Epileptic Seizure Monitoring by One-Class Support Vector Machine

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Abstract—Although refractory epileptic patients suffer from uncontrolled seizures, their quality of life (QoL) may be improved if the seizure can be predicted in advance. On the hypothesis that the excessive neuronal activity of epilepsy affects the autonomic nervous system and the fluctuation of the R-R interval (RRI) of an electrocardiogram (ECG), called heart rate variability (HRV), reflects the autonomic nervous function, there is possibility that an epileptic seizure can be predicted through monitoring RRI data. The present work proposes an HRV-based epileptic seizure monitoring method by utilizing One Class Support Vector Machine (OCSVM). Various HRV features are derived from the RRI data in both the interictal period and the preictal period, and an OCSVM-based seizure prediction model is built from the interictal HRV features. The application results of the proposed monitoring method to a clinical data are reported.

I. INTRODUCTION

Epilepsy is a diverse set of chronic neurological disorders characterized by seizures, that can be usually controlled with appropriate medications. However, about 30% of epileptic patients do not have seizure control even if they use the best available medications [1].

Accidents by convulsions or loss of consciousness associated with uncontrolled seizures may cause serious injuries not only to patients themselves but also people around them. If patients can predict seizures a few minutes prior to the seizure onset, their quality of life (QoL) may be improved because they can ensure safety. An epileptic seizure monitoring algorithm that can predict and alert seizures before its onset should be developed.

Although seizure prediction based on the electroencephalogram (EEG) has been studied [2], the use of EEG in daily living is not realistic because EEG strongly restricts a body and is intolerant to artifacts.

On the other hand, the heart rate pattern changes prior to a clinical seizure, because excessive neuronal activities affect the autonomic nervous system [3]. The R-R interval (RRI) fluctuation of an electrocardiogram (ECG), called heart rate variability (HRV), is a well-known phenomenon which reflects the autonomic nervous function [4], and many HRV features have been proposed for HRV analysis [5]. Gennaro et al. reported that the heart rate of epileptic patients increased prior to the seizure onset [6].

In the present work, an HRV-based seizure monitoring method is proposed. The proposed method consists of two parts: HRV feature extraction from RRI data of epileptic patients, and epileptic seizure monitoring by an One-Class Support Vector Machine (OCSVM) [7] whose inputs are the extracted HRV features. The result of applying the proposed method to a clinical data demonstrates that seizures can be detected at least one minutes prior to the seizure onset.

II. HEART RATE VARIABILITY ANALYSIS

Since HRV reflects autonomic nervous activity, HRV analysis has been used for stress or sleepiness estimation as well as cardiovascular disease monitoring, and various HRV features have been proposed [5], [8], [9]. In this section, the HRV features used for seizure monitoring are explained briefly.

A. RR Interval

A typical ECG trace of the cardiac cycle consists of some peaks as shown in Fig 1, and the highest peak is called the R wave. The R-R interval (RRI) [ms] is defined as the interval between an R wave and the next R wave.

A part of the raw RRI data collected from a healthy person is shown in Fig. 2 (a). Since the raw RRI data are not sampled at equal intervals, it is difficult to analyze them directly. The raw RRI data are interpolated by using spline, and the interpolated RRI data are resampled at equal intervals. Figure 2 (b) shows the resampled RRI data whose sampling interval is one sec.

![Fig. 1. An example of a typical ECG](image-url)
**B. Time Domain Features**

The time domain features can be directly calculated from the RRI data.
- **meanNN**: Mean of RRI.
- **SDNN**: Standard deviation of RRI.
- **RMSSD**: The root mean square of difference of adjacent RRI.
- **Total power**: Variance of RRI.
- **NN50**: The number of pairs of adjacent RRI whose difference is more than 50 msec.

**C. Frequency Domain Features**

The frequency domain features can be obtained through the power spectrum density (PSD) of the resampled RRI data.
- **LF**: The power of the low frequency band (0.04Hz - 0.15Hz) in PSD. LF reflects sympathetic nervous system activity.
- **HF**: The power of the high frequency band (0.15Hz - 0.4Hz) in PSD. HF reflects parasympathetic nervous system activity.
- **LF/HF**: Ratio of LF to HL. LF/HF expresses the balance of the sympathetic nervous system activity with the parasympathetic nervous system activity.

Figure 2 (c) shows a PSD and its LF/HF of the resampled RRI data shown in Fig. 2 (b).

According to the HRV analysis guideline, the RRI data should be measured for at least three minutes for precise frequency analysis [5].

**III. MONITORING METHOD**

In the proposed method, the seizure prediction model is constructed by OCSVM. OCSVM has been used for anomaly detection through estimating a nonlinear boundary that distinguishes between normal and anomaly samples [7].

In seizure monitoring, interictal RRI data and preictal RRI data are defined as normal data and anomalous data, respectively. Although, in general, both normal and anomalous data are needed when a monitoring or discriminant model is constructed, it is difficult to collect a sufficient number of preictal RRI data from epileptic patients, and collecting the interictal RRI data and the RRI data of healthy people is much easier than preictal RRI data collection. On the other hand, OCSVM requires only normal data for modeling, and this point can be its advantage.

The following procedure is adopted for model construction.

(i) Acquire interictal RRI data of epileptic patients, and extract the HRV features.
(ii) Normalize each HRV feature, that is, adjust it to zero mean and unit variance.
(iii) Generate data sets from the normalized HRV features by moving the time window.
(iv) Construct the seizure monitoring model by OCSVM. Using the constructed seizure monitoring model, seizures can be monitored according to the following procedure.

