Intelligence Computing Approach for Seizure Detection Based on Intracranial Electroencephalogram (IEEG)

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Abstract

Epilepsy is a neurological disorder which causes two million people in the United States for suffering. In this research, we proposed a seizure detection method based on intracranial electroencephalogram (IEEG) by using signal processing and intelligence computing approach, which combines filtering, back propagation neural network (BPNN), multi-resolution Teager energy operator (MTEO), smooth window, and data fusion. The system overall performance for detecting seizures onset is achieved 74.9% accuracy, and its specificity and sensitivity reaches 87.7% and 47.3%, respectively.

1. Introduction

Epilepsy is a neurological disorder and it can be defined as a symptom where a sudden and transient disturbance occurs in normal electrical activity of the brain [1]. There exist multiple factors to cause epilepsy such as injury of brain, diseases, light stimulation, and gene. People may have the disorder inborn; however, the epilepsy mechanism is still uncertain.

Epilepsy affects four to five percent of population some time in their life and 1% population has chronic epilepsy [2]. According to the Epilepsy Foundation of America, more than two million people in the United States have a seizure disorder. In Taiwan, especially, there are about 200 thousand people who suffered this disorder [3]. Astonishingly, patients with epilepsy have a mortality rate 2-3 times that of the general population. The epilepsy-related death rate in this population is about 40%, including the underlying disease in symptomatic epilepsy, sudden unexpected death in epilepsy (SUDEP), accidents during epileptic attack, status epilepticus, suicide, and treatment-related death [4]. The death rate is unaccepted high. The treatment methods of epilepsy may include surgery, or special diet, or an implanted system of electrical stimulation of the brain. Based on the Epilepsy Foundation of America, in about 50% to 80% of cases, seizures can be successfully controlled by appropriate medication such as anti-epileptic drugs or anti-convulsants. However, in some cases, the surgery operation is the next thought when above medication cannot control well. Then, intracranial electroencephalogram (IEEG) needs to be monitored before operation to ensure the region of seizure zone. Unfortunately, to analyze these EEG recordings is a time-consuming job for neurology physicians, so there is a need to develop such artificial intelligent (AI) analysis method for seizure onset detection. In addition, the seizure detection method may be utilized on the treatment of electrical stimulation of the brain in the future.

Electroencephalogram (EEG) has long been used as a clinical sign in the diagnosis and monitoring epilepsy. Abnormal spikes under certain conditions in EEG recordings are discriminated as a confirmation for the diagnosis of epilepsy. In order to detect the seizures onset more efficiently, the development of spike or seizure detection algorithms grow very fast nowadays. Osorio et al. [5] developed an algorithm for real-time detection of epileptic seizures based on fast wavelet transform with the Daub 4 family of wavelets and a median filter to detect seizures. In their algorithm, power spectrum density (PSD) with time sequence played an important role for distinguishing seizures. Their real-time generic method achieved high sensitivity and specificity when tested on 125 seizures contained in short segments obtained from 16 subjects.

İnan [1] used fuzzy C-means (FCM) clustering algorithm to detect epileptic spikes. The FCM based two-stage system provides 93.3% sensitivity and 74.1% specificity to detect spikes. However, their experiment data has unbalanced observation on 15 epileptic spike (ES) and 151 non-epileptic spike activities. Hence, their selectivity rate is 26.4% which means many normal brain waveforms mislabeled as ES. After calculation, their overall accuracy is 75.9%. In addition, Worrell et al. [6] suggest that high frequency epileptiform oscillation signatures appear highly localized in the seizure onset zone. The authors noted that the brief spikes of low amplitude and high frequency energy were clinically

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useful for localizing seizure onset zone. Kaiser [7-8] proposed Teager energy operator (TEO) to estimate the energy of an oscillating signal. Choi et al. [9] modified above TEO method as improved multi-resolution Teager energy operator (MTEO) detector that employs smoothing windows normalized by noise power derived from mathematical analyses. Their experimental results prove that this detector achieves higher detection ratios at a fixed false alarm ratio than the TEO detector and the discrete wavelet transform detector.

In this research, our goal is to use fusion technology to develop an intelligence computing approach to detect seizure onset from intracranial EEG, which is different with purely spike detection, such as [1]. Hall [10] indicated levels of the JDL data fusion process: source preprocessing, object refinement, situation refinement, impact assessment, process refinement, cognitive refinement (optional). In addition, back prorogation (BP) artificial neural network was involved in the framework to extract spike patterns in EEG signals that indicate the different types of epileptic conditions.

