

# Home-based Detection of Epileptic Seizures Using a Bracelet with Motor Sensors\*

Chunjiao Dong<sup>1,2</sup>, Lei Chen<sup>3</sup>, Tianchun Ye<sup>1,2</sup>, Xi Long<sup>4</sup>, Ronald M. Aarts<sup>4</sup>, *Fellow, IEEE*,  
Johannes van Dijk<sup>4</sup>, *Senior Member, IEEE*, Chunheng Shang<sup>1</sup>, Xiwen Liao<sup>1</sup>, Yunfeng Wang<sup>1,2</sup>

**Abstract**—Epilepsy is a long-term neurogenic disease that requires caregivers to accompany the patient days and nights. Caregivers have to help the patients immediately when they are having a seizure, which could cause vital injuries or even death. To address this issue, we designed a bracelet containing a three-dimensional accelerometer and a three-dimensional gyroscope to record the movements of the patient and built a Random Forest model to automatically detect seizures in at most 10 seconds upfront. We designed a home-based data-collecting method that allows patients to stay at home or perform their daily activities outside the hospital. Data collected in this method would be similar to the situation in which the patients would actually use wearable monitoring devices at home. The performance was evaluated based on an experimental study of epilepsy detection and classification, where epileptic motor data was collected in the West China Hospital of Sichuan University. Due to the experimental results, our daytime seizure detection model achieved 75.91% sensitivity and 88.90% precision, while our nighttime seizure detection model achieved 88.01% sensitivity and 88.33% precision. These preliminary results indicate that this home-based data collection method can capture seizures efficiently.

## I. INTRODUCTION

According to World Health Organization's report, epilepsy is affecting around 50 million (7%) people worldwide, on the basis of which, the number of epilepsy patients in China would be no less than 9 million, and it is growing by 400,000 a year [1]. Epilepsy has many potential risks, including injury, persistent state of epilepsy and Sudden Unexpected Death in Epilepsy (SUDEP), and the sudden death rate of patients with epilepsy is 2–4 times higher than that of the normal population [2]. They are at risk of seizures randomly for a long time or even lifelong. At present, the mechanism of SUDEP is not very clear. About 70% can be helped with medication but for about 30% medication is not effective. Most sudden deaths occur after generalized tonic-clonic seizures (GTCS). Furthermore, the SUDEP risk increases in association with the increasing frequency of GTCS occurrence. According to "Practice

\*This work was supported by 1.3.5 project for disciplines of excellence, West China Hospital, Sichuan University (No. ZYJC18031) and Science and technology project of Sichuan Province (No. 2019YFSY0030).

<sup>1</sup>Institute of Microelectronics of Chinese Academy of Sciences (IME-CAS), Beijing, 100029, P.R. CHINA

<sup>2</sup>University of Chinese Academy of Sciences (UCAS), Beijing, 100049, P.R. CHINA

<sup>3</sup>Department of Neurology, West China Hospital, Sichuan University, Chengdu, 610041, P.R. CHINA

<sup>4</sup>Eindhoven University of Technology, Department of Electrical Engineering, 5612 AZ Eindhoven, The Netherlands

(Corresponding author Yunfeng Wang, e-mail: wangyunfeng@ime.ac.cn)

guideline summary: Sudden unexpected death in epilepsy incidence rates and risk factors" by American Academy of Neurology and American Epilepsy Society in 2017, the use of monitoring equipment that can alert caregivers to take appropriate measures could reduce respiratory dysfunction and hypoxemia [3]. Epileptic seizures, especially seizures at night, are at risk of being missed by caregivers. Wearable epileptic seizure detection could help improve the living quality and independence of patients, and it also provided a method for a follow-up of the patient and evaluation of his/her treatment.

Seizure detection systems focus on different fields, including electromyography (EMG) [4], photoplethysmography (PPG) [5], electrocardiogram (ECG) monitoring. There have been efforts to develop automatic wearable accelerometer-based epilepsy detection and classification devices [6]–[12]. The traditional motor data recording method is to collect data in a hospital where a patient wears motor-detecting devices and undergoes long-term video-electroencephalography monitoring (VEM) at the same time. Although VEM is the gold standard, it is not suitable because the patient would be limited to be equipped with the VEM all the time [6], [8], [10], which means that the collected data only contains the movements that he/she is doing indoor inconspicuous activities. In this study, we investigate the domestic movement-recording method by designing a bracelet with a mark button (details will be introduced later).

