34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

Seizure Detection On/Off System using Rats' ECoG

Yun S. Park, *Member, IEEE*, Theoden I. Netoff, *Member, IEEE*, Xiaofeng Yang, and Keshab K. Parhi, *Fellow, IEEE*

***Abstract* — We present an enhanced algorithm for seizure onset and offset detection in rats' ECoG. Because a seizure in rats' ECoG evolves much more stereotypically than that in human, analyzing seizure evolution in rats' ECoG is advantageous to understanding the evolution process. The proposed algorithm outperforms a prior automatic seizure detection and termination system in *in-vivo* rats' ECoG. We improve the algorithm by using relevant frequency bands of 14-22 Hz to onsets and 7-45Hz to offsets; by using spectral power rather than spectral amplitudes for its feature; and by replacing the 2-point moving-average filter for postprocessing with a 2nd order Kalman filter. Not only does the proposed algorithm provide better detection statistics, but it lowers the system's complexity by no longer requiring computation of a fast Fourier transform and by using a single structure with the two different spectral power features for onset and offset detection.**

I. INTRODUCTION

Epilepsy is one of the common neurological disorders, where a person experiences repeated seizures. Approximately one in every ten people experiences a seizure in his or her life, and approximately one in one hundred experiences multiple seizures. The latter are classified as epileptics. It is estimated that direct and indirect cost due to epilepsy amount to over 15 billion dollars per year in the USA [1].

One of the most critical issues for epilepsy is that seizures are practically unpredictable [2]. Because they may strike the patients abruptly, their daily lives are significantly impaired in many aspects, such as being restricted to drive a car. A reliable method to detect a pre-seizure or seizure state could enhance therapeutic possibilities [3] and thus improve the quality of the patients' lives.

From the perspective of seizure analysis, rats' brain may be advantageous to understand seizure evolution, because it is much less complex than human. The complex physiology of human brain has prevented seizure mechanism from being understood well. In this sense, to analyze seizure evolution and further testing their anti-seizure methods on simpler brains than human, researchers have used rats' [4-7].

In [5-7], Yang *et al.* developed an automatic seizure detection system in rats' electrocorticogram (ECoG). This automatic system was for their seizure termination experiments by focal cooling [5, 6] and by optical suppression [7]. In this paper, we propose an enhanced approach for the seizure detection in the rats' recordings. We perform time-frequency analysis on seizure onsets and offsets by using spectrograms and figure out more relevant frequency bands to detecting onsets and offsets. Then, we develop an enhanced algorithm that can act faster and more reliably at onsets and offsets. To demonstrate improvement, the proposed algorithm is compared with the previous approach [5-7], and additionally with another feature of line-length [8] that has been widely used for seizure detection.

II. BACKGROUND

In this section, we review the algorithm and system for automatic seizure onset and offset detection of the prior approach [5-7]. As shown in the top panel of Figure 1, this detection system was developed by using commercially available hardware and software, including LabVIEW 6. The algorithm employed in the system is also illustrated in Figure 1. Using the moving window analysis [2, 3], the average of absolute values of spectral amplitudes in 5-35 Hz was extracted as a feature. Then, a 2-point moving-average (MA) filter was applied for postprocessing, and the MA-filtered output was compared with the pre-defined threshold. Finally, the system defined a seizure onset when it received 20 consecutive outputs higher than a user-defined onset threshold. Similarly, it marked an offset with 6 consecutive outputs lower than an offset threshold. The reader is referred to [6] for further details.

