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Seizure Detection in Intracranial EEG Using a Fuzzy Inference System

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***Abstract*— In this paper, we present a fuzzy rule-based system for the automatic detection of seizures in the intracranial EEG (IEEG) recordings. A total of 302.7 hours of the IEEG with 78 seizures, recorded from 21 patients aged between 10 and 47 years were used for the evaluation of the system. After preprocessing, temporal, spectral, and complexity features were extracted from the segmented IEEGs. The results were thresholded using the statistics of a reference window and integrated spatio-temporally using a fuzzy rule-based decision making system. The system yielded a sensitivity of 98.7%, a false detection rate of 0.27/h, and an average detection latency of 11 s. The results from the automatic system correlate well with the visual analysis of the seizures by the expert. This system may serve as a good seizure detection tool for monitoring long-term IEEG with relatively high sensitivity and low false detection rate.**

I. Introduction

Epilepsy is a neurological disorder that affects 1% to 3% of the world population. Seizures are clinical manifestations of abnormal neuronal discharges of the brain [1]. Electroencephalography (EEG) is one of the most efficient tools in the diagnosis of epilepsy.

Traditionally, the long-term EEG has to be visually inspected by the expert to identify seizures. This is a time consuming task and human errors can not be avoided. Over the past three decades, great progress has been made for automatic seizure detection in the EEG with different degrees of success [2]-[5]. The detection methods usually use some rules for integrating temporal and spatial information extracted from raw EEG. These rules are established based on the expert's reasoning to make decisions for seizure detection. The rules are not strict and can be adapted to tolerate the interpatient variability in interictal and ictal activities, and to differentiate interictal epileptiform discharges from ictal activities. For this purpose, a fuzzy logic system can provide a suitable framework to deal with pattern recognition problems whose decision boundaries are fuzzy with gradual class membership [7]-[8]. Another advantage of the fuzzy rule-based systems is the ability to design an expert rule-based interface between features formulated using linguistic information and quantitative measurements [9].

In this paper, we present a fuzzy rule-based tool for detection of epileptic seizures in the IEEG. The system comprises three stages: 1) preprocessing including bandpass filtering and segmentation, 2) feature extraction, and 3) rule-based decision-making. The following sections detail the stages of the system.

II. Materials and Method

We analyzed IEEG recordings from 21 patients with medically intractable focal epilepsy. The IEEG data used in this study were obtained from the Freiburg Seizure Prediction EEG (FSPEEG) database with authorization [10]. The seizure onset and offset have also been determined by the expert based on identification of epileptic patterns preceding clinical manifestation of seizures in IEEG recordings. In total, for all patients, 302.7 h of 4-channel bipolar IEEG recordings containing 78 seizures with an average duration of 121 s (range 9-411 s) were analyzed.

Our seizure detection system comprises three main stages: preprocessing and artifact detection, segmentation and feature extraction, and decision-making as shown in Fig. 1.

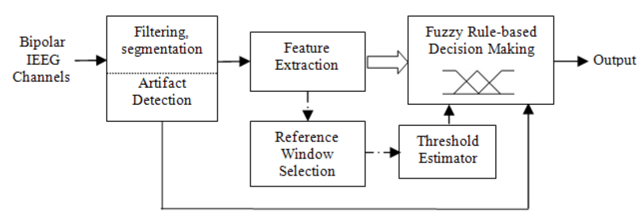

Fig. 1. Block diagram of the seizure detection system.

The IEEG data were bandpass filtered between 0.5 and 100 Hz and notched to remove the 50-Hz line noise. To improve the detection accuracy and to minimize the false detection rate, we used an artifact detection algorithm. First, IEEG parts with constant amplitudes were marked as saturation artifacts. Then, the IEEG segments containing signal with amplitude larger than 1500 μV were considered as movement artifacts.

A. Feature Extraction

To analyze the data, first the IEEG were segmented using a moving window of 2.5 s with 0.5 s overlap between windows.

Then, four features, entropy, dominant frequency,

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average amplitude and coefficient of variation of amplitude were extracted from the IEEG segments for each of the bipolar channels separately [2]-[3], [6], [11].

