Proceedings of the 28th IEEE
EMBS Annual International Conference
New York City, USA, Aug 30-Sept 3, 2006

Seizure Detection by a Novel Wavelet Packet Method

Reza Tafreshi, *Member, IEEE*, Guy Dumont, *Fellow, IEEE*, Donald Gross, Craig R. Ries, Ernie Puil, and Bern A. MacLeod

***Abstract*—We describe a novel wavelet-based method for the detection of seizure in patients with temporal lobe epilepsy. This method uses *local discriminant bases* and *cross-data entropy* algorithms to identify nodes of a wavelet packet dictionary that best discriminate preictal from ictal EEG signals. The algorithms are based on relative entropy criterion as a measure of discrepancy between different classes of signals. The frequency bands associated with these nodes were in the range of interest for seizure events. After selecting two bands, we determined the ratio of energies at the level of wavelet packet chosen by the cross-data entropy algorithm. Preliminary results demonstrate that the wavelet packet energy ratio could serve as a robust criterion in seizure detection.**

I. Introduction

EPILEPTIC seizures of the brain's temporal lobe are characterized by sudden, excessive neuronal discharge, as evident in the electroencephalogram (EEG). The detection of seizures by visually analyzing a patient's EEG data obtained continuously over days, is tedious and time-consuming. A reliable system for detecting seizures would provide an objective record, facilitating treatment. Hence, online and automatic detection of the ictal state is important for long-term monitoring and therapy of patients.

Currently several spike and seizure detectors are available. One system used in clinical diagnosis provides ~76% true detections (sensitivity) with a detection delay of ~16 seconds and a false detection rate (specificity) of 0.84/h [1]. Another experimental system is reported to have sensitivity of 89% with a similar delay time and a false detection rate of 0.22/h [2]. The ultimate aim of our studies is to increase sensitivity and specificity while decreasing detection delay time.

Manuscript received April 7, 2006.

R. Tafreshi is at the Department of Electrical & Computer Engineering at the University of British Columbia (UBC), Vancouver, V6T 1Z4 Canada (e-mail: rezat@ece.ubc.ca).

G. Dumont is at the Department of Electrical & Computer Engineering at UBC, Vancouver, V6T 1Z4 Canada (corresponding author, phone: 604-822-8564; fax: 604-822-8563; e-mail: guyd@ ece.ubc.ca).

B. MacLeod is at the Department of Anesthesiology, Pharmacology & Therapeutics at UBC, V6T 1Z3 Canada (e-mail: bmacleod@interchange .ubc.ca).

E. Puil is at the Department of Anesthesiology, Pharmacology & Therapeutics at UBC, V6T 1Z3 Canada (e-mail: puil@neuro.pharmacology .ubc.ca).

C. Ries is at the Department of Anesthesiology, Pharmacology & Therapeutics at UBC, V6T 1Z3 Canada (e-mail: Craig.Ries@vch.ca).

D. Gross is at the Department of Medicine – Division of Neurology at the University of Alberta, Edmonton, T6G 2B7 Canada (e-mail: Donald.Gross@ualberta.ca).

II. Wavelets and Wavelet Packet Decomposition

A. Wavelets

Wavelet analysis is a good approach for analysis of the non-stationary behavior in the EEG [3]. Wavelets feature an efficient analytical tool in pattern recognition and classification. Wavelets are suitable signal processing tools for the analysis of transient data and noise reduction. As a class of functions, they have information localization ability in both time and frequency.

Wavelets have been utilized in many biomedical applications. Previously, our group defined a wavelet-based index for estimating hypnotic depth in anesthetized patients' EEG signals, to differentiate between the anesthetized and conscious states [4,5]. Wavelets also have been used before in seizure detection. Saab and Gotman used energy, coefficient of variance, and amplitude in levels 3-5 of Daubechies-4 wavelet decomposition to determine seizure probability [6,7]. They reduced the detection delay to 10 seconds without increasing the sensitivity and specificity [cf. 2].

B. Wavelet Packet

Wavelets are windows of varying sizes that extract signal information at localized regions of time and frequency. The standard technique decomposes the frequency axis in dyadic intervals where the length of the bandwidth increases exponentially [8]. A wavelet packet is a generalization that offers a richer range of possibilities for signal analysis than standard discrete wavelet decomposition. Wavelet packet decomposition [9] generalizes the dyadic construction by decomposing the frequency axis into separate intervals of varying length.

