



## Prediction of epileptic seizures using accumulated energy in a multiresolution framework

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### Abstract

Records of brain electrical activity from intracranial EEG of four patients with different types of epilepsy are analyzed to predict the epileptic seizure onset. A method based on the evolution of the accumulated energy using wavelet analysis is introduced. This is an efficient method to predict epileptic seizures: from 13 pre-seizure signals, the seizure onset in 12 of those are predicted.

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**Keywords:** Intracranial EEG; Wavelet analysis; Prediction; Epileptic seizure

### 1. Introduction

One of the most devastating features of epilepsy is the apparently random nature of seizures. In most patients, seizures occur suddenly, without external, previously detected, precipitants. A system able to predict seizures would allow some preventive measures to keep the risk of seizure to a minimum. These measures could improve the quality of life of patients with epilepsy.

Intracranial recordings of patients who are candidates for surgical treatment offers the most precise access to the emergence of a seizure, and will be used in this paper. As it was recently pointed out (Le Van Quyen et al., 2001), changes in scalp electrical activity are similar to those detected from intracranial recordings. Then, the analysis of EEGs from depth electrodes give important information about the onset of seizures that could be applied to scalp records.

In previous papers (Lehnertz and Elger, 1998; Le Van Quyen et al., 2000; Martinerie et al., 1998) was shown that the evolution towards a seizure involves not just two states—interictal and ictal—but also a preictal transitional phase of several minutes that could be the basis to antic-

ipate seizures in clinical applications. This idea is used in this paper.

The first works on forecasting epileptic seizures began in 1975 (Viglione and Walsh, 1975; Viglione et al., 1973). From that times other mathematical techniques were introduced, and different approaches to the problem were intended (Chillemi et al., 2001, 2002; Lehnertz and Elger, 1998; Litt and Echaz, 2002; Litt et al., 1999, 2001; Martinerie et al., 1998).

It was recently described an algorithm for predicting epileptic seizures based on accumulation of energy function calculated from the EEG signal (Litt et al., 1999, 2001). We introduce in this paper a prediction algorithm based on the accumulated energy function but in a multiresolution framework. A multiresolution analysis (Mallat, 1998) split the EEG signal in several frequency bands using a bank of digital filters with decimation. Thus, a detailed analysis of the EEG is obtained, and information hidden in the accumulated energy function proposed in the cited papers is explicated. The results obtained in the study of 13 seizures are shown.

### 2. Materials and methods

The method of prediction introduced in this paper is based on comparisons between the accumulated energy in epochs

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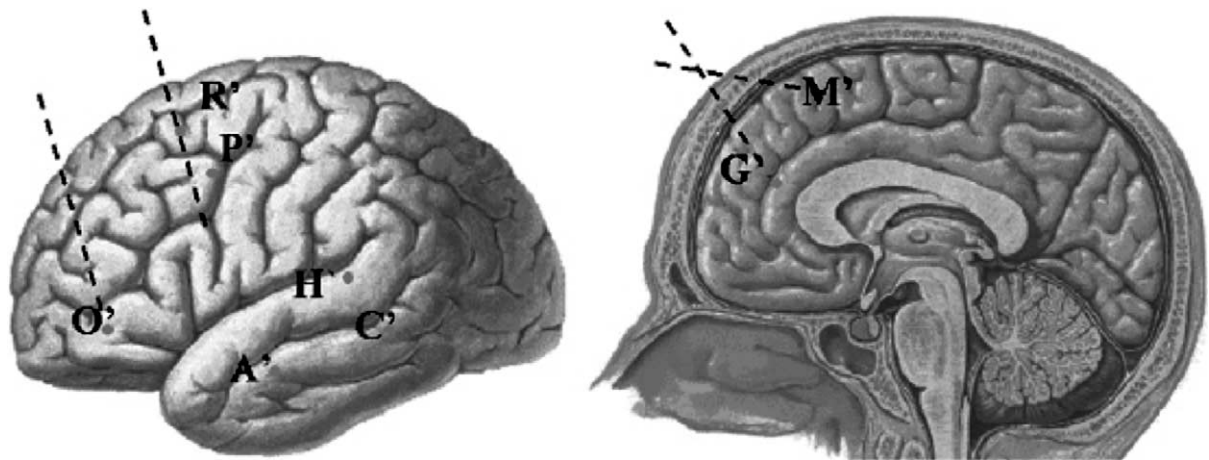


Fig. 1. Placement of electrodes in patient 2.

