An Epileptic Seizure Prediction Algorithm from Scalp EEG Based on Morphological Filter and Kolmogorov Complexity

Guanghua Xu[1], Jing Wang[2], Qing Zhang[2], and Junming Zhu[3]

[1] State Key Laboratory for Manufacturing Systems Engineering, Xi′an Jiaotong University, Xi'an, Shaanxi, 710049, P.R. China
[2] Department of Instrument Science and Technology, Xi′an Jiaotong University, Xi'an, Shaanxi, 710049, P.R. China
[3] Department of Neurosurgery, Zhejiang Provincial People's Hospital, Hangzhou, Zhejiang, 310014, P.R. China
xugh@mail.xjtu.edu.cn, aii@mail.xjtu.edu.cn, Junming_zhu@hotmail.com

Abstract. Epilepsy is the most common neurological disorder in the world, second only to stroke. There are nearly 15 million patients suffer from refractory epilepsy, with no available therapy. Although most seizures are not life threatening, they are an unpredictable source of annoyance and embarrassment, which will result in unconfident and fear. Prediction of epileptic seizures has a profound effect in understanding the mechanism of seizure, improving the rehabilitation possibilities and thereby the quality of life for epilepsy patients. A seizure prediction system can help refractory patients rehabilitate psychologically. In this paper, we introduce an epilepsy seizure prediction algorithm from scalp EEG based on morphological filter and Kolmogorov complexity. Firstly, a complex filter is constructed to remove the artifacts in scalp EEG, in which a morphological filter with optimized structure elements is proposed to eliminate the ocular artifact. Then, the improved Kolmogorov complexity is applied to describe the non-linear dynamic transition of brains. Results show that only the Kolmogorov complexity of electrodes near the epileptogenic focus reduces significantly before seizures. Through the analysis of 7 long-term scalp EEG recordings from 5 epilepsy patients, the average prediction time is 8.5 minutes, the mean sensitivity is 74.0% and specificity is 33.6%.

Keywords: Scalp EEG, Epileptic seizure prediction, Kolmogorov complexity, Morphological filter, Artifact removal.

1 Introduction

Epilepsy is one of the most common neurological disorders and affects almost 60 million people worldwide. About 75% of them can be controlled by medications or curable by surgery. This leaves one-quarter of the patients with refractory epilepsy.

V.G. Duffy (Ed.): Digital Human Modeling, HCII 2007, LNCS 4561, pp. 736–746, 2007.

Over the past decade, researchers have gradually noticed that seizures do not begin abruptly but develop several minutes to hours before clinical symptoms. This discovery leads to the possibility of predicting epileptic seizures, which can greatly improve the quality of life for these patients. For instance, patients can be forewarned to take timely preventive steps such as interrupting hazardous activities or contacting the physician for help. Also, therapeutic concepts could move from preventive strategies towards an on-demand therapy by electrical stimulation in an attempt to reset brain dynamics to a state that will no longer develop into a seizure.

EEG is an effective tool for clinical evaluation of brain activity. Majority of studies on epileptic seizure prediction are based on intracranial EEG [0~0]. However, it requires intensive surgical operations to implant electrodes inside brain, which are hazardous to the patient. Recently, researchers begin to pay their attention to scalp EEG because of its flexibility for outpatient and ambulatory applications [0,0]. Since scalp EEG is often contaminated with noises, a preprocessing of artifact removal is necessary. Corsini [0] presents a seizure prediction approach from scalp EEG. But ocular artifact, one of the most common contaminations, is not concerned.

So, the goal of this paper is to propose an integrated seizure prediction method based on scalp EEG signals, including artifacts elimination, seizure anticipation and analysis of clinical cases. The content of the paper is laid out in 5 sections with this section as the introduction. Section 2 describes the method of removing artifacts. A prediction method of epileptic seizure is presented and the results of applying this algorithm to 7 long-term scalp EEG recordings are given in section 3 and 4, respectively. Finally, conclusions are given in section 5.

2 Artifacts Removal for Scalp EEG

There exist a lot of artifacts in scalp EEG, which may possibly affect seizure prediction results. Due to the different characteristics of these artifacts, it is difficult to remove them with a single filter. So, a complex method is proposed as follows.