A wavelet packet tree is recognized by the triplet index (j,k,m) and respectively represents scale (level), frequency band, and time translation or position. Figure 1 shows a two-level decomposition of wavelet packet tree. Here, $\Omega_{j,k}$ is the space of the basis vectors defined for the node j,k of the binary tree, for $j = 0,1,...,J$ and $k = 0,1,...,2^j - 1$, where $n_0 = \log_2 n \geq J$, n is the signal dimensionality, n_0 is the maximum level of signal decomposition, and J is the maximum level (not necessarily the same as n_0) that we want for decomposing the signal.

Wavelet packet decomposition has been used previously in spike detection but not for seizure detection [10]. In this paper we use wavelet packet decomposition of scalp EEG recordings to detect seizure onset.

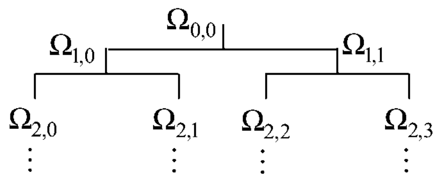

Fig. 1. Decomposition tree in a wavelet packet.

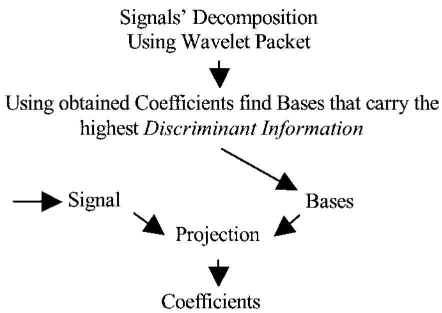

Fig. 2. Main stages of CDE algorithm.

Presently, we have decomposed EEG signals from patients with temporal lobe epilepsy, using the wavelet packet. For seizure detection, we first determined appropriate frequency bands and decomposition level with the *local discriminant bases* (LDB) algorithm and its modified version, the *cross-data entropy* (CDE) algorithm.

C. Cross-data Entropy Algorithm

Both LDB [11] and CDE [12] algorithms use wavelet packets effectively in pattern recognition and classification. The CDE algorithm overcomes some drawbacks of the LDB algorithm by modifying the use of the relative entropy criterion. Hence, we employed the CDE to construct the relative entropy measure that takes into account individual coefficients derived for each training data. This consideration contrasts with the LDB scheme, which uses the sum of coefficient energies of all training data in each class and at each node. By using the CDE, the role of every single data is taken into account in the sense that the relative entropies of each element in the wavelet packet derived for all training data are used to find the appropriate bases. This scheme takes into account the relative entropy distributions of the coefficients in different classes, i.e., discriminant information of every data is considered.

Figure 2 shows the main stages of CDE algorithm. The collected training signals are first decomposed into a wavelet packet tree to obtain coefficients. Then, we determined the relative entropy of coefficient densities in each wavelet packet node. In CDE the relative entropy was used as a measure of discrepancy between different classes of data to reveal the bases of a wavelet packet that distinguish one class of data from another. At this stage, we have localized the most discriminant bases (for the details please refer to [12]). In an online monitoring system, we then projected the incoming signals onto the selected bases to obtain coefficients of each signal. These coefficients can be used in a classification system such as an *artificial neural network* [13], or for finding the signal energy as in our proposed algorithm which we define in the next section.

III. Methods

A. Data Acquisition

The scalp (surface) EEG data used in this paper were collected from two patients with temporal lobe epilepsy. Data were filtered using an anti-aliasing band-pass filter (between 0.5 and 70 Hz) and sampled at 400 Hz. All data collected from 28 channels were examined and the onset of the seizures was determined by a neurologist with EEG fellowship training . Data from channels with the most

