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Epileptic seizure detection using linear prediction filter

Tarek Lajnef[1], Sahbi Chaibi[1], Abednaceur Kachouri[2], Mounir Samet[1]

[1] University of Sfax, National School of Engineering of Sfax, Research Laboratory on Electronics and information Technologies: LETI, Sfax, Tunisia

Lajnef.tarek@gmail.com, sahib.chabi@yahoo.fr,
samet.mounir @enis.rnu.tn

[2] University of Gabes, higher Institute of industrial systems of Gabes

Abdennaceur.Kachouri@enis.rnu.tn

Abstract: *Epilepsy is one of the most common neurological disorders and affects almost 60 million people worldwide; many techniques were used to detect epileptic activities in the EEG recording. In this study we have used detection method based on linear prediction error. The main idea of this method is that LP filter can not track sudden changes caused by spikes and other high frequency transient activities during epileptic seizures. Consequently error energy of epileptic EEG segments is much higher than those of normal ones. In our work we compared three different minimization criterions to reduce prediction error (Akaike, FPE, MDL). Error energy is then estimated and a threshold operation is done to separate epileptic epochs and normal ones .Method was applied to three data sets, the first one contains EEG recording of healthy subjects, the second and the third ones are epileptic EEG recordings. Error energies mean values for these data sets were respectively 3.21* 104, 1.02*106 and 4.25*104. The results of the proposed algorithm are evaluated by calculating sensitivity and accuracy values. The Sensitivity values were 94,5% and 90,4%% for inter ictal and ictal data sets respectively. Accuracy values were 93% and , 91% for both data sets.*

Introduction:

Epilepsy is one of the most common neurological disorders and affects almost 60 million people worldwide. The International League Against Epilepsy (ILAE) and the International Bureau for Epilepsy (IBE) defines an epileptic seizure as "a transient occurrence of signs and/or symptoms due to abnormal excessive or synchronous neuronal activity in the brain", [ILAE 05a] Since its invention in 1929 by Hans Berger, the electro encephalogram (EEG) record, which is a summation of electrical activities generated by cortical neurons, have been widely used in epilepsy seizure detection. Since these records are a long, visual detection becomes more difficult, so it is increasingly necessary to develop a practically applicable method to detect epileptic seizures. The first automatic analysis of epileptic EEG was proposed by Gotman and Gloor in 1976 using mimetic based method, then a multitude of techniques were used; (i) techniques based on time domain analyse, (autocorrelation in the eeg record [Liu, A. 92]), (ii) frequency domain techniques (finding the difference between normal and epileptic frequency domain[Gotman, J 97]) (iii) time frequency domain; (specially wavelet analyse [Latka M 03]) , (iv) Artificial neural networks [Gabor AJ 96], and (v) non linear measures techniques; correlation dimension (CD), largest Lyapunov exponent (LLE) and approximate entropy (ApEn), Renyi entropy [N. Mammone 08a] these values reflect the complexity and predictably of EEG records. [Kannathal, N 05b].

In this study error energy of linear prediction filter, is used to detect epileptic epochs in different EEG records. The main idea of this method is that epileptic EEG segments contain usually high frequency transient activities (spikes), that the predictive filter can not track. Consequently, error energy of these segments would be higher than normal ones [Sultunay 10]. Since EEG signals are non stationary, a windowing operation is firstly applied. Three different error minimization criteria are used: AKAIKE, FPE (Final Prediction Error), MDL (Minimum Description Length) to choose the optimum number of taps. A linear predictive filter is then used and the Error energy of each segment is calculated. We have only to apply a predefined threshold to detect epileptic segments from those normal or inter-ictal.

1. Linear predictive filter:

Linear prediction is a signal processing technique that is used extensively in the analysis of speech signals. It consists on estimating future sample of a discrete time signal from the previous sample.