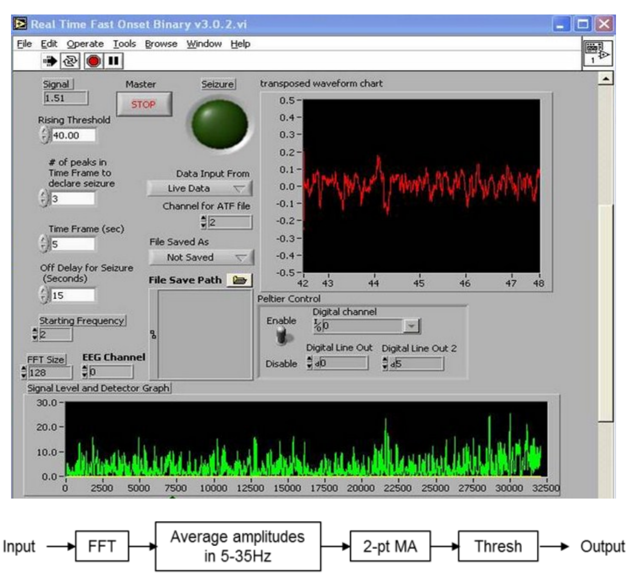


Figure 1. Top panel: LabVIEW front panel for the seizure detection system in [5-7]. Bottom panel: outline of their seizure detection algorithm.

* Research supported by a research grant from the Institute of Engineering and Medicine at the University of Minnesota and by Netoff's CAREER award from the National Science Foundation (0954797).

Yun S. Park was with the University of Minnesota, Minneapolis, MN 55455, USA. He is now is with the Laboratory for Restorative Neurotechnology, Brown University, Providence, RI 02912, USA (email: yun_sang_park@brown.edu).

Theoden I. Netoff is with the University of Minnesota, Minneapolis, MN 55455, USA (email: tnetoff@umn.edu).

Xiaofeng Yang is with the University of Minnesota, Minneapolis, MN 55455, USA (email: yangxf@umn.edu)

Keshab K. Parhi is with the University of Minnesota, Minneapolis, MN 55455, USA (phone: 612-624-4116; fax: 612-625-4583; email: parhi@umn.edu)

978-1-4577-1787-1/12/$26.00 ©2012 IEEE

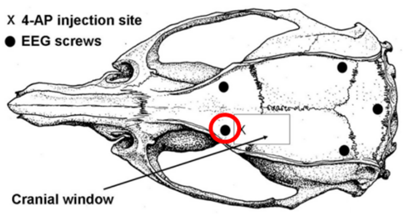
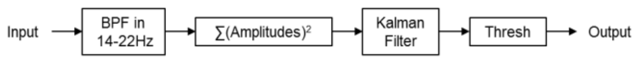
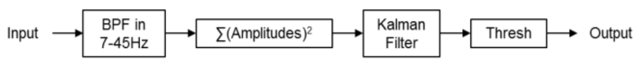


Figure 2. Electrode position [5]. The ECoG from the red-circled electrode is the one used for the main analysis in this paper.



(a) For onset detection



(b) For offset detection

Figure 3. Proposed enhanced algorithm for automatic seizure onset and offset detection.

III. METHODS

To improve the detection algorithm, we first analyzed the rats' ECoG signals on seizure onsets and offsets using spectrograms in time and frequency domains. Then, based on the analysis, we have developed an enhanced detection algorithm, which employs spectral power in bands of 14-22 Hz and 7-45 Hz for onset and offset detection features, respectively, and uses a 2nd order Kalman filter for postprocessing.

A. Dataset Description

The dataset used in this paper is rats' ECoG recordings. They were recorded from the adult male Sprague-Dawley rats by Yang *et al* for their prior work [5, 6], and all the recordings were taken in accordance to Washington University Animal Studies Committee approved protocols. The ECoG usually started being recorded before injection of a seizure-inducing chemical compound, 4-aminopyridine, into the motor cortex and continued though their termination experiments. For more details, refer to [5, 6].

The ECoG signals analyzed in this paper are differential potentials, a bipolar montage. It was measured at a screw electrode, placed as shown in Figure 2, over another electrode installed symmetrically on the other hemisphere. The sampling rate was 200 Hz. 25 seizure events in 4 continuous recordings, totaling approximately 95-min long, have been analyzed in this paper. Seizure onsets and offsets were jointly identified by two of the authors (Yang and Park). For onset identification, specific ECoG samples were marked, but seizure offsets were identified in approximate time periods. This is because offset detection is a much less critical issue than onset.