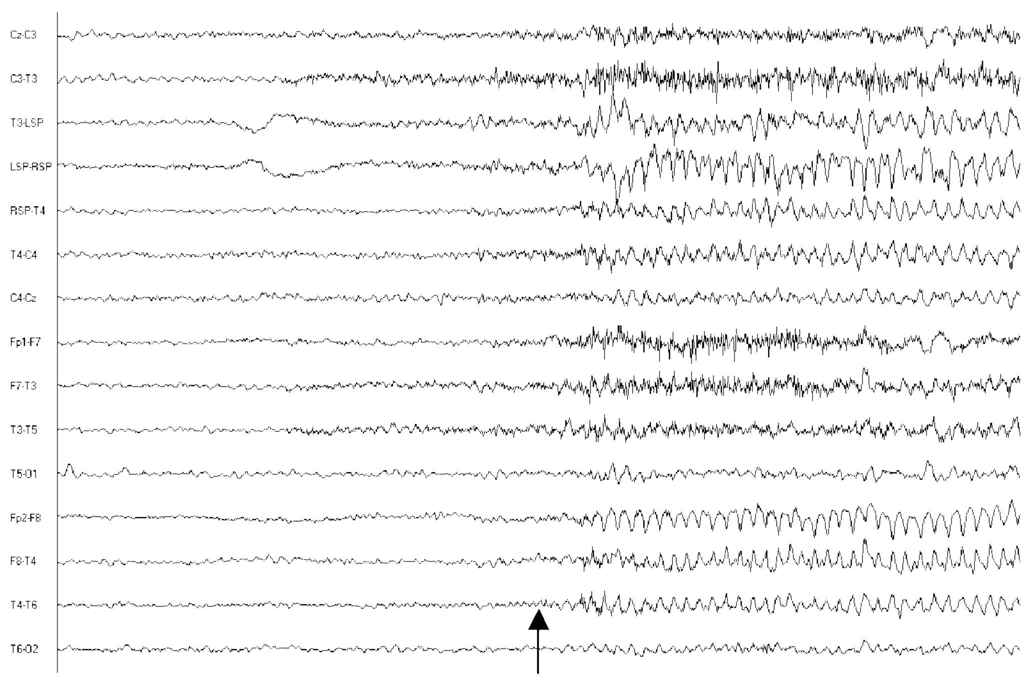

Fig. 3. 10 s segment of EEG in bipolar montage. The arrow indicates seizure onset.

pronounced ictal activity were selected for the analysis. Then, the data were segmented into 2.56-second running windows (1024 sample points). This sample point value is suited to analysis by wavelets, since it is a power of two [8].

Figure 3 shows a 10-second sample of a patient's EEG in bipolar montage with 28 channels, in which the arrow shows the seizure onset.

A. Procedure

The (fast) Fourier transform (FFT) of the signals in each state (preictal and ictal) revealed different frequency contents. Figures 4 and 5 show a 10-second data segment and the FFT of the segment in preictal (20 to 30 seconds before seizure onset) and ictal states (10 seconds after seizure onset) states. For visual clarity, we removed the dc-value in FFT by mean-centering, i.e., the analyzed signal was not mean-centered. Data were notch-filtered at 60 Hz to remove electrical line noise.

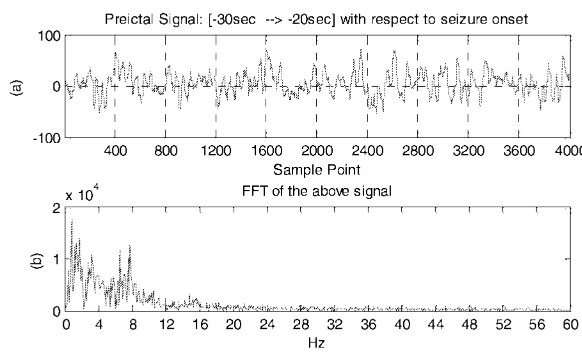

Fig. 4. EEG data and its FFT in preictal state in a 10-second interval between 30 and 20 seconds before seizure onset.

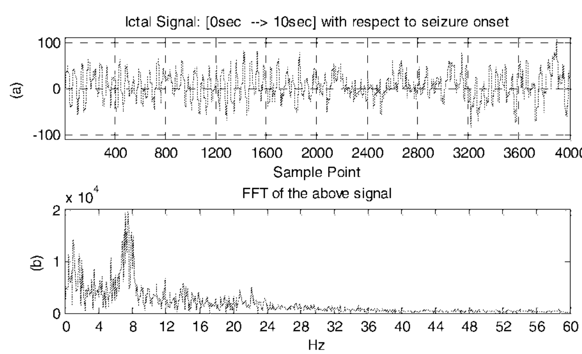

Fig. 5. EEG data and its FFT in ictal state in a 10-second interval that starts immediately after seizure onset.

Seven seizures from two patients were used. Initially, we distinguished two frequency bands (1.5 to 4 Hz and 5.5 to 9 Hz) that were distal to the 12 to 25 Hz band, corresponding to muscle artifacts [6].

Whereas it is difficult to link each of the distinct bands to a specific brain state, we observed that the energy ratio of these bands played a major role in identifying seizure occurrences. This finding was consistent with previous studies that found seizure activity in the 3 to 12 Hz [6] and 3 to 29 Hz [1] bands.