A linear predictive filter estimates the spectral characteristics of the signal window by calculating the coefficients of an FIR filter. This estimation is an optimization process that involves calculation of filter coefficients to achieve the minimum modeling error. Mathematically a linear predictive filter is defined by following equations:

$$y[n] = \sum_{k=1} a_k s(n-k) \qquad (1)$$

Where y[n] is samples predicted by LP filter, a_k are filter coefficients and s[n] is the time series sample. a_k values are determined by minimizing the variance σ_e^2 of the error e [n] which is defined as

$$e[n] = s[n] - y[n] = s[n] - \sum_{k=1} a_k s(n-k) \qquad (2)$$

σ_e^2 is defined by the equation-3

$$\sigma_e^2(a_k) = \frac{1}{N}\sum_{n=0}^{N-1} e^2[n] = \frac{1}{N}\sum_{n=0}^{N-1}(s[n] - \sum_{k=1} a_k s(n-k))^2 \qquad (3)$$

2. Materials and methods:

2.1. Data base:

The EEG data used in this study consists of three different sets. The first set includes

surface EEG recordings that were collected from five healthy subjects using a standardized electrode placement scheme. The subjects were awake and relaxed with their eyes open. The second data set consist of intracranial EEG recordings during seizure free intervals (interictal periods) from within the epileptogenic zone of the brain. The data in the last set was recorded during seizure activity (ictal periods) using depth electrodes placed within the epileptogenic zone. Each data set consists of 100 single channel EEG epochs of 23.6 s duration. The data was recorded with 128-channel amplifier system and digitized at 173.61 Hz sampling rate and 12-bit A/D resolution. [Andrzejak et al., 2001] .

2.2. method :

The method is based on the fact that the predictive filter can not follow sudden changes in the EEG caused by seizure onset.
Consequently, error energy of EEG signal will significantly increase. It is therefore sufficient to calculate this energy and apply a predefined threshold to distinguish epileptic segments from those normal or inter-ictal.
Different steps of this method are described in Fig 1

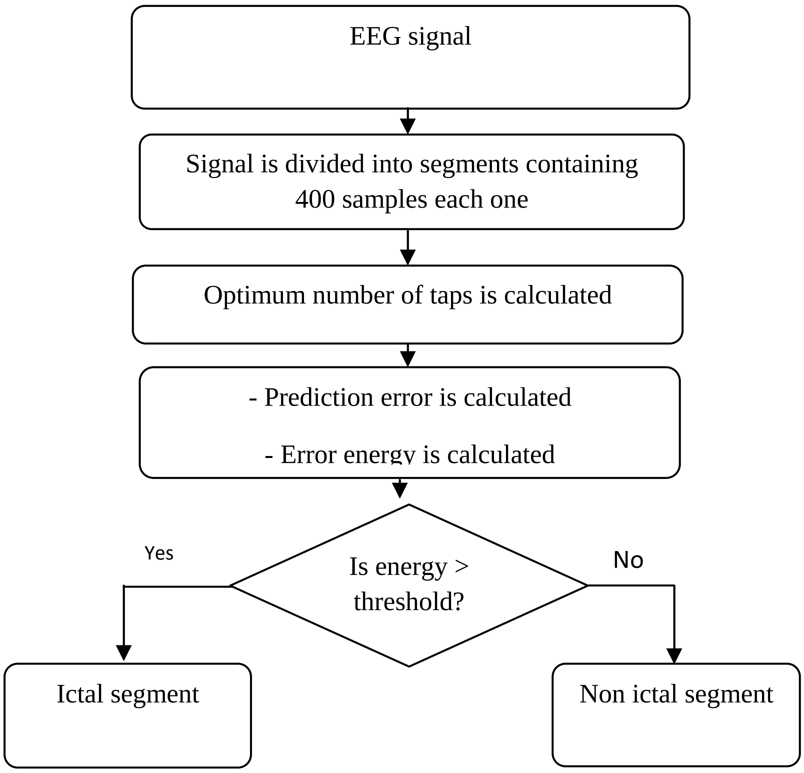

Fig 1: Method flow chart

- EEG signals like most biological signals can be characterized as non stationary signal. However LP filtering requires some stationarity. That is why; we have to divide the row signal into epochs of 400 samples each. after windowing the signal with sufficient length, it can be considered as ‘‘weakly stationary” [Andrjezak et al., 2001],
- Optimum number of taps is then choose using three minimization criterions Akaike , FPE and MDL values,
- Using this optimum number, LP filter included on Matlab is then used and error energy is evaluated,
- A threshold value is then applied. Epochs that have error energy higher than threshold are considered as epileptic ones. And those with error energy lower than threshold are considered normal.

2.3. Predictive filter:

2.3.1. Choice of filter order (number of taps):

Unlike method proposed by S.Altunay [S.Altunay 2010] we have added minimization criterions to choose the filter order. Which are:

- AKAIKE criterion defined in our case as :

  $$AKAIKE(k) = N\ln(Err) + 2K \quad (4)$$

  Where N, ERR and K are data length, prediction error, and number of taps respectively. Fig 2 shows result of application of this criterion to a normal EEG. As it is shown in this figure the lowest error was found with 30 taps.