B. Enhanced seizure onset and offset detection algorithm

The proposed enhanced algorithm for seizure onset and offset detection is as outlined in Figure 3. It consists of feature extraction of spectral power in onset/offset-relevant bands, Kalman-filtering for postprocessing, and comparison with a pre-defined threshold.

For feature extraction, we have selected spectral power, rather than spectral amplitudes. Specifically, we have used the spectral power in *14-22 Hz* for onset detection and that in *7-45 Hz* for offset detection. As illustrated in Figure 4, we have observed typical patterns in spectrograms on onsets and offsets: sudden and intense increases in power in 14-22 Hz right after the onsets and obvious declines in power in 7-45 Hz around the offsets. The spectral power is extracted in a window of 128 ECoG samples with half-overlap of the prior window; we have used the same moving-window analysis approach as the previous one. The spectral power is calculated by bandpass-filtering ECoG samples and squaring the bandpass-filtered amplitudes in time domain.

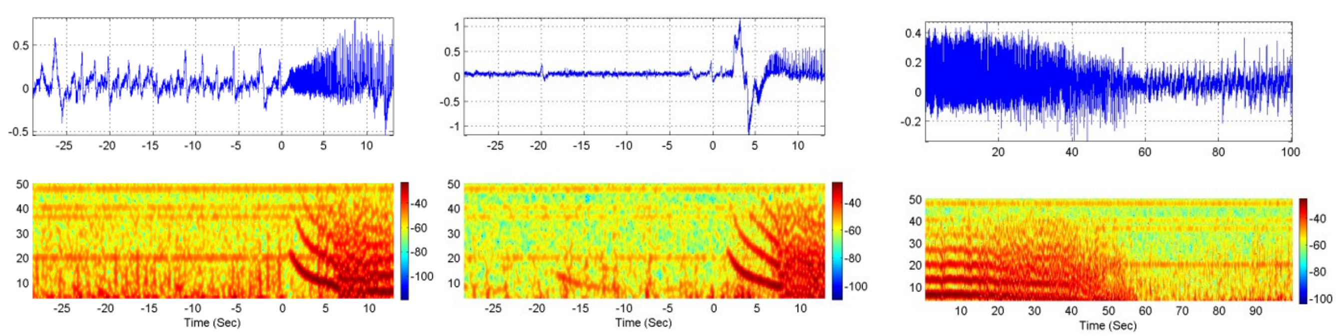
The 2nd order discrete-time Kalman filter is used for post-processing. The Kalman filter is expected to smoothen out sudden and abrupt changes in features and thus reduce the number of potential false alarms. In this sense, the standard deviation of the observation noise σ_v in Kalman-filtering has been selected to be much larger than that of the process noise σ_w: $\frac{\sigma_w}{\sigma_v} = 2^{-10}$ for onset and $\frac{\sigma_w}{\sigma_v} = 2^{-20}$ for offset detection.

C. Additional feature of line-length for comparison

To demonstrate how the spectral power features in our algorithm may outperform the others, we have additionally tested the line-length feature [8-10]:

$$LL(n) = \frac{1}{K} \sum_{k=n-N}^{n} abs[x(k-1) - x(k)]$$

where *LL(n)* is the line length, *x(k)* the k^{th} signal in a window of *N* samples, and *K* is the normalization constant.



(a) Onset

(b) Offset

Figure 4. Examples of ECoG recordings in top and their corresponding spectrograms in bottom (a) on onsets and (b) on an offset

D. ROC analysis and AUC

Receiver operating characteristic (ROC) analysis is a simple but powerful statistical method that uses a plot of true positive rate $\left(\frac{\mathrm{TP}}{\mathrm{TP+FN}}\right)$ as a function of false positive rate $\left(\frac{\mathrm{FP}}{\mathrm{FP+TN}}\right)$ where TP, FN, FP, and TN stand for the number of true positives, false negatives, false positives, and true negatives, respectively. To achieve ROC curves in this paper, 100 threshold values have been selected that are equally allocated between the maximum and minimum of the values to be analyzed. Also, we have quantified binary classifiers' performance using the area under the curve (AUC), which integrates the area under the ROC curve.