62 of preictal activity and background activity. Records of brain  
 63 electrical activity from intracranial electrodes correspond-  
 64 ing to 13 seizures and 7 background epochs were analyzed.  
 65 They correspond to four patients, two males and two fe-  
 66 males, candidates to surgery. For each one a clinic history,  
 67 complete neurological exam, neurophysiological evaluation,  
 68 brain magnetic resonance and video electroencephalography  
 69 were realized. The patients were evaluated with stereoelec-  
 70 troencephalography technique (Binnie et al., 1994; Munari  
 71 et al., 1994). Depth electrodes with 5–15 contacts were im-  
 72 planted in different zones of the brain using the Talairach  
 73 method (Talairach et al., 1974) (see Fig. 1).

74 The regions explored with depth electrodes were def-  
 75 ined as epileptic zones from conclusions obtained from  
 76 non-invasive analysis. The number of electrodes ranges  
 77 from three to six according to the complexity of the epilep-  
 78 tic zone, and their position verified by magnetic resonance.  
 79 The EEG signals were recorded using 200 Hz as sample fre-  
 80 quency. Expert neurologists analyzed these records in visual  
 81 form using Vector EEE32, BioScience, with EEG Harmonie  
 82 Stellate software. The epileptic types are shown in Table 1.

83 The wavelet used in the signal analysis was the  
 84 Daubechies-4 (Daubechies, 1992). It is an orthonormal  
 85 wavelet, and then, the signal energy in each level  $j$  of the  
 86 multiresolution analysis is:

$$E_j = \sum_{i=1}^{N_j} d_j^2(i),$$

87

where  $d_j(i)$  ( $i = 1, \dots, N_j$ ) are the wavelet coefficients in  
 the level  $j$ , and  $N_j$  the amount of wavelet coefficients in the  
 level  $j$ .

The accumulated energy in each level was calculated us-  
 ing the following formula:

$$AE_j(k) = \sum_{i=a(k+1)+1}^{a(k+1)+b} d_j^2(i) + AE_j(k-1), \quad (1)$$

where  $b$  is the width of the window and  $b - a$  the over-  
 lap. Levels  $j = 1, \dots, 8$  are used, because there is no rele-  
 vant information in the levels corresponding to low frequen-  
 cies ( $< 0.5$  Hz). The algorithm of prediction is based on the  
 two following steps:

- (1) the computation of the slope of the least square straight  
line to  $AE_j(k)$  function;
- (2) the evaluation of the ratio between the slopes of the  
preseizure signal and the background signal in each level  
of the multiresolution analysis.

### 3. Results

The results presented in this section correspond to sig-  
 nals recorded from electrode contacts placed in or very close  
 to zones generating the seizures, previously described. The  
 epochs corresponding to the background signal used as ref-  
 erence in the prediction algorithm were chosen several hours  
 before the seizure onset. Fig. 2 shows the behavior of the

Table 1

Epilepsy types corresponding to analyzed patients 13 pre seizure and 7 background signals of 90 min each one were analyzed

Patient	Epilepsy types	Epileptic focus
1	Lateral (or neocortical) temporal lobe seizures	Left gyrus temporal superior cortex
2	Lateral (or neocortical) temporal lobe seizures	Left gyrus temporal superior cortex
3	Medial-lateral temporal lobe seizures	Right amygdala and hippocampus
4	Neocortical occipito-parietal lobe seizures	Right lateral occipito-parietal cortex

The pre seizure signals contain 70 min before the onset of the seizure.

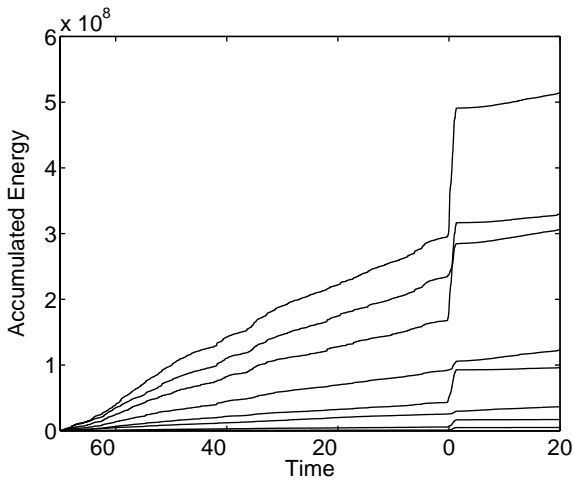


Fig. 2. Accumulated energy in each level of the multiresolution considered, for a pre-seizure epoch.