B. Wavelet Packet Energy Ratio

The wavelet packet energy (WP-E) ratio is defined as the ratio of energies in two dominant frequency bands in the wavelet packet domain. In this method, the LDB and CDE algorithms were first used to identify the most discriminant bases (i.e., bases that can distinguish one class of data from another) in a wavelet packet dictionary. Applied to epilepsy detection, these classes may represent preictal and ictal states and dominant frequency bands are the bands specific for each patient.

In a seizure detection application, CDE can provide two valuable pieces of information:

1) The dominant frequency bands involved in seizure and non-seizure brain activities,

2) The most discriminant nodes and their corresponding level(s) of wavelet packet decomposition.

The frequency bands determined by CDE are consistent with our initial observations as described below. On the other hand, wavelet packet coefficients in the most discriminant nodes can be used to obtain energies in dominant frequency bands, employing a well-localized information in both time and frequency.

TABLE I contains the first 8 bases (columns) selected by the CDE algorithm, as explained in [12]. j, k, and m indicate wavelet packet indices referred to as scale, oscillation, and translation, while LF and UF are the lower and upper frequencies (Hz), corresponding to the selected bases. The selected bands are within the ranges of 1.5 to 4 Hz and 5.5 to 9 Hz, consistent with our initial observations.

To obtain wavelet packet coefficients, we projected the segmented data onto wavelet packet bases in the selected bands. The signal energies in these bands were obtained by summing the squared coefficients.

TABLE I
THE FIRST 8 BASES SELECTED BY CDE

	Wavelet Packet Bases							
	1	2	3	4	5	6	7	8
j	9	10	9	10	9	9	9	10
k	17	14	4	15	3	19	16	11
m	1	0	0	0	0	1	0	0
L.F	**6.6**	**2.7**	**1.6**	**2.9**	**1.2**	**7.4**	**3.5**	**2.0**
U.F	**7.0**	**2.9**	**2.0**	**3.1**	**1.6**	**7.8**	**3.9**	**2.1**

IV. RESULTS

The energy of the 5.5 to 9 Hz band for each running window during 140 seconds before, and 140 seconds after seizure onset, demonstrated a sudden increase in the measure that coincided with the seizure onset (see Fig. 6a). The results for other seizures were similar. The overall measure was not stable and was difficult to set a threshold for seizure detection.

In order to detect seizure onset, two energy-based indices in Fourier domain and wavelet packet domain were introduced as follows:

A. Fourier Domain

The ratio of total energy of the 5.5 to 9 Hz band over total energy of 1.5 to 4 Hz band was calculated in the Fourier domain. To implement and test the method, this energy ratio was calculated for each epoch of 2.56 seconds during the abovementioned period. Fig. 6b shows the result, in which the method distinguished between preictal and ictal states. However, the result was somewhat noisy.

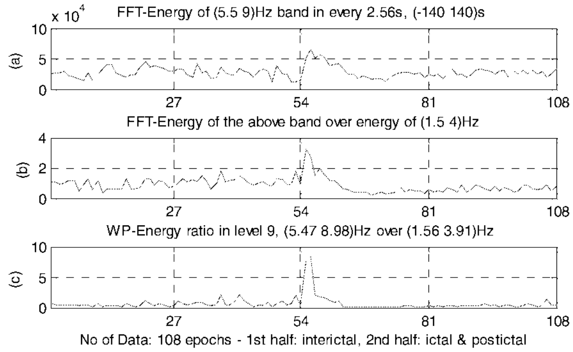

Fig. 6. (a) Fourier domain energy in the 5.5 to 9 Hz band in every 2.56 s in the 280 s interval before and after seizure onset, (b) Fourier domain energy ratio: average energy in the 5.5 to 9 Hz band over average energy in the 1.5 to 4 Hz band in the same interval, (c) Wavelet Packet (WP-) Energy ratio: in level 9, average energies of 5.47 to 8.98 Hz band over 1.56 to 3.91 Hz.

B. WP-E Ratio

This measurement was based on determining the ratio of energy of the 5.5 to 9 Hz band over energy of 1.5 to 4 Hz band in the wavelet packet domain. As the CDE algorithm had mostly selected the wavelet packet bases in scale (level) 9, frequency bands at this level (5.47 to 8.98 Hz and 1.56 to 3.91 Hz) were selected for determining the energy ratio. The selected bases carry important information about the preictal and ictal states.

