

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

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1. Introduction

Epilepsy is a neurological disorder and can be defined as a symptom where a sudden and transient disturbance occurs in the normal electrical activity of the brain (İnan & Kuntalp, 2007). Multiple factors can trigger epilepsy, such as brain injury, disease, light stimulation, and genetics. People may be born with the disorder; however, the exact underlying epilepsy mechanism is still uncertain.

Epilepsy affects four to five percent of the world's population at some point in their lives and 1% of the world's population suffer from chronic epilepsy (Betts, 1998). According to the Epilepsy Foundation of America, more than two million people in the United States have a seizure disorder. In Taiwan, about 200 thousand people suffer from this disorder (Wang, 1998). Alarmingly, the death rate is unacceptably high, as epilepsy increases a person's risk of premature death by about two to three times that of the non-epileptic population. The epilepsy-related death rate among patients is about 40%. Causes of death include the underlying disease in symptomatic epilepsy, sudden unexpected death in epilepsy (SUDEP), accidents during an epileptic attack, status epilepticus, suicide, and treatment-related death (Nouri & Balish, 2006). Hence, the unpredictability of seizures still overshadows the lives of most epilepsy patients.

Treatment options for epilepsy may include surgery, a special diet, or a surgically implanted device which delivers electrical stimulation to the brain. According to the Epilepsy Foundation of America, seizures can be successfully controlled by appropriate medication such as anti-epileptic drugs or anti-convulsants in about 50% to 80% of cases. However, for patients who do not respond well to medication, surgery is the next best option.

Due to the risks associated with the unpredictability of epilepsy, epileptic seizure detection is critically important to physicians. Nowadays, video- Electroencephalogram (EEG)-monitoring is the gold standard for the diagnosis of epilepsy. EEG is the recording of electrical activity produced by the firing of neurons within the brain, and has long been used as a clinical test in the diagnosis and monitoring of epilepsy. Prior to surgery, intracranial electroencephalogram (IEEG) needs to be monitored in order to confirm the seizure zone. Unfortunately, analyzing these EEG recordings is a time-consuming task for neurology physicians, and patterns indicating epilepsy can sometimes be confused with

those of other disorders producing similar seizure-like activity (Kalaycı & O'zdamar, 1995). Hence, there is a strong need to develop an artificial intelligent (AI) system for epileptic seizure detection.

Osorio et al. (Osorio, Frei, & Wilkinson, 1998) developed an algorithm for real-time detection of epileptic seizures based on the fast wavelet transform with the Daub 4 family of wavelets and a median filter to detect seizures. In their algorithm, power spectral density (PSD) in a time sequence played an important role in distinguishing seizures. Their real-time method achieved high sensitivity and specificity when tested on 125 seizures in short time segments from 16 subjects. Tezel (Tezel & o'zbay, 2009) presented three neural network models with different adaptive activation functions (NNAAF) within hidden neurons to detect epileptic seizures. Activation functions included the sigmoid function, sum of sigmoid function and sinusoidal function, and Morlet Wavelet function. Previous research (Wongsawat, 2008) also demonstrated the use of phase congruency to robustly detect epileptic seizure, calculated using Log-Gabor wavelets. The number of spikes detected from the phase congruency of two classes of EEG data (epilepsy and seizure-free) were used as distinctive features. In addition, Worrell et al. (Worrell et al., 2004) suggested 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 useful for localizing the seizure onset zone. Kaiser's (Kaiser, 1990, 1993) proposed the Teager energy operator (TEO) to estimate the energy of an oscillating signal. Choi et al. (Choi, Jung, & Kim, 2006) modified Kaiser's TEO method with an 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 both the TEO detector and the discrete wavelet transform detector.

In response to the need for detecting seizure onset more efficiently, the development of spike or seizure detection algorithms has grown rapidly. Abnormal spikes under certain conditions in EEG recordings are indicators used for the diagnosis of epilepsy (Kiloh, McComas, Osselton, & Upton, 1981; Niedermeyer & Silva, 1993), so abnormal spike detection plays a crucial role in epileptic seizure detection. İnan et al. (İnan & Kuntalp, 2007) applied the fuzzy C-means (FCM) clustering algorithm on certain epileptic spike features, such as time durations. The FCM based two-stage system provides a 93.3% sensitivity and 74.1% specificity to detect spikes (a total of 166 individual waves with 15 epileptic spike and 151 non-epileptic spike activities). However, the selectivity of spikes was only 26.4%, which means that just over 1/4 of all waves labelled as epileptic spikes were truly epileptic spikes. Xu et al. (Xu, Wang, Zhang, Zhang, & Zhu, 2007) tried to solve the same problem by using an improved morphological filter and comparing it to the traditional morphological filter and wavelet analysis using the Mexican hat function. Their method results in a 7.52% overall false detection rate based on 957 spikes.