IV. Results

We first compared features that were employed in the previous and proposed algorithms for onset detection as well as line-length. For efficient comparison, the features were tested on 25 pieces of partial ECoG recordings, each of which contains recordings from 30-sec prior to a seizure event to 13-sec after it. Then, we tested our algorithm on a 12.6-min-long continuous recording with 4 seizures.

To compare the algorithms' performance for onset detection objectively, we tested the postprocessed features that were actually used in the algorithms: 2-point moving-averaged spectral amplitudes in 5-35 Hz for the previous algorithm, Kalman-filtered spectral power in 14-22 Hz for the proposed algorithm, and additionally Kalman-filtered line-length. Figure 5 is an example of a plot of one raw feature and its post processed output in the partial recordings after performing the ROC analysis with 100 threshold values. Figure 6 demonstrates visual comparison between the features tested on the same recording with an onset.

Table 1 demonstrates the AUC calculation for the three features. Our approach produced the AUC of 0.9407, only slightly less than the previous one's AUC of 0.9476; however, this was caused by the AUC estimation based on the number of windows, not on the number of seizure events. Table 1 also shows sensitivity $\left(\frac{\mathrm{TP}}{\mathrm{TP+FN}}\right)$, the number of false positives, and the average latency between actual onsets and alarms generated by the algorithm with two selected threshold values. One threshold value was chosen as the lowest number where the algorithm can achieve 100% sensitivity with no false positives. The other was the lowest value that resulted in the algorithm producing the fewest false positives with 100% sensitivity.

Combining the onset detection approach with the offset one, which uses spectral power in 7-45 Hz for the feature and the Kalman filter for postprocessing, we tested our proposed algorithm on a continuous recording, as shown in Figure 7.

Table 1. Performance comparison in postprocessed features

Feature	AUC	Thres hold	Sensitivity & # FPs	Ave. latency (sec)
2-pt MA-filtered spectral amplitude in 5-35 Hz	0.9476	0.55	100%, no FP	3.23
		0.41	100%, 4 FPs	2.26
Kalman-filtered spectral power in 14-22 Hz	0.9407	0.0278	100%, no FP	2.10
		0.0147	100%, 2 FPs	1.72
Kalman-filtered line-length	0.9251	0.033	100%, no FP	2.62
		0.031	100%, 2 FPs	2.48

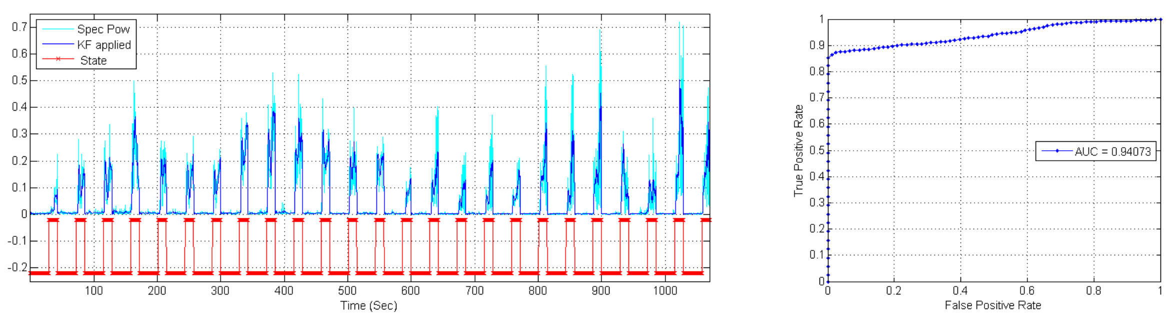
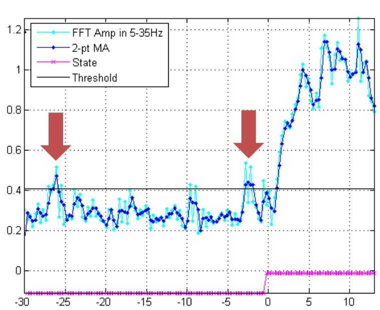
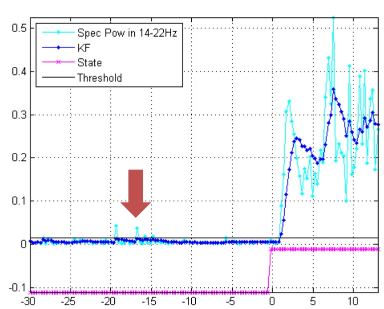