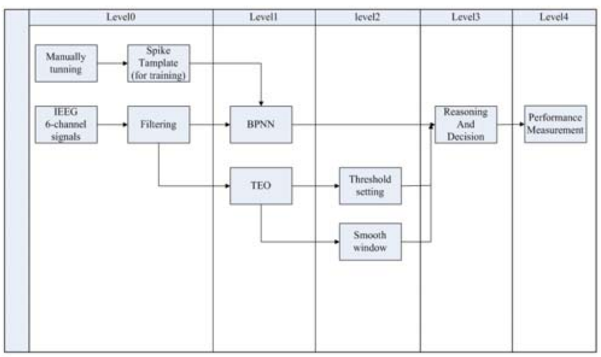

Figure 1. System structure of seizure detection

2. System Structure of Seizure Detection

The system structure of seizure detection involved the above fusion processing. Level 0 processing includes EEG signal processing and filtering. BP network and TEO provides feature extraction. Because of highly correlation between EEG channels, Level 1 processing evaluates number of spikes and TEO energy on multiple EEG channels. In Level 2, the above values are interpreted to meaning of seizure onset by setting certain number of thresholds. Level 3 processing utilizes the expert system to make decision. Level 4 processing measures the performance. However, the fusion control did not be involved in our system. Level 4 processing compute the measures of performance. The block diagram is shown is fig. 1.

3. Methodology

The methods for implementing above system structure are listed as follows:

3.1. Experiment Databases

Our experiment data came from two sources: One source comes from Tzu Chi Hospital as our training data for spike detection. The raw data of electrocorticography (ECoG) and depth EEG from patients who underwent epileptic surgery with chronic intracranial recordings were analyzed. The program developers were blind to these files.

The testing data came from FSPEEG database [11] with authorization. The FSPEEG database contains invasive EEG recordings of 21 patients suffering from medically intractable focal epilepsy. The data were recorded during invasive pre-surgical epilepsy monitoring at the Epilepsy Center of the University Hospital of Freiburg, Germany. In eleven patients, the epileptic focus was located in neocortical brain structures, in eight patients in the hippocampus, and in two patients in both. The detail information of 21 subjects is listed on Table 1. The database has sampling rate at 256 Hz and 16-bit sample rate. Notch or band pass filters have not been applied. Matlab 7.x and Visual Studio 2005 C# are used to implement our method.

Table 1. Information of 21 subjects on FSPEEG database

Patient	Sex	Age	Seizure Type	Origin	Seizures Analyzed
1	F	15	SP	Frontal	4
2	M	38	SP,CP,GTC	Temporal	3
3	M	14	SP,CP	Frontal	5
4	F	26	SP,CP,GTC	Temporal	5
5	F	16	SP,CP,GTC	Frontal	5
6	F	31	CP,GTC	Temporo/ Occipital	3
7	F	42	SP,CP,GTC	Temporal	3
8	F	32	SP,CP	Frontal	2
9	M	44	CP,GTC	Temporo/ Occipital	5
10	M	47	SP,CP,GTC	Temporal	5
11	F	10	SP,CP,GTC	Parietal	4
12	F	42	SP,CP,GTC	Temporal	4
13	F	22	SP,CP,GTC	Temporo/ Occipital	2
14	F	41	CP,GTC	Fronto/ Temporal	4
15	M	31	SP,CP,GTC	Temporal	4
16	F	50	SP,CP,GTC	Temporal	5
17	M	28	SP,CP,GTC	Temporal	5
18	F	25	SP,CP	Frontal	5
19	F	28	SP,CP,GTC	Frontal	4
20	M	33	SP,CP,GTC	Tempro/ Parietal	5
21	M	13	SP,CP	Temptral	5

SP=simple partial CP=complex partial GTC=generalized tonic-clonic

3.2. Spike template selection for ANN training process

In general, there are about 10 type epileptiform discharges. Fig. 2 listed most common types of spikes (spike, sharp wave, spike-and-wave complexes, and polyspike complex). One hundred most common spike templates and fifty background normal IEEG templates were manually selected for training. Three types of feature waves are extracted (fig. 3): up waves and down waves from epileptic spikes, background normal IEEG waves as well.