2.1 Baseline Excursion and 50Hz Frequency Component

The artifact of baseline excursion often occurs on temporal and frontal lobe with frequency of less than 1Hz because of sweat. In addition, most recordings present a 50Hz frequency component on all electrodes. Therefore, a band-pass filter with cutoff frequency of 0.5 and 45 Hz is utilized to eliminate these artifacts, as shown in Fig. 1.

2.2 Ocular Artifact

Eye blinks may cause ocular artifact on Fp1 and Fp2 electrodes. Owing to the frequency overlap between eye blinks and basic rhythm in scalp EEG, a band-pass filter will eliminate not only the artifacts, but also some useful information which affects seizure prediction result. Morphological filter can decompose EEG signal into several physical parts according to geometric characteristics, by using certain

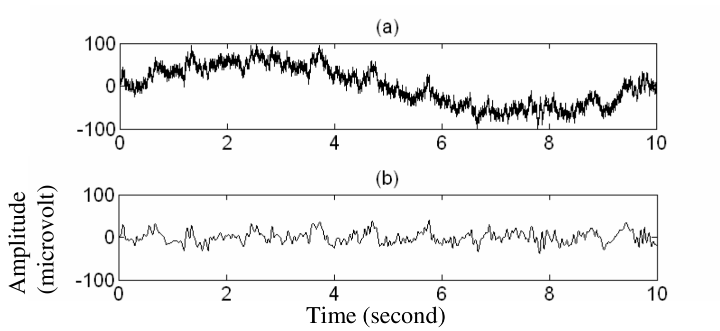

Fig. 1. Artifact removal: (a) Scalp EEG with artifacts of baseline excursion and 50Hz frequency component; (b) processed data with band-pass Butterworth filter

structure elements. Maragos [0] put forward four basic morphological operations shown in equation (1)~(4):

Erosion:

$$(f \Theta g^s) = \min_{\tau \in D}\{f(\tau) - g(-(t-\tau))\} \tag{1}$$

Dilation:

$$(f \oplus g^s) = \max_{\tau \in D}\{f(\tau) + g(-(t-\tau))\} \tag{2}$$

Opening:

$$(f \circ g)(t) = [(f \Theta g^s) \oplus g](t) \tag{3}$$

Closing:

$$(f \bullet g)(t) = [(f \oplus g^s) \Theta g](t) \tag{4}$$

where $f(t)$ is the original time series, and $g(t)$ is a structure element function. $g^s(t)$ points to reflection of $g(t)$, which is defined as $g^s(t) = g(-t)$. D means the set of real number. According to the characteristics of ocular artifact, clos-opening operation is employed to eliminate ocular artifact, as shown in equation (5):

$$CO(f(t)) = f(t) \bullet g_1(t) \circ g_2(t) \tag{5}$$

In order to separate the ocular artifact and background EEG, structure elements, which can insert into shape of background EEG but not into spike waves, are constructed by $g_1(t)$ and $g_2(t)$. The structure element pair is determined in (6) and shown in Fig. 2.

$$g_i(t) = a_i t^2 + b_i, \qquad i = 1,2 \tag{6}$$

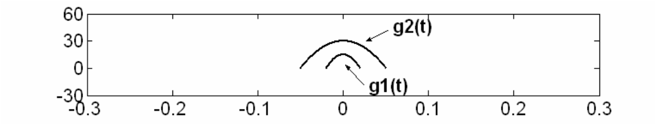

Fig. 2. Structure elements

where a_i accounts for the width and b_i stands for the center amplitude of the structure elements. Since eye-blink signals of different patients may have various amplitude and frequency, the structure elements should be adjusted to proper size where the eye-blink component can be best extracted. Suppose that $s(t)$ is the original EEG data and $x(t)$ is calculated with $x(t) = s(t) - CO(s(t))$, the structure elements are optimized as follows:

$$K = I_f / R_{pz} \tag{7}$$

for which

$$I_f = \hat{x} / \overline{x} \tag{8}$$

and

$$R_{pz} = N_{pz} / N \tag{9}$$

where I_f is the pulse index for the input signal x and R_{pz} points to the zero-pass rate of signal x. Thereinto $\hat{x}$ is the peak value of x obtained by $\hat{x} = \max\{|x(t)|\}$, $\overline{x}$ is the average amplitude of x calculated with $\overline{x} = \int_{-\infty}^{+\infty} |x| \, p(x) dx$. N is total data length of x and N_{pz} is the number of zero-pass points in signal x determined by