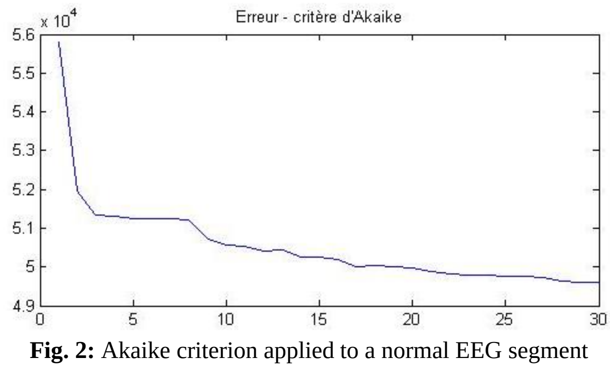

Fig. 2: Akaike criterion applied to a normal EEG segment

  We apply the same criterion with epileptic segments (ictal and inet ictal) we have found that the optimum number of taps was 26, 30 respectively.

- MDL (Minimum Description Length) criterion is defined as :

  $$MDL(k) = N\ln(Err) + K * \ln(N) \quad (5)$$

Where Where N, ERR and K are data length, prediction error, and number of taps respectively. Fig3 shows result of application of this criterion to normal EGG segment. As it is shown in this figure optimum number taps for normal segments is 29.

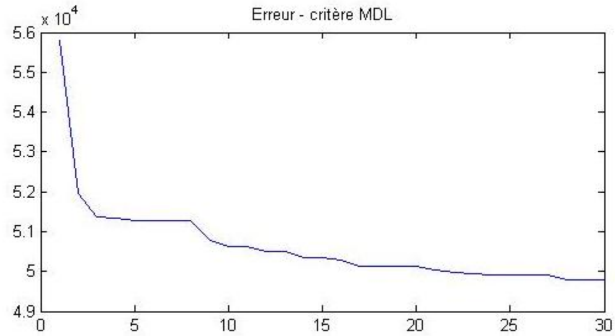

Fig.3: MDL criterion applied to normal EEG segment

Applying the same criterion to epileptic segments (ictal and inter ictal) we have found that optimum number of taps was 19 and 6 respectively.

- FPE (Final Prediction Error) criterion is defined as

$$FPE(k) = Err * (N + K + 1)/(N + K - 1) \quad (6)$$

The result of application of this criterion to a normal EEG segment is shown in figure 4. As we can see in this figure optimum number of taps for a normal EEG segment using FPE criterion is 29.

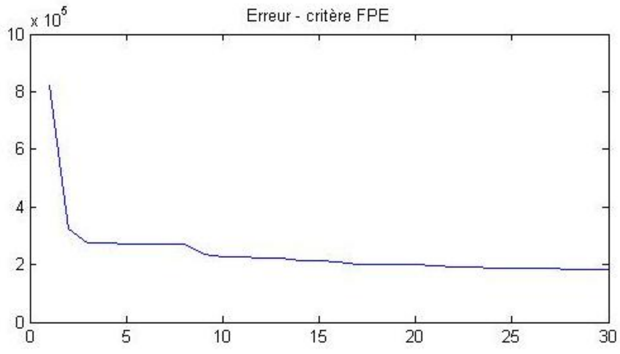

Fig.4: EPL criterion application to a normal EEG segment

By applying this criterion to epileptic segment we have found that the optimum order for an ictal segment is 26 and this for inter ictal segment is 30.

Comparing the three different criterions we find that AKAIKE criterion ensure the optimum error minimization. This criterion is then used to estimate predictive sample using LP filter.

2.3.2. Error energy estimation:

Prediction error for both normal and epileptic signals is calculated as defined in equation 2.Figures 5 and 6 show respectively the prediction error for both normal and epileptic EEG segments. As we can see in these figures, prediction error of an epileptic segment is higher than those for a normal one.