Using a Daubechies-10 filter, we first decomposed every segment of data into a wavelet packet tree. Next, we calculated the sum energies of the abovementioned bands to obtain the ratio of these energies in each epoch. Figure 6c shows the WP-E ratio, which demonstrates an efficient and robust measure for distinguishing preictal from ictal states. The results were consistent for different seizures of two patients, supporting the superiority of WP-E ratio.

V. Discussion

The cross-data entropy algorithm is computationally fast, i.e., in the order of $n \log n$. We would not need to employ this portion of the software beyond the start of online monitoring if the dominant frequency bands do not change in different brain states. Given nodes that can distinguish between preictal and ictal states, we can expect minimal delay in seizure detection once the online system recognizes the most discriminant nodes of wavelet packet.

The algorithm computational time was negligible compared to the epoch length (2.56 s). Since there is a sudden jump in the WP-E ratio right after seizure onset (cf. Fig. 6c), the maximum delay in detection is less than 2.56 s.

The results were reproducible in the application of this method to different preictal and ictal data segments in each of two patients. The method as described was effective in detecting all seven seizures in two patients; there were no undetected seizures. Hence, this method would improve the detection of seizures in patients.

Our next step is to apply this method to data from a larger number of patients, to confirm those Preliminary results and to determine the method's sensitivity and specificity.

Acknowledgment

Authors acknowledge the contributions of Dr. Juhn Wada in EEG visual interpretation.

References

[1] J. Gotman, "Automatic seizure detection: improvements and evaluation," *Electroencephalography and Clinical Neurophysiology,* vol. 76, pp. 317-324, Oct. 1990.

[2] S. Grewal and J. Gotman, "An automatic warning system for epileptic seizures recorded on intracerebral EEGs." *Clinical Neurophysiology,* vol. 116, pp. 2460, 2005.

[3] M. Le Van Quyen, J. Soss, V. Navarro, R. Robertson, M. Chavez, M. Baulac and J. Martinerie, "Preictal state identification by synchronization changes in long-term intracranial EEG recordings." *Clinical Neurophysiology,* vol. 116, pp. 559, 2005.

[4] S. Bibian, T. Zikov, G. A. Dumont, C. R. Ries, E. Puil, H. Ahmadi, M. Huzmezan and B. A. MacLeod, "Estimation of the anesthetic depth using wavelet analysis of electroencephalogram," *Engineering in Medicine and Biology Society, 2001. Proceedings of the 23rd Annual International Conference of the IEEE,* vol. 1, pp. 951-955, 25-28 Oct. 2001.

[5] T. Zikov, S. Bibian, G. A. Dumont, M. Huzmezan and C. R. Ries, "Quantifying Cortical Activity During General Anesthesia Using Wavelet Analysis," *IEEE Transactions on Biomedical Engineering,* vol. 53, pp. 617-632, April. 2006.

[6] M. E. Saab and J. Gotman, "A system to detect the onset of epileptic seizures in scalp EEG," *Clinical Neurophysiology,* vol. 116, pp. 427-442, Feb. 2005.

[7] Y. U. Khan and J. Gotman, "Wavelet based automatic seizure detection in intracerebral electroencephalogram." *Clinical Neurophysiology,* vol. 114, pp. 898, 2003.

[8] S. Mallat, "A wavelet tour of signal processing," *Academic Press,* 1999.

[9] R. R. Coifman, Y. Meyer and M. V. Wickerhauser, "Wavelet analysis and signal processing, Wavelets and their applications," *Jones, Barlett, Ruskai, Editors, Boston,* pp. 153-178, 1992.

[10] Gutiérrez, J Alcántara, R Medina,V., "Analysis and localization of epileptic events using wavelet packets." *Medical Engineering Physics,* vol. 23, pp. 623, 2001.

[11] N. Saito, R. R. Coifman, F. B. Geshwind and F. Warner, "Discriminant feature extraction using empirical probability density estimation and a local basis library," *Pattern Recognition,* vol. 35, pp. 2841-2852, 2002.

[12] R. Tafreshi, "Feature extraction using wavelet analysis with application to machine fault diagnosis," *Ph. D. Dissertation, the University of British Columbia,* 2005.

[13] R. Tafreshi, H. Ahmadi, F. Sassani and G. Dumont, "Malfunction detection in multi-cylinder engines using wavelet packet dictionary," *SAE Noise and Vibration Conference and Exhibition,* May. 2005.