Entropy: Entropy, a measure of "irregularity" or "uncertainty", was initially introduced by Shannon [12]. To compute the entropy for short and noisy time series data, in this paper, we used Sample Entropy (SampEn), a variant of the ApEn to calculate the entropy feature for each IEEG segment [13].

Dominant Frequency: In the spectrum of a signal, the dominant frequency (f_Δ) is defined as the peak with maximum spectral power. In this study, to find the dominant frequency for each IEEG segment, first the spectral frequency band was determined by autoregressive (AR) modeling. We used Akaike's information criterion (AIC) to determine the appropriate AR model order for a good approximation of the shape of the spectrum [14]. We considered this order to be the maximum of the orders estimated for seizure and non-seizure segments (20 in this study). The Burg method was used for extracting AR coefficients. Then, the spectral power of each segment was estimated by the AR coefficients. For every spectral peak, the spectral frequency band is defined in [f_l , f_h] where f_l and f_h are the left- and right-side frequencies of the peak, with amplitudes equal to half the amplitude of the peak [4].

Average Amplitude: To calculate this feature, every IEEG segment was highpass filtered above 3 Hz to remove low-frequency activities. Then, all peaks were detected using a peak detection algorithm based on zero-crossings of the first derivative of the IEEG signal. The amplitudes of the peaks were computed by averaging the amplitudes of their half waves. Then, the average of the peak amplitudes was computed as the average amplitude feature (μ_{am}) [4],[11].

Rhythmicity: Seizures are characterized by the rhythmicity. The coefficient of amplitude variation gives a measure of rhythmicity of the ictal signal. The coefficient of variation was computed as:

$$\delta_{cv} = \frac{A_{std}}{A_\mu} \tag{1}$$

where A_{std} and A_μ are the standard deviation and mean of the amplitudes of the IEEG segment, respectively.

A. Decision Making

A fuzzy inference system used as the intermediate decision-maker was designed to relate feature values and the least number of segments necessary to declare any preliminary seizure detection. The intermediate decision maker works on a single channel basis. For each channel, a sub-system produced a single output that was defuzzified using the fuzzy sets. This subsystem receives two input variables with crisp values. The first input is features (F_i) extracted from the segments of the IEEG bipolar channels and the second input is the number of consecutive segments exhibiting the same feature level (N_s).

Before fuzzifying feature variables, first, they were normalized to the reference statistics calculated as follows. For each IEEG recording, a relatively long seizure-free reference window (300 s) was selected from the beginning of the IEEG recording with the same starting time for all bipolar channels. Then, for any given feature and channel, we calculated the mean μ and standard deviation σ over the feature values extracted from the segments within the reference window. The feature values for all the IEEG segments for the same channel were normalized as $\widehat{F}_{ik} = \left|\frac{F_{ik} - \mu}{\sigma}\right|$ where F_{ik} is the value of the given feature for the *ith* segment and *kth* channel. The $\widehat{F}_{ik}$ values were fuzzified using three membership functions, negative (N), zero (Z), positive (P) (Fig. 2a) where T_c is a threshold to be determined in Section C.

For the same channel, to fuzzify the second variable of the subsystem, N_s, for any segment j, the number of previous segments exhibiting the same feature level as the current segment was counted. To this end, three feature levels were considered, $(F_i > T_c)$, $(-T_c < F_i < T_c)$, and $(F_i < -T_c)$. Then, this value was fuzzified using two membership functions: low (L) and high (H), defined using two threshold values (N_{s1} and N_{s2}) (Fig. 2b). N_{s1} was defined as the minimum IEEG data length required to reject false spike-wave burst lasting less than 5 s. N_{s2} was defined as the minimum expected seizure length. For each IEEG recording, N_{s2} was determined by the method described in Section C.

The output membership functions of the subsystem were defined as "INT" for interictal state, "SZP" for seizure pattern, and "NSP" for non-specific pattern (Fig. 2c). Therefore, the output level (η_L) varies in response to the variation of the feature level (F_i) and the number of segments (N_{s2}) exhibiting the same feature level.