110 eight levels of the accumulated energy as function of time,  
 111 corresponding to patient 1.

112 In all cases, the least square line that approximates the  
 113 accumulated energy function (AE) in the pre-seizures epoch  
 114 in each multiresolution level has a slope  $S_S$  different to that  
 115 of the least square line that approximates the accumulated

116 energy function in the background epoch,  $S_B$ . The ratio  $r =$   
 117  $S_S/S_B$  is proposed as parameter in order to predict the seizure  
 118 onset. Fig. 3a–d show representative examples of values of  
 119  $r$  corresponding to two channels in four seizures, one for  
 120 each patient.

121 Table 2 summarizes the results obtained. When  $r = 1$ ,  
 122 there is no difference between the epochs analyzed. A thresh-  
 123 old should be defined for deciding if there is a difference  
 124 between the behavior of the AE in the pre-seizure epoch and  
 125 in the background epoch. In the case of awake patients, the  
 126 ratio  $r$  becomes greater than 1, but in asleep patients, the  
 127 ratio  $r$  is smaller than 1. Taking into account this fact, two  
 128 thresholds defined,  $\varepsilon_1 > 0$  and  $\varepsilon_2 > 0$ . Values  $r > 1 + \varepsilon_1$   
 129 (awake cases) or  $r < 1 - \varepsilon_2$  (asleep cases), indicate that the  
 130 seizure onset is near. The smaller  $\varepsilon_1$  and  $\varepsilon_2$ , the greater the  
 131 possibility of false alarms. For the group of patients stud-  
 132 ied, we choose  $\varepsilon_1 = 0.3$  for awake state and  $\varepsilon_2 = 0.35$  for  
 133 asleep state. The seizure is predicted when  $r > 1.3$  in the  
 134 first case, and  $r < 0.65$  in the second case, in the three first  
 135 levels of the multiresolution accumulated energy. The results  
 136 are shown in Table 2. In the first column named “Pred”,  
 137 the results corresponding to the multiresolution analysis are  
 138 presented: Y means yes, i.e., the seizure is predicted using  
 139 the parameter  $r$ , and N means no. As can be seen, only in  
 140 one case the method fails. Using the accumulated energy  
 141 function without the multiresolution analysis, the results are