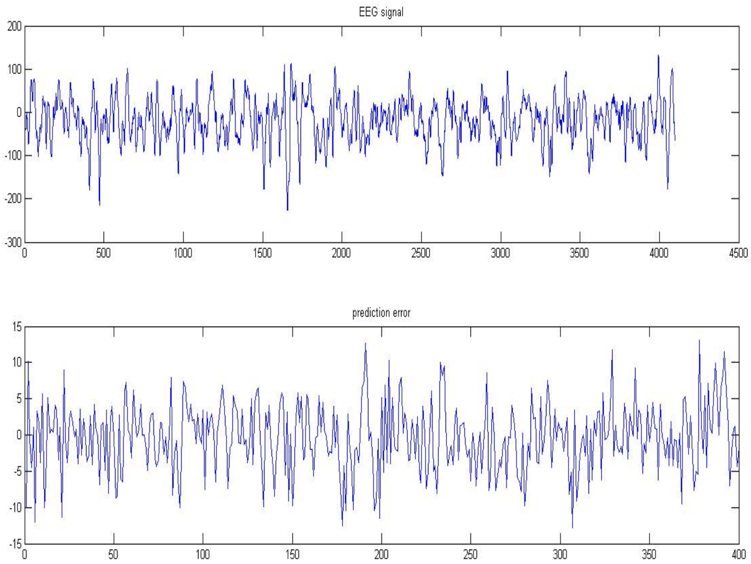

Fig.5: prediction error of a normal EEG segment

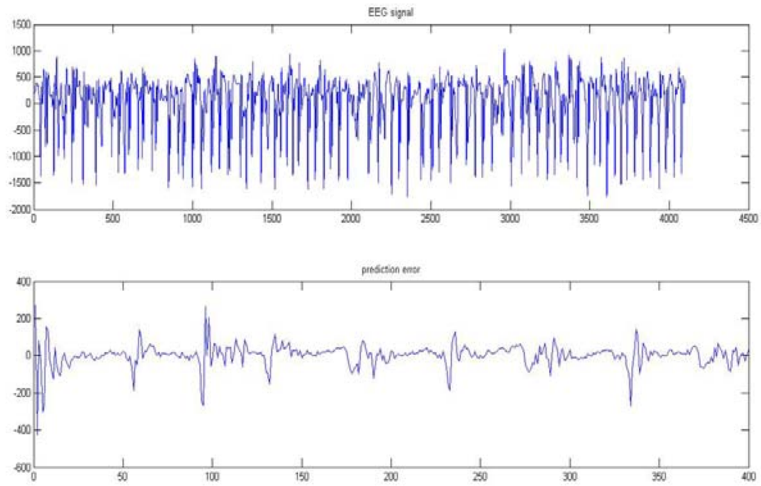

Fig.6: prediction error of an epileptic segment

The error energy of each epoch is then calculated using the following equation:

$$E = \sum_{N} e^2 \qquad (7)$$

2.4. Thresholding:

To determine the threshold values we have to apply the method to different segments of our data set. We estimate the threshold value to $4*10^4$. Epochs with error energies higher than this threshold are considered as epileptic ones those with error energies lower this value are considered as normal ones.

3. Results and discussion:

3.1. Error energy estimation:

Error energy values of each epoch are evaluated using equation 7. The mean values of these energy for healthy subjects, epileptic subjects (ictal period and inter ictal) were $3.21*\ 10^4$, $1.02*10^6$ and $4.25*10^4$ respectively. As expected error energy of the epileptic segments (ictal period) is much higher than those of the two other sets due to high frequency transients such us spikes that are potentially present during epileptic seizures. The

3.2. Method performances:

To evaluate the method performance two metrics are used: The Sensitivity and the accuracy [Mer et all 07] as defined in equations 8 and 9 respectively.

$$\text{Sensitivity} = 100 * \frac{TP}{TP + FN} \tag{8}$$

$$\text{Accuracy} = 100 * \frac{TP}{TP + FP + FN} \tag{9}$$

Where TP (true positive): number of epileptic epochs correctly classified

FN (false negative): number of normal epochs detected as epileptic ones

FP (false positive): number of non detected epileptic epochs.

Sensitivity and accuracy values are presented in table 1

Table 1: Sensitivity and accuracy values

	Sensitivity	Accuracy
Set2 (epileptic inter ictal)	94.5%	93%
Set3 (epileptic ictal)	90.4%	91%

Conclusion:

This study proves that linear predictive error energy can be an indicator of epileptic seizure. However, EEG signals are usually noisy and contain many types of artifacts which could affect the performance of the method. In fact, some artifacts are respectively considered as high frequency components. A pretreatment stage to remove artifacts an solve this problem.

This method can also be combined with the other methods such as wavelets, spectral analysis and entropy in order to realize more efficient algorithms. Further developments such as calculating a defined error energy threshold value can also be carried out by using extended EEG data sets, advanced adaptive threshold calculation algorithms and artificial intelligence.

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