The following rules were drawn-up as the intermediate decision making rules. For two fuzzy variables with 3 and 2 membership functions, four rules covered all possible input combinations as follows:

$$\begin{array}{l} \textit{If } (N_s \textit{ is } L) \textit{ then } (\eta_L \textit{ is INT}) \\ \textit{If } (F_i \textit{ is } N) \textit{ and } (N_s \textit{ is } H) \textit{ then } (\eta_L \textit{ is NSP}) \\ \textit{If } (F_i \textit{ is } Z) \textit{ and } (N_s \textit{ is } H) \textit{ then } (\eta_L \textit{ is INT}) \\ \textit{If } (F_i \textit{ is } P) \textit{ and } (N_s \textit{ is } H) \textit{ then } (\eta_L \textit{ is SZP}) \end{array} \tag{2}$$

The output results at this stage are primary detected sections containing ictal or interictal activities in bipolar channels independently. Then, the output results of the intermediate decision maker were scanned segment by segment. For each segment, a channel counter counted the number of channels containing ictal activities. If more than two channels showed ictal activities, a multichannel seizure section was declared [15]. This step was repeated for each feature independently.

The results of decisions made for seizure detection using all the features were then integrated by a simple rule to make the final decision about seizure detections. For any segment, if at least N_F (out of 4) features confirmed a pattern, seizure or non-seizure, the segment was labeled as that pattern. N_F was determined using the method described in Section C.

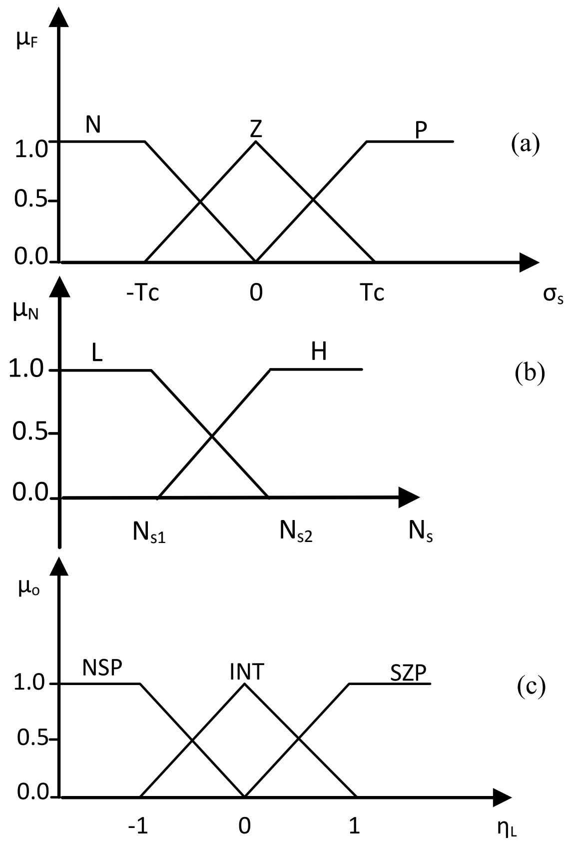

Fig. 2. Membership functions used to define input fuzzy variables (a) feature, and (b) number of consecutive segments. (c) Output membership functions. μ_F, μ_N , and μ_o are degrees of membership for input and output variables. σ_s, N_s, and η_L are feature level, number of segments and output level, respectively.

In the postprocessing stage, short-length detections lasting less than 5 s and artifact-contaminated segments were rejected. Then, to unify detected seizure parts, a minimum time interval was allowed between two different seizure detections [16]. The minimum time interval value was adjusted in a way to achieve the best system performance (30 s in this paper).

B. *Threshold Estimation*

Because the interictal activities were different from patient to patient, to estimate T_c, N_{s2} and N_F, a two-layer back-propagation neural network (BNN) was trained [17]. The BNN consisted of an input layer with 5 nodes (5 reference statistics), one hidden layer with 50 and an output layer with 3 nodes (three threshold parameters). The five reference statistics were the average of the standard deviations of the raw data over the bipolar channels within the reference window and the corresponding average standard deviations for the four features used in this paper.

