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A fuzzy rule-based system for epileptic seizure detection in intracranial EEG

A. Aarabi [a,*], R. Fazel-Rezai [b], Y. Aghakhani [c]

[a] Department of Electrical and Computer Engineering, University of Manitoba, Winnipeg, MB, Canada
[b] Department of Electrical Engineering, University of North Dakota, Grand Forks, ND, USA
[c] The Section of Neurology, Department of internal Medicine, University of Manitoba, Winnipeg, MB, Canada

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ABSTRACT

Objective: We present a method for automatic detection of seizures in intracranial EEG recordings from patients suffering from medically intractable focal epilepsy.
Methods: We designed a fuzzy rule-based seizure detection system based on knowledge obtained from experts' reasoning. Temporal, spectral, and complexity features were extracted from IEEG segments, and spatio-temporally integrated using the fuzzy rule-based system for seizure detection. A total of 302.7 h of intracranial EEG recordings from 21 patients having 78 seizures was used for evaluation of the system.
Results: The system yielded a sensitivity of 98.7%, a false detection rate of 0.27/h, and an average detection latency of 11 s. There was only one missed seizure. Most of false detections were caused by high-amplitude rhythmic activities. The results from the system correlate well with those from expert visual analysis.
Conclusion: The fuzzy rule-based seizure detection system enabled us to deal with imprecise boundaries between interictal and ictal IEEG patterns.
Significance: This system may serve as a good seizure detection tool with high sensitivity and low false detection rate for monitoring long-term IEEG.

1. Introduction

Epilepsy is a neurological disorder that affects 1–3% of the world's population. Epileptic seizures are clinical manifestations of abnormal and excessive neuronal discharges in the brain (Hauser et al., 1996). Electroencephalography (EEG) is a non-invasive tool to measure the electrical activity of the brain. Long term video-EEG monitoring is one of the most efficient ways for diagnosis of epilepsy by providing information about patterns of brain electrical activity, type and frequency of seizures, and seizure focus laterality. This information helps physicians to treat patients with antiepileptic drugs (AEDs). Surgery should be considered for patients with medically intractable epilepsy. Epilepsy surgery is successful if sites of origin of seizures are accurately identified. When scalp EEG as well as neuroimaging scans fail to provide enough information to accurately localize epileptic focus, intracranial EEG (IEEG) is recorded by placing intracranial electrodes into the brain or on the cortex by a surgical procedure. However, there is always a risk of infection and cerebral edema related to the presence of electrodes in the brain (Bauman et al., 2005). Thus, time plays an important role in the surgical treatment of medically intractable epilepsy.

Long term IEEG recordings are visually inspected by experts to identify seizures. This is a time consuming task. Therefore, automatic seizure detection tools have been highly in demand for EEG-Video monitoring units. The perfect tools for clinical use should reduce the amount of data to be inspected by experts. They should also have high sensitivities, low false detection rates and short detection latencies. Over the past three decades, great progress has been made for automatic seizure detection in IEEG with different degrees of success (Gotman, 1982; Murro et al., 1991; Qu and Gotman, 1995; Grewal and Gotman, 2005; Srinivasan et al., 2007). Gotman (1982) developed an automatic tool to detect a variety of different types of seizures in scalp and intracranial EEGs. It was based on the decomposition of EEG into waves and the detection of rhythmic paroxysmal bursts using the average amplitude of the waves, their duration and rythmicity. To detect complex partial seizures in IEEG, Murro et al. (1991) developed a computerized method that used the time domain and frequency domain features including relative amplitude, dominant frequency, and rhythmicity of the EEG, based on the discriminant analysis. In a more comprehensive way to reduce false detections, Qu and Gotman (1995) developed a warning system relied on the avail-

* Corresponding author. Address: E1-571, Department of Electrical and Computer Engineering, University of Manitoba, Winnipeg, MB, Canada R3T 2N2. Tel.: +1 204 474 8122.
E-mail address: aarabi@EE.UManitoba.CA (A. Aarabi).

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ability of a sample seizure as the template for subsequent detection of similar seizures in scalp and intracranial EEG recordings. This system was patient-specific and needed expert intervention for selecting templates. Recently, Grewal and Gotman (2005) developed a seizure detection system based on EEG data filtering in multiple bands, spectral feature extraction, Bayes' theorem, and spatio-temporal analysis. As a different approach, Srinivasan et al. (2007) developed an automated neural network-based seizure detection system using approximate entropy (ApEn) as the input feature.