2. Fusion System Structure of Epileptic Seizure Detection

In this chapter, the goal is to use fusion technology (Hall & McMullen, 2004) to develop an intelligence computing approach to detect seizure onset from intracranial EEG (IEEG), which is different from pure spike detection (İnan & Kuntalp, 2007; Xu et al., 2007). The fusion technology indicates levels of the Joint Directors Of Laboratories (JDL) data fusion

process through source preprocessing, object refinement, situation refinement, impact assessment, process refinement and cognitive refinement (optional (Bosse, 2007)).

The system structure of seizure detection for the above fusion processing begins with Level 0 processing, which includes EEG signal processing and filtering. Because of the high correlation between EEG channels, Level 1 processing evaluates the number of spikes and TEO energy on multiple EEG channels. Back propagation artificial neural network (BPNN), fuzzy C-means (FCM), ant colony k-means (AK) and TEO provide for feature extraction. In Level 2 processing, the above values are interpreted to mean seizure onset by meeting a certain number of thresholds. Level 3 processing utilizes the expert system to make a decision. Level 4 processing measures the performance. However, fusion control is optional in this system. The block diagram is shown in fig. 1. In Level 1, Either BPNN, FCM or AK was applied and compared to the framework to extract spike patterns in EEG signals indicating different types of epileptic conditions.

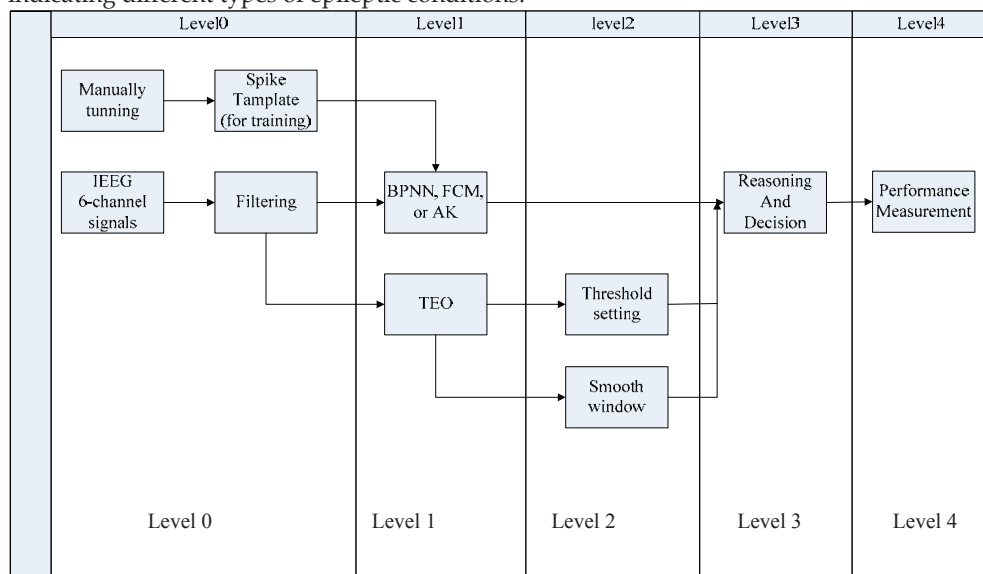


Fig. 1. Fusion system structure of seizure detection

3. Methodology

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

3.1 Experiment Databases

Our experimental data came from two sources. The training data for spike detection came from Tzu Chi Hospital in Taiwan. 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 electroencephalography came from the FSPEEG database (Aschenbrenner-Schiebe et al., 2003; Maiwald et al., 2004; Winterhalder et al., 2003) with authorization. The

data were recorded during invasive pre-surgical epilepsy monitoring at the Epilepsy Center of the University Hospital of Freiburg, Germany. The EEG database contains invasive EEG recordings of 21 patients suffering from medically intractable focal epilepsy. Of the 21 patients, 11 have their epileptic focus locations in neocortical brain structures, 8 in the hippocampus, and 2 in both. Detailed information on the 21 subjects is listed in Table 1. The database has a sampling rate of 256 Hz with 16-bit resolution without notch or band pass filters applied at the beginning. Matlab 7.x (Mathworks Inc.) and Visual Studio 2008 C# (Microsoft Inc.) were used for implementation.

Patient	Sex	Age	Seizure Types	Regions	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	Temporo/Parietal	5
21	M	13	SP,CP	Temptral	5

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

Table 1. Summary of 21 subjects on FSPEEG database

3.2 Level 0: Filtering and Spike Template Selection for Training Process

Unlike other databases, the database: was recorded directly from focal areas, benefiting from the advantage of a high signal-to-noise ratio. Nonetheless, there was still a need to remove power-line interference, signal-line stretch, and baseline wander artifacts for signal quality assurance. Hence, three digital filters were applied, including a 50/60Hz notch filter, a 0.1-70Hz band pass filter, and a median filter.