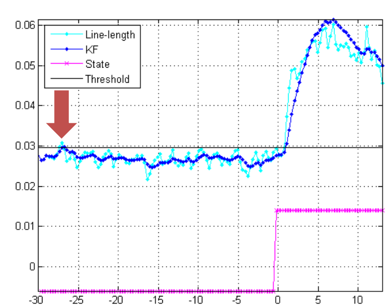
Figure 5. Left panel: raw features of spectral power in 14-22 Hz in cyan and their Kalman-filtered values in blue for the proposed algorithm. Logic high and low in red represent "on seizure events" and their pre-states, respectively. Right panel: ROC analysis for the postprocessed values in the left panel.



(a) Spectral amplitudes in 5-35Hz



(b) Spectral power in 14-22 Hz



(c) Line-length

Figure 6. Comparison of features on the same onset. Raw features are in cyan; their postprocessed ones in blue; and, their actual seizure states in pink. Given threshold values in black, "bumpy" outputs indicated by the arrows may cause false detections. Note that spectral power in 14-22 produces the most even outputs in the pre-seizure state, so that it can lead to the fewest false alarms.

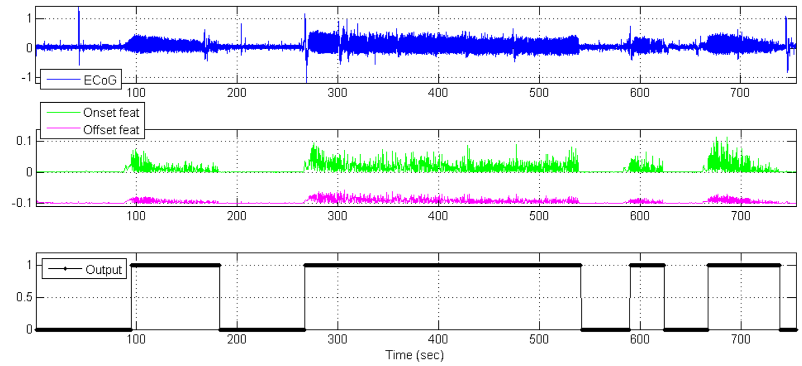


Figure 7. Seizure onset and offset detection by the proposed algorithm in a continuous recording. Top panel: 12.6-min-long ECoG recording with 4 seizure onsets at 84.0, 264.4, 581.6, and 660.5-sec ,and their offsets approximately at 180, 538, 625, and 740-sec. Middle panel: the onset feature of spectral power in 14-22 Hz in green and the offset one in 7-45 Hz in pink. Bottom panel: final binary outputs in black by the onset and offset threshold values of 0.0278 and 0.001, respectively. For stable offset detection, an offset was declared when the postprocessed offset features kept lower than the threshold five times in a row.

V. DISCUSSIONS

We have developed an enhanced algorithm for automatic seizure onset and offset detection in rats' ECoG recordings. It outperforms a prior algorithm in following ways. First, the proposed algorithm employs *spectral power* in the band of *14-22 Hz* for its onset feature. We observed that the frequency band in 14-22 Hz acts more relevantly and robustly to onsets than the band in 5-35 Hz that was employed in the previous algorithm (see Figure 4). Furthermore, using spectral power is more advantageous to onset detection than spectral amplitude. Because power is proportional to square of amplitude, the spectral power feature can enlarge spectral differences between pre-onsets and onsets.

Using the Kalman-filtered feature of spectral power in 14-22 Hz was more effective for onset detection than the other approaches. For example, as illustrated in Figure 6, the Kalman-filtered output in blue in the middle panel was the most flat and stable with distinguishable values at the onset. Also, in Table 1, the proposed feature produced only two false positives, when the threshold value dropped approximately 47% of the lowest threshold value that resulted in no FPs with 100% sensitivity. The other two features, spectral amplitude in 5-35 Hz and line-length, produced four and two FPs, when the lowest threshold values with no FPs and perfect sensitivity decreased approximately 25% and 6%, respectively.