The IEEG of epileptic patients contain epileptiform discharges including spikes, sharp waves, and spike-and-slow wave discharges. Since interictal epileptiform discharges correlate with the site of seizure onset (Bassel et al., 2003), there is a high degree of similarity between interictal epileptiform discharges and ictal patterns. For this reason, it is difficult for seizure detection systems to assign binary decision labels ("seizure" or "non-seizure") to EEG patterns including interictal and ictal activities. In general, experts, guided by general definitions for ictal discharges and interictal epileptiform activities, use additional criteria based on temporal and spatial contextual information and other heuristics to visually detect seizures and to exclude non-seizure activities. These criteria are usually applied in terms of expert established rules to EEG for detection of seizures. These rules are not strict and can be adapted based on the information embedded in the shapes of interictal and ictal EEG patterns. Therefore, using expert established rules, seizure detection systems would be able to differentiate ictal discharges from interictal epileptiform activities and to tolerate the intersubject variability in ictal and interictal EEG patterns. For this purpose, a fuzzy inference system can provide a suitable framework to deal with pattern recognition problems whose decision boundaries are fuzzy with gradual class membership (Bezdek, 1981; Zimmermann, 1987). Another advantage of fuzzy rule-based systems is their ability in playing the role of expert rule-based interface between features formulated using linguistic information and quantitative measurements (Pedrycz, 1997). In these systems, membership functions are defined for features to provide an estimate of missing or incomplete knowledge. This characteristic gives these systems a high level human-like reasoning capability.

To date, little work has been done in the area of seizure detection using fuzzy inference systems. Subasi (2006) introduced a dynamic fuzzy neural network for detection of epileptic seizures. The system was fed by surface EEG signals decomposed into frequency sub-bands using discrete wavelet transform (DWT).

In this paper, we present a novel fuzzy rule-based system for detection of epileptic seizures in the IEEG recordings. The system comprises three stages; (1) preprocessing including bandpass filtering, artifact detection and segmentation, (2) feature extraction, and (3) rule-based decision-making. The last stage mimics experts' reasoning by appropriately integrating spatial and temporal contextual information of IEEG patterns and rejecting artifacts. This paper is organized as follows. Section 2 describes the Materials and method. Results are presented in Section 3. The Discussion and conclusion are summarized in Section 4.

2. Materials and method

2.1. EEG recordings

The IEEG data used in this study were obtained from the Freiburg Seizure Prediction EEG (FSPEEG) database (Maiwald et al., 2004) with authorization. The database contains IEEG from 21 patients with medically intractable focal epilepsy. All IEEG data were recorded using a Neurofile NT digital video-EEG system with 128 channels, 256 Hz sampling rate, and a 16 bit analog-to-digital converter, from grid-, strip-, and depth-electrodes surgically inserted inside the brain or placed on the cortex of the patients at the Epilepsy Center of the University Hospital of Freiburg, Germany. In this database, for each patient, six contacts were selected by visual inspection of IEEG data by experienced epileptologists, three near the epileptic focus (epileptogenic zone), and three in remote locations involved in seizure spread and propagation. Seizure onset and offset times were determined by the experts based on identification of epileptic patterns preceding clinical manifestation of seizures in IEEG recordings. No subclinical seizures were included in our analysis. In total, 302.7 h of IEEG data containing 78 seizures with an average duration of 121 s were analyzed. Table

Table 1
Summary of the IEEG data selected for analysis, including patient number, total data length, gender, age, seizure type, seizure origin, the number of analyzed seizures, and average seizure duration per patient. The acronyms used in the table are SP: simple partial seizure, CP: complex partial seizure, and GTC: generalized tonic–clonic seizure.

Patient	Data length (h)	Gender F: Female M: Male	Age	Seizure type	Seizure origin	Number of analyzed seizures	Average seizure duration (s)
1	12	F	15	SP	Frontal	3	15.1
2	11.62	M	38	SP,CP,GTC	Temporal	3	118.2
3	14.18	M	14	SP,CP	Frontal	5	92.7
4	16	F	26	SP,CP,GTC	Temporal	5	87.4
5	15.89	F	16	SP,CP,GTC	Frontal	5	44.9
6	12.41	F	31	CP,GTC	Temporo/Occipital	3	66.9
7	12	F	42	SP,CP,GTC	Temporal	3	153.5
8	9.58	F	32	SP,CP	Frontal	1	163.7
9	15.3	M	44	CP,GTC	Temporo/Occipital	5	113.7
10	16.4	M	47	SP,CP,GTC	Temporal	5	411
11	11	F	10	SP,CP,GTC	Parietal	2	91.1
12	19.46	F	42	SP,CP,GTC	Temporal	4	55.1
13	10	F	22	SP,CP,GTC	Temporo/Occipital	2	158.3
14	14	F	41	CP,GTC	Fronto-Temporal	4	216.4
15	12	M	31	SP,CP,GTC	Temporal	3	89.6
16	16.69	F	50	SP,CP,GTC	Temporal	5	379.8
17	20.15	M	28	SP,CP,GTC	Temporal	5	86.2
18	13.97	F	25	SP,CP	Frontal	3	16.7
19	14.89	F	28	SP,CP,GTC	Frontal	2	13.8
20	18.8	M	33	SP,CP,GTC	Temporo-Parietal	5	85.7
21	16.37	M	13	SP,CP	Temporal	5	83.1
Total	302.7	8 M/13 F	29.9	–	–	78	121.1