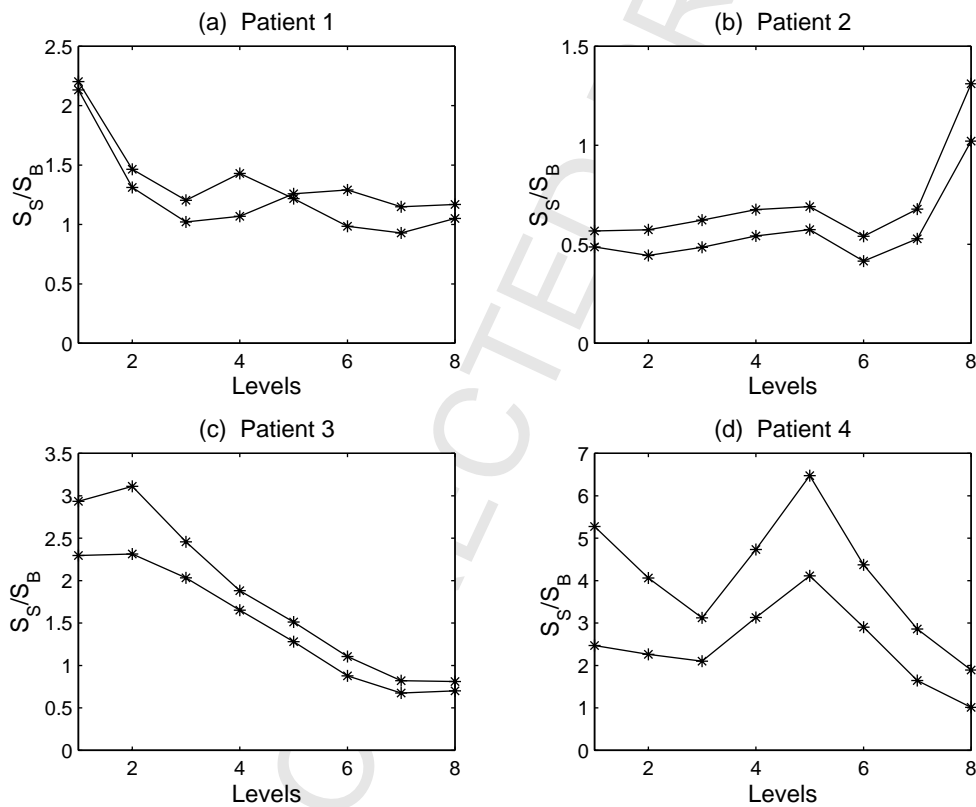


Fig. 3. The  $r$  values in two channels placed in or near the seizure foci, in each level of the multiresolution. In (a–d), the patients were awake and in (b), the patient was asleep.

Table 2

Ratio between the slopes in each level of the multiresolution analysis and the total accumulated energy

Seizure	State	Patient	AEP <sub>j</sub> /AEB <sub>j</sub> levels									AEP/AEB	
			1	2	3	4	5	6	7	8	Pred	Total	Pred
1	Awake	1	1.3	1.5	1.8	2.0	2.6	2.9	3.0	4.1	Y	2.65	Y
2	Awake	1	2.1	1.3	1.0	1.1	1.3	1.3	1.1	1.2	Y	1.21	N
3	Awake	1	1.9	2.0	1.7	1.8	1.9	2.0	2.6	3.1	Y	2.01	Y
4	Awake	2	1.1	1.3	1.4	1.4	1.3	1.1	0.9	1.0	N	1.18	N
5	Awake	2	1.4	1.4	1.4	1.5	1.4	1.2	1.2	1.2	Y	1.21	N
6	Awake	3	2.9	3.1	2.5	1.9	1.5	1.1	0.8	0.8	Y	1.27	N
7	Awake	3	2.3	2.7	2.4	2.1	1.8	1.6	1.2	1.0	Y	1.62	Y
8	Awake	4	5.2	3.3	1.3	1.3	1.2	0.8	0.8	0.8	Y	1.04	N
9	Awake	4	2.5	2.2	1.6	1.8	1.6	0.8	0.6	0.5	Y	1.16	N
10	Asleep	1	0.5	0.4	0.4	0.6	0.8	0.8	0.6	0.6	Y	0.68	Y
11	Asleep	1	0.1	0.2	0.4	0.5	0.6	0.6	0.3	0.3	Y	0.49	Y
12	Asleep	1	0.3	0.4	0.6	0.9	1.3	1.6	0.9	0.7	Y	1.11	N
13	Asleep	2	0.5	0.4	0.5	0.5	0.6	0.4	0.5	1.0	Y	0.51	Y

The seizure forecast is more effective in the first case.

141 shown in the last column of Table 2. With the same values  
 142 of the thresholds, only 6 out of the 13 cases are predicted. In  
 143 order to improve this performance, the value of the thresh-  
 144 old should be smaller, but then the possibility of false alarms  
 145 is greater. This fact shows the advantage of the use of the  
 146 accumulated energy function in the framework of multires-  
 147 olution analysis.

148 Some remarks about the prediction algorithm introduced  
 149 in this paper:

- 150 (1) In order to get a fast algorithm, the lifting method  
 151 (Daubechies and Sweldens, 1998) for calculating the  
 152 wavelet coefficient is used. This method leads to a  
 153 speed-up of around two times when compared to the  
 154 standard implementation and allows for an in-place  
 155 implementation of the fast wavelet transform.  
 156 (2) The results obtained do not depend neither the width  
 157 nor the overlapping in Eq. (1); and, as a consequence,  
 158 the choice is made taking the computational burden into  
 159 account.  
 160 (3) The value of  $\varepsilon_1$  and  $\varepsilon_2$  can change for different patients.