$$N_{pz} = \sum_{n=1}^{N-1} \mu[x(n) * x(n+1)] \tag{10}$$

assuming

$$\mu(x) = \begin{cases} 0 & x > 0 \\ 1 & x \le 0 \end{cases} \tag{11}$$

I_f is sensitive to peak and valley values in eye-blink signals and R_{pz} reflects the degree of restraining the background activities. So, a larger K shows that eye-blink component in EEG signals is better extracted and background activities are better restrained. In the present paper, the amplitude and width of the structure elements are optimized respectively with the mentioned K criterion, as described in Fig. 3.

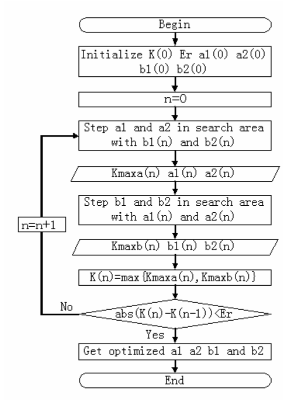

Fig. 3. Optimization of structure elements

Giving a is a typical EEG signal with ocular artifact in Fig. 4(a), the process of ocular artifact elimination is as follows:

(i) Firstly, the search area on amplitude and width of structure elements are decided: $K(0)=0$, $a_1(0)=-1.23\times10^4$, $a_2(0)=-4.80\times10^3$, $b_1(0)=100\mu V$, $b_2(0)=300\mu V$. There into, $b_1(0)$ and $b_2(0)$ indicate the probable amplitude of ocular artifact. Since the sample rate of EEG signal is 256 Hz , $a_1(0)$ and $a_2(0)$ determine that the initialized width of the structure elements are 0.18 s and 0.5 s , which covers the frequency range of ocular artifact;

(ii) With a certain structure element pair in the search area, clos-opening operation is implemented followed by its subtraction with original EEG signal: $x(t)=f(t)-CO(f(t))$;

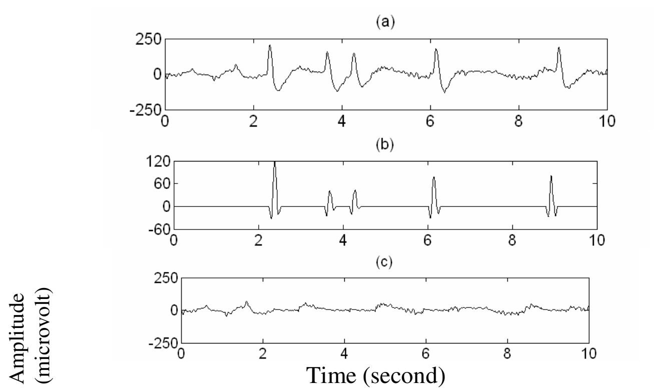

Fig. 4. Ocular artifact removal: (a) EEG signal with ocular artifact; (b) Detected ocular artifacts; (c) Artifact removal result

(iii) Parameter K for $x(t)$ is calculated with equation (7);

(iv) Repeat step (ii) and (iii) to get the K matrix;

(v) The maximum of K corresponds to the optimized structure elements: $a_1 = -3.13\times10^3$, $a_2 = -2.33\times10^3$, $b_1 = 180\mu V$, $b_2 = 210\mu V$;

(vi) Background activity is fully restrained, using optimized strcture elements. With a $10\mu V$ threshold, the ocular artifact is detected in Fig. 4(b);

(vii) Ocular artifact is replaced with normal background activity in Fig. 4(c).

3 Prediction Algorithm Based on Kolmogorov Complexity

EEG signals result from the complex processes inside the brain. Since epileptic neuronal networks are essentially complex nonlinear structures, the theory of complexity can be used to quantify its dynamics.