In general, there are about 10 types of epileptiform discharges. Fig. 2 lists the most common types of spikes (spike, sharp wave, spike-and-wave complexes, and polyspike complex). Fifty of the most common spike templates and fifty background normal IEEG templates were manually selected for training purposes.

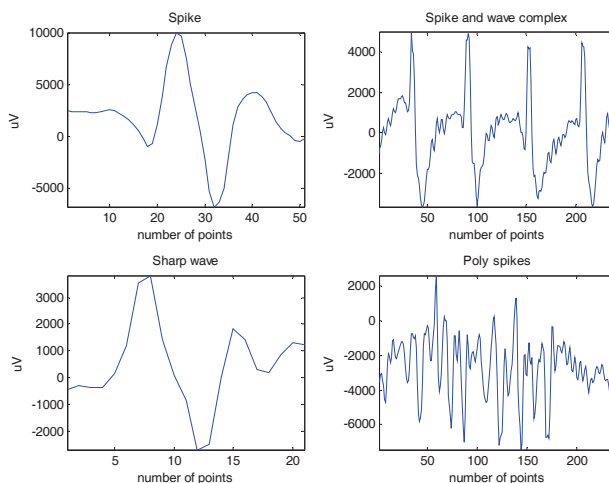


Fig. 2. Four most common types of spikes (spike, sharp wave, spike-and-wave complexes, and polyspike complex)

Our neurology expert carefully marked typical epilepsy spikes and non-spikes for algorithm development. In Fig. 3, three types of feature waves were extracted from templates, including up waves and down waves from epileptic spikes and background normal IEEG waves were extracted, as well as up waves and down waves from epileptic spikes and background normal IEEG waves.

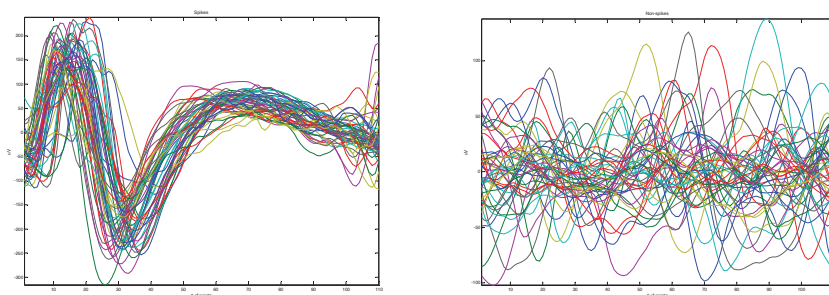


Fig. 3. Training templates typical spikes (left) and non-spikes (right)

For the following sections, three intelligent computing techniques (BP, FCM and AK) are introduced.

3.3 Level 1: Spike Pattern Recognition

As mentioned, epileptic spike detection methods can be categorized as: (1) morphology-based and (2) feature-based. The concept of the morphology-based method is to compare the entire spike waveform to a spike template. Any spike waveforms close to the template are

classified as epileptic spikes. The other distanced waveforms are distinguished as normal IEEG. In comparison, the concept of the feature-based method is to extract possible spike features from IEEG waveforms for classification. The following computational intelligence methods are able to be applied on both categories.

3.3.1 Back propagation neural network

Back propagation neural network (BPNN) (Haykin, 2008) is a supervised neural network. BPNN is a well-known artificial neural network. BPNN includes three layers: the input layer, hidden layer, and output layer as show in fig. 4.

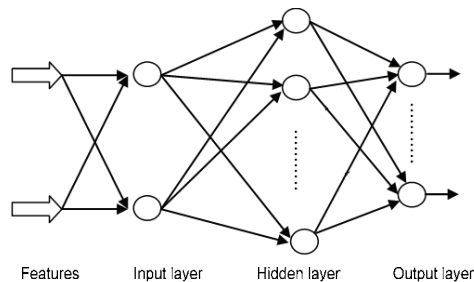


Fig. 4. Three layers in BPNN

The sigmoid function was used as an activation function. The output of the j -th neuron in the output layer is given by

$$Y_j = f(\text{net}_j^Y) \quad (1)$$

where net_j^Y is the sum of the j -th neuron in the output layer

$$\text{net}_j^Y = \sum_h W_{hj}^{HY} H_h + \theta_j^Y \quad (2)$$

where W_{hj}^{HY} is the weight between the h -th neuron in the hidden layer and the j -th neuron in the output layer, H_h is the output of the h -th neuron in the hidden layer, θ_j^Y is the bias of the j -th neuron in the output layer. One output neuron indicates epileptic spikes, and the other output neuron represents normal EEG rhythms. The output of the h -th neuron in the hidden layer is given by