#### 161 4. Conclusions

162 Through the results obtained we conclude that the  
 163 wavelet-based method applied to the accumulated energy  
 164 would contribute for predicting epileptic seizure onset from  
 165 EEGs signals. Using the accumulated energy in a wavelet  
 166 framework, we could forecast the onset of epileptic seizures  
 167 70 min before in the cases analyzed. This analysis can sup-  
 168 ply complementary information potentially useful from a  
 169 clinical point of view.

#### 170 Uncited reference

Viglione et al. (1970).

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#### References

- Binnie C, Elwes R, Polkey C. Utility of stereoelectroencephalography in  
 preoperative assessment of temporal lobe epilepsy. *J Neurol Neurosurg*  
*Psychiatry* 1994;57:58–65.  
 Chillemi S, Balocchi R, Barbi M, Di Garbo A, Ferri R, Migliore M.  
 Early trends in seizure onset: a nonlinear approach. In: D'Attellis  
 CE, Kluev VV, Mastroakis NE, editors. *Mathematics and computers*  
*in science and engineering*. Word Scientific and Engineering Society  
 Press; 2001. p. 156–60.  
 Chillemi S, Balocchi R, Barbi M, Di Garbo A, D'Attellis CE, Gigola S,  
 et al. Detection of a preseizure state in intracranial EEG signals: a  
 case study. *WSEAS Trans Circuits* 2002;1:159–64.  
 Daubechies I. *Ten lectures on wavelets*. SIAM; 1992.  
 Daubechies I, Sweldens W. Factoring wavelet transforms into lifting steps.  
*J Fourier Anal Appl* 1998;4:247–69.  
 Lehnertz K, Elger C. Can epileptic seizures be predicted? *Phys Rev Lett*  
 1998;80:5019–22.  
 Le Van Quyen M, Adam C, Martinerie J, Baulac M, Clemenceau S,  
 Varela F. Spatio-temporal characterizations of nonlinear changes in  
 intracranial activities prior to human temporal lobe seizures. *Eur J*  
*Neurosci* 2000;12:1224–34.  
 Le Van Quyen M, Martinerie J, Navarro V, Boon P, D'Have M, Adam C,  
 et al. Anticipation of epileptic seizures from standard EEG recordings.  
*Lancet* 2001;357:183–8.  
 Litt B, Esteller R, D'Alessandro M, Echaz J, Shor R, Bowen C, et al..  
 Evolution of accumulated energy predicts seizures in mesial temporal  
 lobe epilepsy. In: *Proceedings of the First Joint BMES/EMBS Con-*  
*ference, Atlanta, GA, 13–16 October 1999*. p. 440.  
 Litt B, Esteller R, Echaz J, D'Alessandro M, Shor R, Henry T, et al.  
 Epileptic seizures may begin hours in advance of clinical onset: a  
 report of five patients. *Neuron* 2001;30:51–64.  
 Litt B, Echaz J. Prediction of epileptic seizures. *Lancet Neurol*  
 2002;1:22–9.  
 Mallat S. *A wavelet tour of signal processing*. 1st ed. Academic Press;  
 1998.

- 209 Martinerie J, Adam C, Le Van Quyen M, Baulac M, Clemenceau S,  
210 Renault B, et al. Epileptic seizures can be anticipated by non-linear  
211 analysis. *Nature* 1998;4(10):1173–6.
- 212 Munari C, Tassi L, Kahane P, Francione S, Di Leo M, Quarato P. Analysis  
213 of clinical symptomatology during stereo-EEG recorded mesiotemporal  
214 lobe seizures. In: Wolf P, editor. *Epileptic seizures and syndromes*.  
215 London: John Libbey; 1994. p. 335–59.
- 216 Talairach J, Bancaud J, Szicla G, Bonis A, Geier S. Approche  
nouvelle de la chirurgie de l'épilepsie: methodologie stereo-  
taxique et resultats therapeutiques. *Neurochirurgie* 1974;20(1):1–  
217 240. 218
- Viglione S, Ordon V, Risch F. A methodology for detecting ongoing  
219 changes in the EEG prior to clinical seizures. *21st Western Institute*  
220 *of Epilepsy*; 1970. 221
- Viglione S, Ordon V, Martin W, Kesler C. Epileptic seizure warning  
222 system. US Patent 3,863,625; 1973. 223
- Viglione S, Walsh G. Epileptic seizure prediction. *Electroencephalogr*  
224 *Clin Neurophysiol* 1975;39:435–6. 225

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