3.1 Improved Kolmogorov Complexity

In 1965, Kolmogorov suggested that complexity of a given string with zeros and ones was decided by the length of the shortest computer program which can generate this string. An appropriate measure of Kolmogorov complexity was put forward by Lempel and Ziv [0]. Usually, the symbol '0' or '1' is assigned to each sample by comparing it with the average of the signal. However, this transformation may neglect a lot of useful information in the original signal. Many modifications have been proposed to overcome the disadvantage. In [0], spikes with high amplitude, a typical epileptic activity in EEG signal, are reserved as '1' after binary symbolization, while others are set to '0'. This means that many important epileptic characteristics, such as slow-amplitude spikes and spike-slow complex, are ignored. Here, we present a new method to extract all the epileptic activities in EEG, which is described as follows.

(i) Suppose $x(n) = \{x_1, x_2, ..., x_N\}$ is the original EEG signal and the average value of the time series is $x_p = [\sum_{i=1}^{N} x_i]/N$.

(ii) Calculate the absolute value of the subtraction between $x(n)$ and $x(p)$. $y(n) = \{y_1, y_2, ..., y_N\}$, where $y_i = \left|x_i - x_p\right|$, and the average value of $y(n)$ is obtained by $y_p = [\sum_{i=1}^{N} y_i]/N$.

(iii) Absolute difference of $x(n)$ is defined as $derx(n) = \{derx_1, derx_2, ...derx_N\}$, where $derx_j = \begin{cases} 0, & j = 1 \\ \left|x_j - x_{j-1}\right|, & otherwise \end{cases}$.

(iv) The average value of $derx(m)$ is acquired with $derx_p = [\sum_{i=1}^{N} derx_i]/N$.

(v) Binary symbolization of $x(n)$ is denoted as $bs(n) = \{bs_1, bs_2, ... bs_N\}$, which is decided by $bs_i = \begin{cases} 1, & y_i > y_p \;\; or \;\; derx_i > derx_p \\ 0, & otherwise \end{cases}$.

Thus, background activities in the original EEG signal are symbolized with ‘0’, and epileptic characteristics are expressed with ‘1’, which constitute a new series $bs(n)$. Then, Kolmogorov complexity of $bs(n)$ is calculated with the mentioned method in [0] to evaluate the dynamic features of $x(n)$.

3.2 Seizure Prediction Algorithm

The basic idea of our seizure prediction algorithm is to identify the change of brain activities from interictal state to preictal state. The decreases of Kolmogorov complexity at the electrodes near the epileptogenic focus are considered as the main identifier for preictal state. The algorithm can be described in detail as follows:

(i) Artifacts removal. Band-pass filter and morphological filter are employed to eliminate 50Hz frequency component and ocular artifact mentioned in section 2.

(ii) Electrode selection. Only electrodes near epileptogenic focus shows apparent changes when seizures are coming [0]. These electrodes are obtained knowledge through clinical diagnosis, shown in Table 1. The detailed information of the clinical EEG data for the patients will be explained in section 4.

(iii) Kolmogorov complexity computation. The Kolmogorov complexities on focal region electrodes are calculated according to the method proposed in section 3.1, with a sliding window of 40s and moving step of 3s. For comparison, Kolmogorov complexity of an electrode in remote focal area is also calculated. We take an EEG segment (SEG1) of patient 1 for example and the result is shown in Fig. 5.

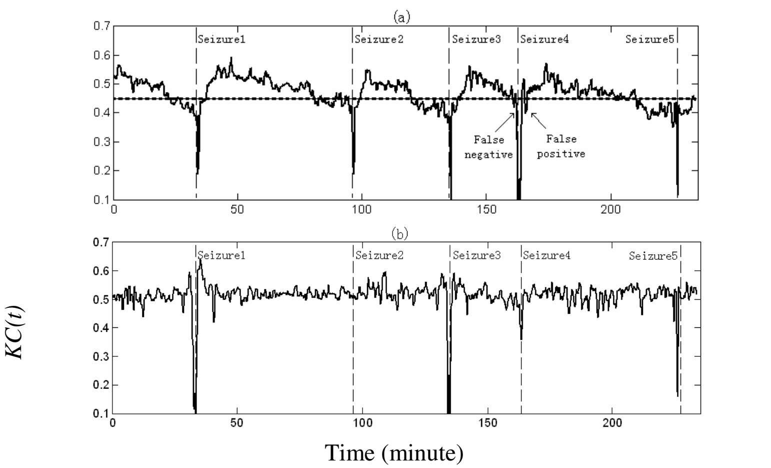

Fig. 5. Changes of Kolmogorov complexity: (a) Epileptogenic region (Fp2 and F4); (b) Remote region (C3)