$$H_h = f(\text{net}_h^H) \quad (3)$$

where net_h^H is the sum of the h -th neuron in the hidden layer

$$\text{net}_h^H = \sum_i W_{ih}^{XH} X_i + \theta_h^H \quad (4)$$

where W_{ih}^{XH} is the weight between the i -th neuron in the input layer and the h -th neuron in the hidden layer, X_i is the i -dimensional input data, θ_h^H is the bias of the h -th neuron in the hidden layer. Our BPNN structure for epileptic spike detection is N-15-2, meaning that the template length is N with 15 neurons in the hidden layer and 2 neurons in the output layer.

3.3.2 Fuzzy C-means clustering

Fuzzy C-means is an algorithm that follows the same steps as the k-means (Haykin, 2008) algorithm. However, instead of binary indicators, FCM applies degrees of memberships as indicators. This method finds the minimum distance D between input vector x and specific classes.

$$D = \frac{1}{M} \sum_{i=1}^M d_{\min}(x_i) \tag{5}$$

The main procedures are as follows,

1. Initialize the indicators to make the sum of indicators equal to one

$$\sum_{j=1}^M I_{ji} = 1, \forall j = 1, \dots, n \tag{6}$$

2. Calculate the codebook w_i by using indicators and input vector x

$$w_i = \frac{\sum_{j=1}^n I_{ji}^m x_j}{\sum_{j=1}^n I_{ji}^m} \tag{7}$$

3. Re-compute the new indicators by using new codebook w_i

$$I_{ji} = \frac{1}{\sum_{s=1}^k \left(\frac{\|x_j - w_i\|}{\|x_j - w_s\|} \right)^{\frac{2}{m^*-1}}} \tag{8}$$

where m^* is set as 2.

4. The distance of fuzzy C-means is calculated by

$$D = \sum_{i=1}^M \sum_{j=1}^n I_{ji}^m \|x_j - w_i\|^2 \tag{9}$$

Then run steps 1 through 4 until all codebooks are convergent.

3.3.3 Ant K-means clustering (AK)

Ant colony optimization (ACO) is a recently proposed metaheuristic approach for solving hard combinatorial optimization problems (Dorigo & Stützle, 2000). In particular, the ant k-means (AK) clustering method is one branch of the biomimetic approach proposed by R.J. Kuo (Kuo, Wang, Hu, & Chou, 2005). Instead of using general clustering methods, biomimetic computing is a biology-inspired technology which is flourishingly used in system modeling, social science, and artificial intelligence (AI). This method simulates the interaction of an ant society to solve clustering problems without using any machine training processes. This self-organized structure is based on a certain probability, so-called pheromone, and results in a robust clustering method. It is proved that this method can be

applied to many different kinds of clustering problems, or combined with data mining techniques to achieve more promising results in other industries (Kuo et al., 2005).

Ants exhibit many characteristics that solve different problems. As mentioned, ACO is an approach for solving optimization problems, and the ant k-means deals with clustering problems. The main idea behind the ants algorithm depends on a chemical material called "pheromone." A higher pheromone concentration guides ants toward their clustering targets. On the other hand, pheromone naturally evaporates over time, so that longer travel paths can cause low pheromone concentration. Hence, the optimal path is guaranteed. This kind of self-organized social behavior is applied to solve clustering problems by constructing the best pathway for clustering. The AK algorithm assigns each data point to a specific cluster (class) and each ant gives its own clustering solution. Ants aggregate to centers of classes by a probability P .

$$P_{ij}^k = \frac{\tau_{ij}^\alpha \eta_{ij}^\beta}{\sum_{l=1}^c \tau_{il}^\alpha \eta_{il}^\beta} \quad (10)$$

where τ is the pheromone, η is the inverse of the distance between the two points, α is the relative importance of the trail ($\alpha \geq 0$), β is the relative importance of the visibility ($\beta \geq 0$), c is the cluster, and n_c is the number of clusters. After m ants have done their clustering, the best solution is chosen and assigned a new pheromone.

$$\tau_{ij}(n+1) = (1-\rho)\tau_{ij}(n) \times \frac{Q}{\text{TWCV}} \quad (11)$$

where ρ is the pheromone decay parameter ($0 < \rho < 1$), Q is a constant, TWCV is the total within cluster variance. By continuing this process, the clusters are distinguished. The new centers are calculated by Eq. 13.

$$\sum_{k=1}^c \sum_{i \in T_k} (O_i - O_{\text{center}}(T_k))^2 \quad (12)$$

where O_i is the i -th data, and T_k is the ant set T within class k .

