 2009, pp. 1963-1966.

[28] A. L. Goldberger, L. A. N. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, *et al.*, "Physiobank, physiotoolkit, and physionet components of a new research resource for complex physiologic signals," *Circulation,* vol. 101, pp. e215-e220, 2000.

[29] W. De Clercq, A. Vergult, B. Vanrumste, J. Van Hees, A. Palmini, W. Van Paesschen, *et al.*, "A new muscle artifact removal technique to improve the interpretation of the ictal scalp electroencephalogram," in *Engineering in Medicine and Biology*

*Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference of the*, 2006, pp. 944-947.

[30] A. Vergult, W. De Clercq, A. Palmini, B. Vanrumste, P. Dupont, S. Van Huffel*, et al.*, "Improving the Interpretation of Ictal Scalp EEG: BSS–CCA Algorithm for Muscle Artifact Removal," *Epilepsia,* vol. 48, pp. 950-958, 2007.

[31] R. Ferdousy, A. I. Choudhory, M. S. Islam, M. A. Rab, and M. E. H. Chowdhory, "Electrooculographic and electromyographic artifacts removal from EEG," in *Chemical, Biological and Environmental Engineering (ICBEE), 2010 2nd International Conference on*, 2010, pp. 163-167.

[32] A. Delorme and S. Makeig, "EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis," *Journal of neuroscience methods,* vol. 134, pp. 9-21, 2004.

[33] B. R. Greene, S. Faul, W. P. Marnane, G. Lightbody, I. Korotchikova, and G. B. Boylan, "A comparison of quantitative EEG features for neonatal seizure detection," *Clinical Neurophysiology,* vol. 119, pp. 1248-1261, 2008.

[34] S. W. Smith, *Digital signal processing: a practical guide for engineers and scientists*: Access Online via Elsevier, 2003.

[35] B. R. Greene, G. B. Boylan, W. P. Marnane, G. Lightbody, and S. Connolly, "Automated single channel seizure detection in the neonate," in *Engineering in Medicine and Biology Society, 2008. EMBS 2008. 30th Annual International Conference of the IEEE*, 2008, pp. 915-918.

[36] I. Osorio, M. G. Frei, and S. B. Wilkinson, "Real-time automated detection and quantitative analysis of seizures and short-term prediction of clinical onset," *Epilepsia,* vol. 39, pp. 615-627, 1998.

[37] M. A. Navakatikyan, P. B. Colditz, C. J. Burke, T. E. Inder, J. Richmond, and C. E. Williams, "Seizure detection algorithm for neonates based on wave-sequence analysis," *Clinical Neurophysiology,* vol. 117, pp. 1190-1203, 2006.

[1]