Furthermore, for effective detection, the proposed algorithm used two different features: spectral power in 14-22 Hz and 7-45 Hz for onset and offset detection, respectively. The previous algorithm employed one single feature for detecting both, so that it performed less effectively. Nonetheless, while our algorithm had different parameters for onset and offset detection, including frequency bands in feature extraction and noise ratios in Kalman-filtering, our algorithm requires a single structure. Ours consists of a band-pass filter, summation of amplitudes in time domain, the Kalman filter, and a comparator. For different detection of onset and offset, the system may just need to modify the parameters in the components. Thus, the system's complexity may not increase even though it employs two separate features.

Lastly, we reduced the system's complexity remarkably by not using the fast Fourier transform (FFT) computation. In the previous algorithm, the FFT computation was required, because it used spectral amplitudes for its feature. However, the proposed algorithm employs spectral power, which can be estimated by bandpass-filtering and squaring band-passed amplitudes in time domain (refer to Parseval's theorem). Because the feature is calculated in time domain, the FFT computation that has high complexity is no longer necessary. Additionally, replacing the simple 2-point moving-average filter with 2nd order Kalman filter for postprocessing may not increase the system's complexity much: the 2nd order Kalman filter just requires 7 multipliers and 18 adders. Our proposed algorithm may be much more favorable, when seizure detection comes to a power-consumption-sensitive device, such as an implantable device.

REFERENCES

[1] Epilepsy Association website. Available at: http://www.epilepsyinfo.org/Events/Events.shtml.

[2] F. Mormann, R. G. Andrzejak, C. E. Elger, and K. Lehnertz, "Seizure prediction: the long and winding road," *Brain,* vol. 130, pp. 314-33, Feb 2007.

[3] Y. Park, L. Luo, K. K. Parhi, and T. Netoff, "Seizure prediction with spectral power of EEG using cost-sensitive support vector machines," *Epilepsia,* vol. 52, pp. 1761-1770, Oct 2011.

[4] G. W. Mathern, F. Cifuentes, J. P. Leite, J. K. Pretorius, and T. L. Babb, "Hippocampal EEG excitability and chronic spontaneous seizures are associated with aberrant synaptic reorganization in the rat intrahippocampal kainate model," *Electroencephalogr Clin Neurophysiol,* vol. 87, pp. 326-39, Nov 1993.

[5] X. F. Yang and S. M. Rothman, "Focal cooling rapidly terminates experimental neocortical seizures," *Ann Neurol,* vol. 49, pp. 721-6, Jun 2001.

[6] X. F. Yang, D. W. Duffy, R. E. Morley, and S. M. Rothman, "Neocortical seizure termination by focal cooling: temperature dependence and automated seizure detection," *Epilepsia,* vol. 43, pp. 240-5, Mar 2002.

[7] X. F. Yang, B. F. Schmidt, D. L. Rode, and S. M. Rothman, "Optical suppression of experimental seizures in rat brain slices," *Epilepsia,* vol. 51, pp. 127-35, Jan 2010.

[8] R. Esteller, J. Echauz, T. Tcheng, B. Litt, and B. Pless, "Line length: an efficient feature for seizure onset detection," in *Engineering in Medicine and Biology Society, 2001. Proceedings of the 23rd Annual International Conference of the IEEE*, 2001, pp. 1707-1710 vol.2.

[9] A. B. Gardner, A. M. Krieger, G. Vachtsevanos, and B. Litt, "One-class novelty detection for seizure analysis from intracranial EEG," *Journal of Machine Learning Research,* vol. 7, pp. 1025-1044, Jun 2006.

[10] R. Esteller, J. Echauz, and T. Tcheng, "Comparison of line length feature before and after brain electrical stimulation in epileptic patients," *Conf Proc IEEE Eng Med Biol Soc,* vol. 7, pp. 4710-3, 2004.