Table 1. Electrodes selection

Patient	Epileptic focus	Electrodes for seizure prediction
1	Right frontal lobe	Fp2 F4
2	Right temporal lobe	F8 T4 T6
3	Left temporal lobe	T3 T5
4	Left frontal lobe	Fp1 F3
5	Left frontal lobe	Fp1 F3 F7

The change of Kolmogorov complexity in epileptogenic region is revealed in Fig. 5(a). Seizures are denoted as Seizure1, Seizure2, … and the Kolmogorov complexity at time t is denoted as $KC(t)$. The $KC(t)$ in Fig. 5(a) is an average value of Kolmogorov complexity of electrodes in focal area (Fp2, F4). We can see an obvious decrease of $KC(t)$ from several to tens of minutes before seizure. The curve reaches minimum during seizure and re-increases gradually after seizure. This phenomenon cannot be found in that of remote region (C3), as shown in Fig. 5(b).

(iv) Warning criteria. By comparing the difference of $KC(t)$ between epileptic region and remote region, we have the following criteria on seizure prediction: A warning alarm will be triggered when the average $KC(t)$ in recent 1 minute is lower than a preset threshold. In this paper, the threshold is set to 0.45.

4 Clinical Results

4.1 Data Acquisition

The clinical scalp EEG data were collected from five patients of Zhejiang Provincial People's Hospital, China, with detailed information shown in Table 2. Data acquisition system is Phoenix Unique Ambulatory EEG of EMS Handelsges.mbH company, Austria. The EEG data are amplified with band-pass filter of 0.15 - 60 Hz and the sampling rate is set to 256 Hz. Exploring cup electrodes were fixed according to the International 10 - 20 System. Video recordings are acquired synchronously with EEG, by which an experienced physician confirms the clinical onset.

Table 2. Summary of clinical data

Patient	Sex	Segment	Duration of recordings (min)	Number of seizures
1	Male	SEG1	236	5
		SEG2	119	2
2	Male	SEG3	120	2
3	Female	SEG4	60	1
		SEG5	120	3
4	Male	SEG6	179	7
5	Female	SEG7	180	9

4.2 Definition of Evaluation Criterion

An alarm can be either true or false, depending on whether it is followed by a clinical seizure or not. So, it is necessary to define a prediction range that points to the period within which a seizure is expected after an alarm. If a seizure arises after alarm within prediction range, it is defined as " true positive (TP)", otherwise regarded as "false positive (FP)". Also, if a seizure is not preceded by an alarm within prediction range, this will be thought of as "false negative (FN)". In this paper, the prediction range is determined to 15 minutes. Typical FP and FN can be found in Fig. 5(a).

Most studies have reported specificity in false prediction per hour, i.e., count all FPs and divide this number by the total duration of the recording. This definition ignores a fact that no FP will be announced in prediction range once an alarm arises. So, we employ a revised definition of specificity rates proposed in [0], which can be described as follows.

$$SPF = \frac{N_{FP} \times T_{PRE}}{T_A - N_{TP+FN} \times T_{PRE}} \tag{12}$$

where N_{FP} is the number of FPs, T_{PRE} means prediction range, T_A points to the total duration of the recording, and N_{TP+FN} denotes the number of clinical seizures. SPF indicates the portion of time from the interictal period during which a patient is not in the state of falsely waiting for a seizure.

Another assessing criterion of prediction algorithm performance is sensitivity shown in (13).

$$SEN = \frac{N_{TP}}{N_{TP+FN}} \tag{13}$$

Where N_{TP} is the number of TPs.

Finally, "Mean Prediction Time (MPT)" is utilized to evaluate the average forewarning time of the algorithm.

4.3 Statistics of Clinical Application

Using the proposed prediction algorithm in section 3, the prediction results for the EEG recordings shown in Table 2 are listed as follows.