The steps of the algorithm are described below::

1. Initialize pheromone (equal to 1), the number of clusters (k) and number of ants (m).
2. Initialize m ants to k different random cluster centers.
3. For each ant, let each input vector x belong to one cluster with the probability given in Eq. 10.
4. Calculate new cluster centers.
5. If the TWCV is changed, go to next step. Otherwise, go to Step 3.
6. Update the pheromone level in all data according to the new solution.
7. Update cluster centers according to the new solution.
8. If the distances of cluster centers to zero or less than ε , merge the centers.
9. If the termination criterion is satisfied, go to the next step. Otherwise, go to Step 3.
10. Output the clustering results.

Various clustering techniques with no training process required have been widely applied in many fields, including gene selection and expression (Liu, Wan, & Wang, 2006; Tseng & Kao, 2005), artificial intelligence, and epileptic spike detection. Thus, it is necessary to understand the advantages and limitations among various clustering techniques (k-means, FCM, and

AK). Hence, the UC Irvine Machine Learning Repository database was tested to compare three clustering algorithms (kmeans, FCM, and AK). Table 2 lists the investigated databases and their descriptions and Table 3 compares the accuracy among various clustering algorithms. Promisingly, the results show that the AK method provided the best overall results in those datasets.

Machine learning datasets	Number of instances	Number of attributes	Number of classes
Iris	150	4	3
Lung Cancer	32	56	3
Breast Cancer Wisconsin (Diagnostic)	569	32	2
Wine	178	13	3
Pen-Based Recognition of Handwritten Digits	10992	16	10

Table 2. Machine learning database description

Name of dataset	AK	Kmeans	FCM
Iris	90.66%	70.88%	84.64%
Lung Cancer	62.34%	50%	48.15%
Breast Cancer Wisconsin (Diagnostic)	90.54%	85.41%	88.05%
Wine	70.22%	65.36%	69.67%
Pen-Based Recognition of Handwritten Digits	71.48%	45.24%	28.69%

Table 3. Accuracy comparison on various clustering algorithms

The Iris dataset, which contains 3 classes, can be used to illustrate an example. One class is linearly separable, while the others are non-linearly separable. In this dataset, the AK method demonstrated the best performance compared to the k-means and FCM algorithms. Both the AK and FCM algorithms process non-linear datasets with a high degree of accuracy. Fig. 5 plots the Iris dataset with two attributes (1&2) for visualization. The k-means algorithm works well when handling linearly separable distributions, but the AK and FCM algorithms have an advantage by being able to separate non-linearly separable data. Due to the pheromone factor, performance of AK improved dramatically.

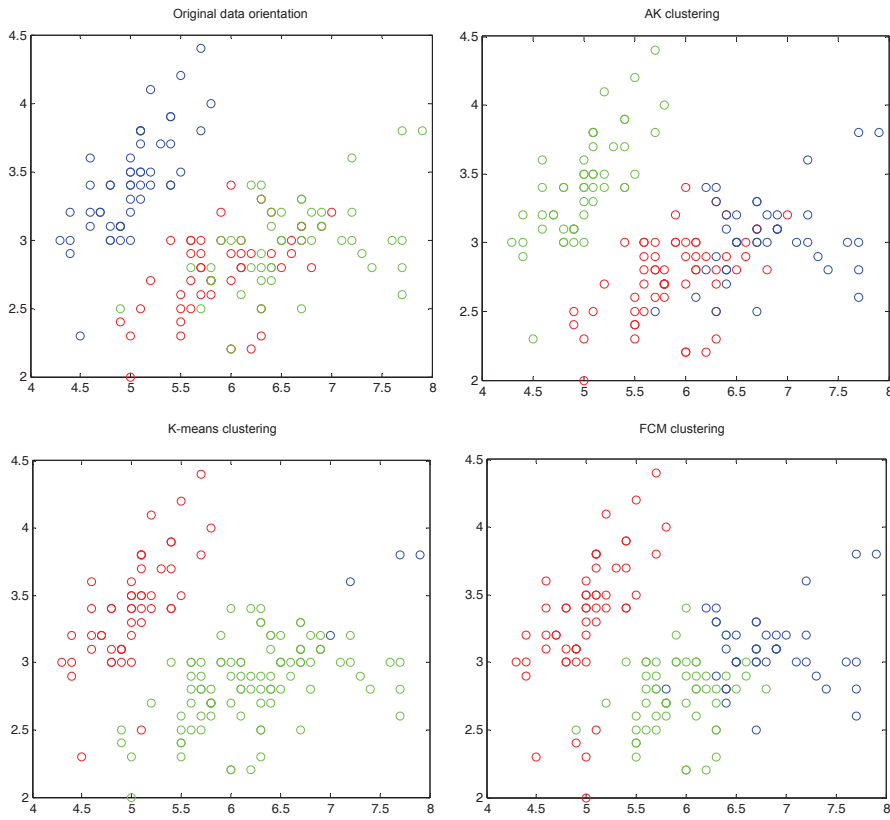


Fig. 5. Comparison of the cluttering results among AK, K-means, and FCM methods

3.4 Level 1 & 2 Teager Energy Operator (TEO) And Smooth Window

Multi-resolution teager energy operator (MTEO)(Choi et al., 2006) as shown in Eq.13 is one kind of filter to enhance action potential.