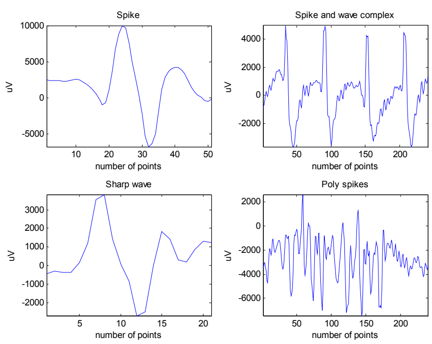

Figure 2. Four most common types of spikes (spike, sharp wave, spike-and-wave complexes, and polyspike complex)

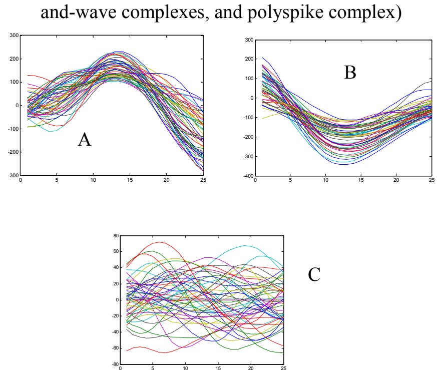

Figure 3. Training templates (A) up waves (B) down waves (C) normal EEG waves

3.3. BP Neural Network Classifier

Back propagation neural network (BPNN) is a supervised neural network. BPNN includes three layers: input layer, hidden layer, and output layer. Sigmoid function was used as activation function. Our BPNN structure for epileptic spike detection is 25-15-2. The nodes of input layer are template length n (about 25 points). In addition, there are 15 neurons for hidden layer and 2 neurons for output layer.

3.4. Teager energy operator (TEO) and smooth window

Multi-resolution teager energy operator (MTEO) [9] as shown in eq. (2) is one kind of filter to enhance action potential.

$$\psi(x(n)) = x^2(n) - x(n+k)x(n-k) \quad \ldots (1)$$

where x(n) is an IEEG signal and k is a constant. MTEO is used here because some properties of action potential waves are like to spikes. It can change the value of k to reduce noise. In this study, the tuning value k equals 10. In addition, smoothing window (eq. 2) is used to the enhance signal x^* after MTEO.

$$y(n) = \frac{\sum_{i=1}^{sw} x^*(i)}{sw} \quad \ldots \qquad (2)$$

where *sw* denotes length of window (here *sw*=50). The method is used for distinguishing seizure onset by setting threshold as 1900 μV^2.

3.5. Reasoning for Data Fusion

The reasoning for data fusion has been developed by following five principles: 1) sudden desynchronization of background EEG pattern, 2) changing of frequency into a distinct rhythm, 3) showing spiky phase of the oncoming rhythmical waves, 4) creasing in voltage of the new rhythm, and 5) propagation of the new EEG activity into adjacent regions or channels were encoded into the program for seizure onset detection and description of the seizure zone.

4. Results

For training process, 86.37% of accuracy in the seizure onset detection and the seizure zone illustration is obtained. Adding more training samples will be expected to increase the system performance.

For the testing data, all seizure durations within FSPEEG database are given. There are total of 21 IEEG recordings from different subjects and their epilepsy types are different, the number of seizure onset times is different as well. Our experiment extracted 2 minutes before and after seizure occurs (4 minutes total). Then, the data was segmented by every 10 seconds for evaluating performance of seizure detection. After above data arrangement, there are total of 348 minute EEG for processing, including 107 minute seizure onset time. The ratio of seizure onset time and non-seizure onset time is about 1/3. Table 2 showed system performance by evaluate individual data.

Table 2. System performance for each individual

Patient	Sensitivity	Specificity	Selectivity	Accuracy
1	50%	80%	38.46%	78.13%
2	70.97%	95.12%	42.73%	84.72%
3	65.21%	100%	39.47%	86.67%
4	53.13%	85.71%	38.26%	85.71%

5	0%	99.01%	0%	83.33%
6	57.89%	100%	36.37%	88.89%
7	48%	95.74%	33.39%	79.17%
8	25%	70.83%	26.09%	47.92%
9	66.67%	92.31%	41.94%	83.33%
10	0%	100%	0%	63.33%
11	85%	58.93%	59.06%	69.79%
12	52.38%	78.67%	39.97%	72.92%
13	25%	100%	20%	68.75%
14	46.51%	98.11%	32.16%	75%
15	61.11%	100%	37.93%	85.42%
16	7.96%	100%	7.14%	60%
17	85.71%	53.85%	61.41%	65%
18	80%	60.87%	56.79%	61.67%
19	20%	91.21%	17.98%	87.5%
20	83.33%	97.62%	46.05%	93.33%
21	0%	100%	0%	65%
Overall	**47.3%**	**87.7%**	**64.14%**	**74.9%**