Table 3. Prediction results of clinical data

Patient	Segment	Number of seizures	TPs	FPs	SPF (%)	SEN (%)	MPT (s)
1	SEG1	5	4	1	16.9%	80%	613
	SEG2	2	1	1	9.3%	50%	400
2	SEG3	2	1	0	0%	50%	365
3	SEG4	1	1	1	13.4%	100%	488
	SEG5	3	3	1	100%	100%	515
4	SEG6	7	5	1	20.3%	71.4%	562
5	SEG7	9	6	2	75%	66.7%	620
Total		29	21	7	33.6%	74.0%	509

The specificity is affected by factors such as duration of recordings, number of seizures and true positive. Once a patient undergoes several seizures in short time and a *FP* is announced, the interictal period decreases largely and therefore, *SPF* increases exceedingly. The result of average *SPF* indicates that the patients spend one third of their intericatal time on falsely awaiting a seizure.On the other hand, we get an average sensitivity of 74.0% and mean prediction time of more than 8 minutes, which demonstrates the validity of the proposed seizure prediction method.

5 Conclusion

In this paper, a method for epileptic seizure prediction from scalp EEG using morphological filter and Kolmogorov complexity is proposed. Firstly, the artifacts in the original signals are removed by a complex method. Baseline excursion and 50Hz frequency component are eliminated with a band-pass filter, while ocular artifact on Fp1 and Fp2 are removed with morphological filter. Thereinto, two aspects are focused on: a) clos-opening operation is utilized to extract ocular artifact in EEG data; b) the structure elements of the morphological filter are decided by two parabolas according to the geometric characteristics of ocular signals, and a new criterion is put forward to optimize the width and center amplitude of the structure elements. Secondly, a forewarning system based on Kolmogorov complexity is constructed. We present a new symbolization method to extract epileptic activities including spikes with different amplitude and slow waves, which is reasonable in clinical analysis. The proposed method is applied to 7 EEG segment from 5 epilepsy patients. Statistical results show that the mean prediction time (MPT) is 8.5 minutes, the mean sensitivity is 74.0% and specificity is 33.6%. In the future research work, we will focus on achieving sufficient sensitivity and specificity of seizure prediction techniques, and ultimately, establish an on-line prediction system based on scalp EEG.

References

1. Iasemidis, L.D., Shiau, D.S., Pardalos, P.M., Chaovalitwongse, W., Narayanan, K., Prasad, A., Tsakalis, K., Carney, P.R., Sackellares, J.C.: Long-term prospective on-line real-time seizure prediction. Clinical Neurophysiology 116, 532–544 (2005)
2. Alessandro, M.D., Esteller, R., Vachtsevanos, G., Hinson, A., Echauz, J., Litt, B.: Epileptic seizure prediction using hybrid feature selection over multiple intracranial EEG electrode contacts: a report of four patients. IEEE Trans. on biomedical and engineering 50, 603–615 (2003)
3. Corsini, J., Shoker, L., Sanei, S., Alareon, G.: Epileptic seizure predictability from scalp EEG incorporating constrained blind source separation. IEEE Trans. on biomedical and engineering 53, 790–799 (2006)
4. Hively, L.M., Protopopescu, V.A., Munro, N.B.: Enhancements in epilepsy forewarning via phas-space dissimilarity. Journal of clinical neurophysiology 22, 402–409 (2005)
5. Maragos, P., Schafer, W.: Morphological filters—part 1:Their set-theoretic analysis and relations to linear shift-invariant filters. IEEE Trans. on ASSP 35, 1153–1169 (1987)

6. Lempel, A., Ziv, J.: On the complexity of finite sequences. IEEE Trans. on information theory 22, 75–81 (1976)
7. Jia, W.Y., Kong, N., Li, F., Gao, X.R., Gao, S.K., Zhang, G.J., Wang, Y.P., Yang, F.S.: An epileptic seizure prediction algorithm based on second-order complexity measure. Physiological Measurement 26, 609–625 (2005)
8. Mormann, F., Elger, C.E., Lehnertz, K.: Seizure anticipation: from algorithm to clinical practice. Current Opinion in Neurology 19, 187–193 (2006)