To train the network, 40% of the IEEG recordings from all patients were used. For any IEEG recording, the threshold parameters were determined by the trial-and-error method in a way to simultaneously maximize the detection sensitivity and selectivity of the system for discriminating ictal from non-ictal activities. Using this approach, we found that the ranges of variation for T_c, N_{s2} and N_F were $Tc \geq 0.5$ (with an increment of 0.1), $8 \leq N_{s2} \leq 10$ (with an increment of 1), and $2 \leq N_F \leq 4$ (with an increment of 1). At each run, five reference statistics as explained above were computed. Finally, for each IEEG recording a pair of input-output vectors was provided. The reference statistics were the elements of the input vector and the optimal threshold parameters were the elements of the output vector. Proceeding in the same manner, a training matrix including the input and output vectors was constructed from the training IEEG recordings.

Once the training matrix was provided, the fast supervised back-propagation training algorithm provided in MATLAB [18] was used for training the BNN. The weights were initially set to small random values in the range [-0.5, 0.5]. The learning rate and the momentum were set at 0.1 and 0.8, respectively. The network was trained 10000 epochs. Once the training was carried out, the network was used to estimate the thresholds for all the IEEG recordings analyzed in this study.

C. *System Evaluation*

Based on non-seizure/seizure labels assigned to IEEG segments at the output of the intermediate decision maker, the performance of the system was assessed in terms of the sensitivity and selectivity [15]. All measures were computed in percent.

As the system was designed for clinical use, three performance measures, sensitivity, false detection rate, and detection latency were also calculated [5], [15], [19]. To measure the sensitivity and the false detection rate, the start and end time of all automated seizure detections were compared with those marked by the expert for the analyzed seizures. Any seizure detection that overlapped with the start and end time of a seizure was defined as a true seizure detection. All other detections were defined as false detections. The detection latency is defined as the time lag associated with a seizure detection. The average detection latency was computed by averaging the time lags between the seizure onsets marked by the expert and the system over all the analyzed seizures.

III. Results

Table I shows the results of the seizure detection and false detection rate per patient. As shown, 77 (of 78) seizures were detected correctly. This gives a sensitivity of 98.7%.

The average false detection rate of 0.81/h was obtained before post-processing. After rejecting false detections including artifacts as well as short-length detections, the false detection rate was reduced to 0.27/h. Rejecting short-length detections reduced the false detection rate by 62.3%. In addition, 4.5% improvement in false detection rate was achieved after rejecting artifacts. The average detection latency was 11 s from the electrographic onset of the seizure with a standard deviation of 6 s. The only missed seizure had a short length less than 10 s.

TABLE I
NUMBER OF SEIZURES AND FALSE DETECTION RATE PER PATIENT.

Patient	Number of expert-detected seizures	Number of system-detected seizure	False detection/h
1	3	3	1.5
2	3	3	0
3	5	5	0
4	5	5	0
5	5	5	0
6	3	3	0.08
7	3	3	0.08
8	1	1	0.42
9	5	5	0.13
10	5	5	0.06
11	2	2	0
12	4	4	0.15
13	2	2	0.1
14	4	4	0.21
15	3	3	0.58
16	5	5	0.3
17	5	5	0.1
18	3	2	1.21
19	2	2	0.07
20	5	5	0.21
21	5	5	0.49
Total	**78**	**77**	**0.27**

IV. DISCUSSIONS

Our system makes considerable use of spatial and temporal information to detect seizures of different types. A sensitivity of 98.7% and a false detection rate of 0.27/h (one false detection every 3.7 hours) were obtained using the system. Table 2 compares the performance of different seizure detection tools in the reviewed literature.

TABLE II
COMPARISON BETWEEN THE ACCURACY OF DIFFERENT SEIZURE DETECTION TOOLS IN THE REVIEWED LITERATURE.

Author(s)	Year	Sesitivity %	False detection (/h)	Average detection latency (second)
Gotman	1982	75.8	1.35	-
Murro et al.	1991	90-100	1.5-2.5	-
Qu et al.	1995	100	0.37	9.35
Grewal et al.	2005	89.4	0.22	17.1
Gardner et al.	2006	97.1	1.56	-7.58
Our system	2009	98.7	0.27	11

Our future work will focus on the application of the system on the IEEG and surface EEG recordings with more channels as well as designing a dynamic threshold estimator.

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