Finally, the system overall accuracy is 74.9%, and its specificity and sensitivity are 87.7% and 47.3%, selectivity is 64.14% respectively. The reason for causing low sensitivity could be lack of number of EEG channels. The FSPEEG database only provided 6 channels (not full 20 channels) - 3 infocus and 3 outfocus channels. Because epileptic discharges would spread, so it is hard to make a decision with just few channels. However, 74.9% accuracy and 87.7% specificity means our method can be used as a non-seizure eliminator. System interface is shown in fig. 4.

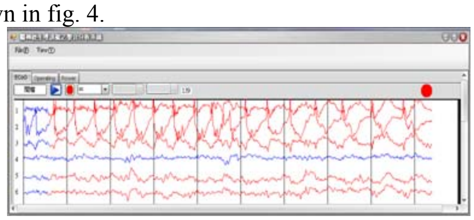

Figure 4. System interface- Once seizure is detected, the circle on the right top turn into red with sound alert. Spikes also are marked as red.

5. Conclusions and Discussions

In ANN training phase, the selected spikes should be increased to improve the system performance. However, TEO plus smooth window can detect energy change well, therefore non-seizure part is easy to identify. Background EEG has to be used for calibration to avoid those outliers with small background EEG. Small EEG amplitudes would cause high FP because the unobvious of energy changing. That cause our system marked all small amplitude EEG data as non-seizure events. Besides, the baseline wander would cause high TN because the sensitive of TEO. However, it marked input data that has heavy baseline wander as seizure.

6. Future works

Our prime aim in the near future is to develop a program and analyze patient data with the goal of finding and predicting anatomic seizure for the context of epilepsy surgical plan. Although the EEG analysis system still has room for improving, the preliminary results are encouraging. The tools developed for seizure identification should serve in future neurological expert system development, brain computer interface (BCI), or mental tasks on a patient.

7. Acknowledgements

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8. References

[1] Z. H. İnan, M. Kuntalp, A study on fuzzy C-means clustering-based systems in automatic spike detection, Computer in Biology and Medicine, vol.37, p.p.1160-1166, 2007.

[2] T. Betts, What is epilepsy? Electrical Engineering and Epilepsy: A Successful Partnership, IEE, Savoy Place, London, 1998.

[3] Pen-Jung Wang, Taiwan Epilepsy Association, vol.2-4, http://www.epilepsyorg.org.tw/contents/nice-topics01.asp?classno=204 .

[4] Shahin Nouri, Marshall Balish, et al., Sudden Unexpected Death in Epilepsy, eMedicine, http://www.emedicine.com/neuro/topic659.htm, May 17, 2006.

[5] Osorio I. Frei MG, Wilkinson SB, Real-time automated detection and quantitative analysis of seizures and short-term prediction of clinical onset, Epilepsia, vol. 39(6), p.p 616-627, 1998;.

[6] G. A. Worrell, L. Parish, and et al., High-frequency oscillations and seizure generation in neocortical epilepsy, Brain, vol.127, p.p. 1-11, 2004.

[7] J.F. Kaiser, On a simple algorithm to calculate the energy of a signal, in Proc. of ICASSP, Albuquerque, New Mexico, April 3-6, pp.381-384, 1990.

[8] J.F. Kaiser, Some useful properties of Teager's energy operators. In Proc. IEEE ICASSP, Minneapolis, Minnesota. vol. 3, pp146-152, April 1993.

[9] J. H. Choi, H. K. Jung, and T. Kim, A New Action Potential Detector Using the MTEO and Its Effects on Spike Sorting Systems at Low Signal-to-Noise Ratios, IEEE Trans. on Biomed. Eng., vol. 53, no. 4, p.p.738-746, 2006.

[10] D. L. Hall, and S. A. H. McMullen, Mathematical Techniques in Multisensor Data Fusion, 2nd ed., Artech House Inc, Norwood, MA, p.p.37-66, 2004.

[11] T. Maiwald, M. Winterhalder, R. Aschenbrenner-Scheibe and et al., Comparison of three nonlinear seizure prediction methods by means of the seizure prediction characteristic, Physica D, vol.194, p.p. 357-368, 2004.