1) Measure the RRI data representing the current autonomic nervous function from an epileptic patient.
2) Extract the HRV features described in Sec. II from the measured RRI data.
3) Normalize the HRV features with the mean and the variance obtained at the model construction procedure (ii).
4) Judge the normalized HRV features by using the constructed seizure monitoring model at the model construction procedure.
5) Alert a near future seizure to the patient when the constructed seizure monitoring model detects anomaly.
6) Return to step (1).

**IV. APPLICATION TO CLINICAL DATA**

In this section, an actual application result of the proposed seizure monitoring method to a clinical data is reported.

**A. Data Collection**

The interictal and preictal RRI data of patients with refractory epilepsy were collected for pre-surgical tests at the department of neurosurgery of Tokyo Medical and Dental University (TMDU) hospital. This retrospective evaluation of clinically acquired data was approved by Medical Research Ethics Committee of TMDU and individual patient consent was not required.

The video, ECG and EEG data of patients were simultaneously recorded for about 24 - 72 h by using the long-term video-EEG monitoring system (Neuro Fax EEG-1200, NIHON KOHDEN). These pre-surgical tests took place in the shield room for EEG recording.

Two clinical epilepsy specialists, certified by Japan Epilepsy Society, defined the clinical seizure onset by consulting the EEG data and the seizure video. The ECG data 15 minutes before and 5 minutes after the seizure onset were stored as the preictal ECG dataset. On the other hand, the ECG data
TABLE I
PATIENTS DEMOGRAPHIC AND CLINICAL CHARACTERISTICS

<table>
<thead>
<tr>
<th>Patient</th>
<th>Sex</th>
<th>Age</th>
<th>Seizure type</th>
<th>Epilepsy syndromes</th>
<th>Medication* [mg/day]</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>male</td>
<td>27</td>
<td>generalized</td>
<td>Lennox-Gastaut syndrome</td>
<td>VPA 1200, LEV 2000, CZP 2</td>
</tr>
<tr>
<td>B</td>
<td>male</td>
<td>46</td>
<td>partial</td>
<td>left frontal lobe epilepsy</td>
<td>VPA 1600, CBZ 800, ZNS 400, TPM300</td>
</tr>
<tr>
<td>C</td>
<td>male</td>
<td>25</td>
<td>partial</td>
<td>right frontal lobe epilepsy</td>
<td>CBZ 800</td>
</tr>
<tr>
<td>D</td>
<td>male</td>
<td>30</td>
<td>partial</td>
<td>left temporal lobe epilepsy</td>
<td>CBZ 400, CLB 10</td>
</tr>
<tr>
<td>E</td>
<td>male</td>
<td>14</td>
<td>partial</td>
<td>localization-related epilepsy</td>
<td>TPM 550, PHT 250, CLB 20, LTG 400</td>
</tr>
</tbody>
</table>


recorded in the interictal period were organized as some interictal ECG datasets for seizure prediction model construction, and their length was 20 min.

B. Patients

The interictal and preictal ECG datasets were collected from five epileptic patients with generalized epilepsy or localization-related epilepsy. Tables I and II show the patient profile and their collected datasets, respectively. In Table I, Medication means the anticonvulsant dosage [mg/day] on the inspection day. The total numbers of collected preictal ECG dataset and interictal ECG dataset are six and thirteen, respectively. The patients were all male unintentionally, and the preictal ECG data of patients D and E could not be recorded.

C. HRV Features

The R waves in the collected ECG data were detected and each RRI was calculated. The obtained raw RRI data was resampled so that its sampling points were arranged at equal intervals to calculate the frequency domain features. In this work, the third-order spline was used for RRI interpolation, and the sampling interval of the interpolated RRI was one sec.

A rectangular sliding window was applied to the original and resampled RRI data, and eight HRV features described in Sec. II were calculated within each window. The window size was three min, as determined by trial and error. An AR model was used to calculate frequency domain features, and its order was ten.

The obtained HRV features of preictal and interictal episodes A2 and B’3 are shown in Figs. 3 and 4. Red vertical lines in Fig. 3 shows the seizure onset.

These figures show that the RRI dramatically changes shortly after the seizure onset in all episodes, and it indicates that the seizure certainly affects the autonomic nervous function. The HRV features of episode A2 shows that almost all features changed about three minutes before its seizure onset.

D. Seizure Monitoring

The seizure monitoring model were constructed from seven interictal datasets A’1, B’1-3, D’1 and E’1-2. All HRV features calculated in Sec. IV-C were used as inputs.

Seizures in all preictal episodes and six interictal episodes A’2, B’4, D’2-4 and E’2 were monitored by the constructed seizure monitoring model. Figures. 5 and 6 show monitoring results of preictal episodes A2 and C3, and Figs. 7 and 8 show monitoring results of the interictal episodes D’2 and E’2. The seizure monitoring model could predict all seizures, and there were rarely false-positive in the interictal epodes. Therefore seizures could be predicted at least three min before the seizure
V. Conclusion

A new HRV-based epileptic seizure monitoring method is proposed, by which the RRI data recorded from epileptic patients are translated into the HRV features, and the seizure is monitored by using OCSVM. In future work, the proposed seizure monitoring algorithm will be realized as a smartphone app for monitoring seizure in real time.

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References