$$x^*(n) = \psi(x(n)) = x^2(n) - x(n+k)x(n-k) \tag{13}$$

where $x(n)$ is an IEEG signal and k is a constant. MTEO is used here because some properties of action potential waves are similar to spikes. It can also change the value of k to reduce noise. In addition, smoothing window is used to the enhance signal x^* after MTEO as follows,

$$y(n) = \frac{\sum_{i=1}^{SW} x^*(i)}{SW} \tag{14}$$

where sw denotes length of window (here $sw=50$). The method is used for distinguishing seizure onset by setting the threshold to $1900 \mu V^2$.

3.5 Level 3: Reasoning for Data Fusion

The reasoning behind data fusion is based on the following five principles: 1) sudden desynchronization of background EEG pattern, 2) changing of frequency into a distinct rhythm, 3) showing the spiky phase of the oncoming rhythmical waves, 4) increasing 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. Level 4. Performance Measurement and Results

Using the training dataset, an accuracy rate of 86.37% and 97.33% for seizure onset detection and seizure zone illustration was obtained with the BPNN-based and AK-based systems, respectively. It must be noted however, that BPNN was under supervised learning and AK was a non-supervised learning process, so the training dataset for the AK-based system is for comparison purposes only. Adding more training samples for BPNN is expected to increase the system performance.

In the testing data, all seizure durations within the FSPEEG database were given. There were a total of 21 IEEG recordings from different subjects, each with different types of epilepsy and varying seizure onset times. For the performance evaluation purpose, our extracted the 2 minutes before and after seizure occurrence (4 minutes total). The data was then divided into 10-second segments for evaluating performance of seizure detection. After arranging the data, there was a total of 348 minutes of EEG for processing, including 107 minutes of seizure onset. The ratio of seizure onset time to non-seizure onset time is about 1/3. Table 4 shows the morphology-based system performance as an example by evaluating each individual's data. Accuracy, sensitivity, and specificity are general indexes for performance measurement.

$$\text{Sensitivity} = \frac{TP}{TP+FN} \times 100\% \quad (15)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \times 100\% \quad (16)$$

where, TP-true positive is the number of epileptic seizure (ES) waves correctly detected by the system, TN-true negative is the number of non-ES waves correctly detected by the system, FP-false positive is the number of waves incorrectly labeled as ES activity by the system, and FN-false negative is the number of waves incorrectly labeled as non-ES activity by the system.

Patient #	Sensitivity		Specificity		Accuracy	
	BPNN	AK	BPNN	AK	BPNN	AK
1	50%	66.67%	80%	68.89%	78.13%	68.75%
2	70.97%	54.84%	95.12%	92.68%	84.72%	76.39%
3	65.21%	62.79%	100%	97.26%	86.67%	84.48%
4	53.13%	69.77%	85.71%	87.01%	85.71%	80.83%
5	0%	15.79%	99.01%	95.05%	83.33%	82.5%
6	57.89%	35%	100%	100%	88.89%	91.94%
7	48%	33.33%	95.74%	80.43%	79.17%	59.76%
8	25%	50%	70.83%	70.83%	47.92%	60.42%
9	66.67%	16.67%	92.31%	91.03%	83.33%	65%
10	0%	34.09%	100%	90.79%	63.33%	70%
11	85%	80%	58.93%	69.64%	69.79%	73.96%
12	52.38%	45%	78.67%	88.16%	72.92%	79.17%
13	25%	50%	100%	92.86%	68.75%	75%
14	46.51%	30.23%	98.11%	90.57%	75%	63.54%
15	61.11%	19.44%	100%	81.67%	85.42%	58.33%
16	7.96%	28.85%	100%	97.06%	60%	67.5%
17	85.71%	33.33%	53.85%	96.15%	65%	47.17%
18	80%	80%	60.87%	80%	61.67%	80%
19	20%	40%	91.21%	89.01%	87.5%	86.46%
20	83.33%	40%	97.62%	95%	93.33%	76.67%
21	0%	13.95%	100%	93.51%	65%	65%
Overall	47.3^o	40.1^o	87.7^o	88.2^o	74.6^o	73.2^o

Table 4. System performance of ten-second window periods for two morphology-based methods.

Based on our results, the morphology- AK based method performs the promising results. In Fig. 6, upper and lower figures show the spike and normal templates in sequence (250, 500, and 1000 epochs if thirty ants were chosen), respectively. Each process loop includes random data selecting, centers computing, and pheromone updating.

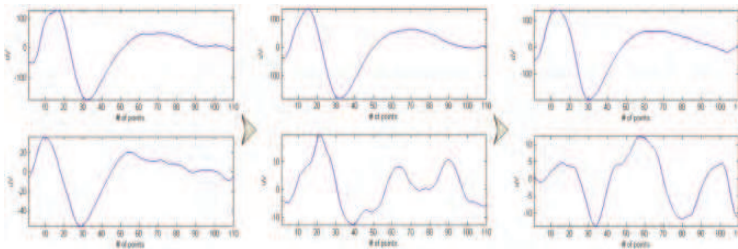


Fig. 6. In AK process, from left to right, it shows the results when 250, 500, and 1000 epochs applied.

Hence, the method is also applied on FSPEEG database and the method detects epileptic spikes accurately in Fig 7.

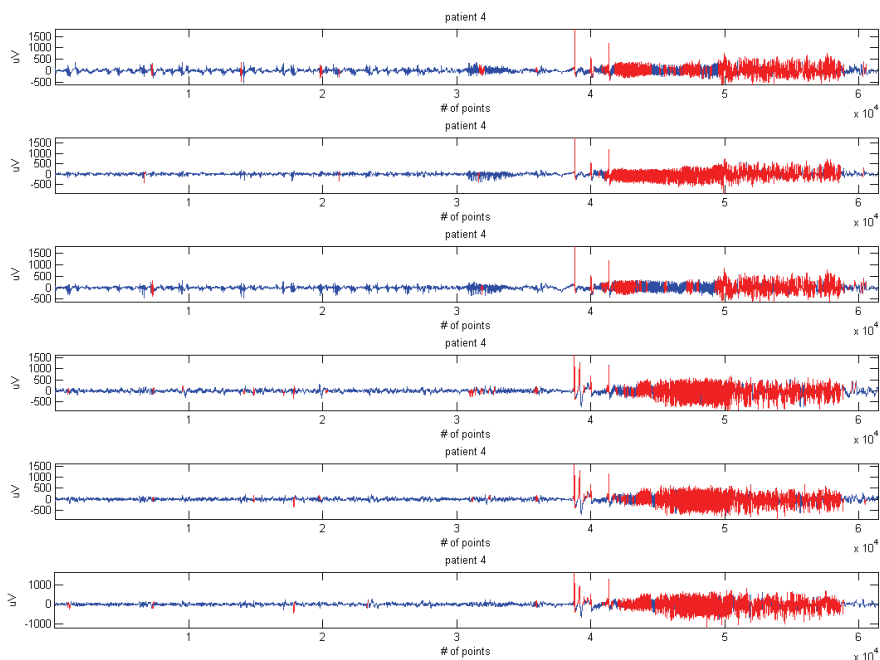


Fig. 7. Applied morphology-AK based method on FSPEEG database for six-channel IEEG: The red waveforms indicate spikes which are detected accurately.

The BPNN based system has an overall accuracy of 74.6%, with a specificity and sensitivity of 87.7% and 47.3%, respectively. The AK based system has an overall accuracy of 73.2%, with a specificity and sensitivity of 88.2% and 40.1%, respectively. The reason behind low sensitivity could be due to the lack of EEG channels. The FSPEEG database provided 6 channels (instead of the full 20 channels) - 3 infocus and 3 outfocus channels. Because epileptic discharges spread, it is hard to make a decision based on just a few channels. However, the 74.9% accuracy and 87.7% specificity means that our method can be used as a non-seizure eliminator. If the system performance only considers whether the seizure is detected during the ictal stage, the BPNN-based and AK-based systems provide a detection rate of 90.5% (19 out of 21) and 100% (21 out of 21), respectively. Fig.8. shows that the fusion system for epileptic seizure detection is implemented by Visual Studio 2008 C#.

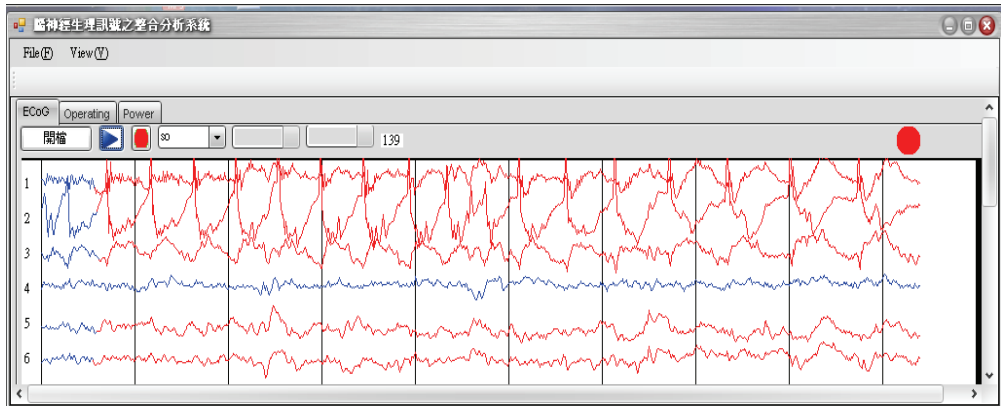


Fig. 8. System interface: Once seizure is detected, the circle on the right top turns into red with sound alert. Spikes also are marked as red.

5. Conclusion and Discussion

It has to be noted that the BPNN-based system has 0% sensitivity and almost 100% specificity for patients #5, 10, and 21. This means that the system missed the seizure completely and marked it as a non-seizure. However, in the AK-based system, no 0% sensitivity cases appeared. This means that although the system may not detect seizure onset during its entire time period, the epileptic seizure can be detected at some point during the seizure occurrence. Overall, the two systems have different characteristics in seizure detection. Overall, the ant k-means (AK) provide an effective, accurate, and adaptive method for spike detection. In addition, no training or pre-knowledge is required on AK algorithm. However, unlike traditional k-means, ant k-means reaches higher accuracy because ant k-means has the pheromone probability to jump out of the local minima. The result shows that AK worked successfully well in our epilepsy patient data.

In the BPNN training phase, the selected spikes should be increased to improve system performance. However, the TEO plus smooth window can detect energy change well, and therefore, the non-seizure part is easy to identify. Background EEG must be used for calibration to avoid outliers with small background EEG. Small EEG amplitudes cause high FP because of the subtle energy change. This caused our system to label all small amplitude EEG data as non-seizure events. Moreover, the baseline wander would cause high TN due to the sensitivity of TEO. However, the system marked input data with heavy baseline wander as seizures.

6. Future research

Although the epileptic seizure detection system still has room for improvement, the preliminary results are encouraging. Future research may focus on predicting anatomic seizure in the context of an epilepsy surgical plan. Seizure prediction (Aschenbrenner-Schiebe et al., 2003; Winterhalder et al., 2003) is essential because of the various aspects associated with the disorder, including diagnosis, treatment options, physical risks, social

implications, loss of self-efficacy, depression and anxiety. Risks of delaying a correct diagnosis through this method occur among patients who meet a physician infrequently in the interictal state. In addition, seizure prediction provides a new way for drug treatment to maximize intended drug effects, minimizes possible side-effects, and can serve as a guide toward developing an effective acute intervention in the early phase (Schelter, Timmer, & Schulze-Bonhage, 2008); Early diagnosis is beneficial, because long-term antiepileptic treatment increases a person's risk of premature death, can have hormonal effects on fertile females, trigger liver failure, and cause mood disorders. Unfortunately, seizure prediction with a time horizon of minutes to hours remains a challenge and a clinically applicable solution is still not available. The tools developed for seizure identification should serve in future neurological expert system development, brain computer interface (BCI), or investigation of mental tasks by a patient.

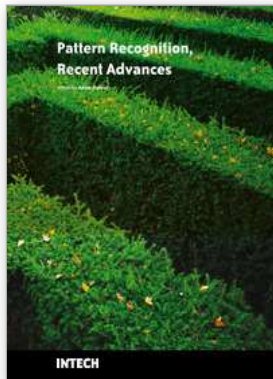
7. Acknowledgements

This research is supported by Tzu Chi University / General Hospital and the project serial number is TCMRC-P-97006. Thanks to Dr. Yue-Loong Hsin and Dr. Tomor Harnod in the Department of Neurology of Tzu Chi Hospital for providing the necessary support. Also special thanks to group researchers of the University Freiburg and the University Hospital Freiburg in providing the EEG database (<https://epilepsy.uni-freiburg.de/>) for this research.

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Pattern Recognition Recent Advances

Edited by Adam Herout

ISBN 978-953-7619-90-9

Hard cover, 524 pages

Publisher InTech

Published online 01, February, 2010

Published in print edition February, 2010

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Tsu-Wang Shen and Xavier Kuo (2010). Intelligence Computing Approaches for Epileptic Seizure Detection Based on Intracranial Electroencephalogram (IEEG), Pattern Recognition Recent Advances, Adam Herout (Ed.), ISBN: 978-953-7619-90-9, InTech, Available from: <http://www.intechopen.com/books/pattern-recognition-recent-advances/intelligence-computing-approaches-for-epileptic-seizure-detection-based-on-intracranial-electroencep>

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