Machine learning classification models have been widely investigated in the epileptic seizure detection field, with potential clinical applications, such as threshold value method [9], K Nearest Neighbors [7], and Support Vector Machine [13]. These traditional methods are based upon the assumption that the number of seizures and normal movements is balanced, which is not the case in practice. Therefore, a technique that can overcome the imbalance of data would be more suitable for epileptic seizure detection using motor data. Then we investigate the practicability of the bracelet and the performance of detecting seizures based on home-collected data.

## II. METHOD

### A. Devices design

We designed a bracelet with built-in microelectromechanical systems including a three-dimensional (3-D) accelerometer and a 3-D gyroscope, as shown in Figure 1, and collected motor data from patients of West China Hospital, Sichuan University. The bracelet has an 800 mA battery and it could



Fig. 1. The wireless bracelet has a mark button in red color. The patient (or his/her caregivers) would press this button after having a seizure, and the marks would help to upgrade the algorithm to detect seizures.

continuously work for more than 24 hours. The collected data was stored in an SD card temporarily, where data of more than 3 days can be stored. We asked the subjects (or their caregivers) to upload the collected data every night before they went to bed.

The red button, as shown in Figure 1, is designed to mark the seizure time by the patient or his/her caregivers.

The 3-D acceleration (ACC) and 3-D angular (ANG) signal were sampled at 100 Hz, and synchronized with home video recordings by updating the time from the same network.

### B. Data Acquisition

Data acquisition was carried out in each subject's home, and we selected patients who had GTCS and had been admitted to the West China Hospital for over one year. The selected patients were trained on how to use the bracelet to collect data at home and how to mark all epileptic seizure events.

Five patients (3 males; age 24–35 years, median 29 years), at risk of GTCS, were recruited in the hospital. The total time of monitoring was 2,808 h (range 120–1344, mean 561.6, median 504).

During the whole recording time, there were cameras set around the subject. The quality of all collected data was checked by experts of the West China Hospital by comparing it with the video recordings of subjects at home. By doing this, we could collect more daily activities such as brushing teeth, walking around, playing video games, and so on than traditional collecting methods. It is assumed that the greater diversity of movements we collected, the more practical the bracelet would be.

This data collection method allows patients to have different kinds of activities in daily life and gives them enough respect and comfort. The experts of the hospital reviewed all the annotations. Only one mark was kept if the subject pressed the button more than once when having a seizure, while if the subject forgot to press the button, a mark was added. If the subject marked one seizure more than once or forgot to press the mark button after having a seizure, the experts of the West China Hospital would correct the raw data by deleting or adding a mark. This research was approved by the West China Hospital of Sichuan University

Biomedical Research Ethics Committee (No. 2018(590)) and every patient (or his/her caregiver) provided written informed consent.

### C. Pre-Processing

The raw monitoring data spans over 24 hours. The total raw data contained two main kinds of data: moving segments (seizures and non-seizure movements) and not moving segments. To increase the efficiency of data processing, before calculating features, we preprocessed the raw data to get rid of the segments containing no valid information and only kept patients' moving segments. Later, moving segments would be further separated into seizure movements and non-seizure movements.

The raw data consists of 10 channels, including 3-D ACC ( $ax, ay, az$ ), 3-D ANG ( $gx, gy, gz$ ), and 4-D quaternion ( $q0, q1, q2, q3$ ). 3-D ACC and 3-D ANG were collected directly from a six-axis gyroscope. The quaternion was calculated from the following equations:

$$\begin{cases} q0 = q0 + (-q1 * gx - q2 * gy - q3 * gz), \\ q1 = q1 + (q0 * gx + q2 * gz - q3 * gy), \\ q2 = q2 + (q0 * gy - q1 * gz + q3 * gx), \\ q3 = q3 + (q0 * gz + q1 * gy - q2 * gx). \end{cases} \quad (1)$$

All movement events, including seizures and normal movements, are extracted as follows:

- 1) First, due to the mechanical inertia of the musculoskeletal system, muscular contractions would not be higher than 20 Hz [14]. As a consequence, we used a low-pass filter with a 35 Hz cutoff frequency to eliminate noise.
- 2) Next in this step, the total ACC  $acct$  ( $acct = \sqrt{ax^2 + ay^2 + az^2}$ ) was calculated and analyzed in sliding windows of 2 s with half-window-size overlap. In each window, two values were calculated to identify if the subject was moving. One is the standard deviation of  $acct$ , and the other is the zero-crossing count in each window.
- 3) If the standard deviation is higher than a threshold of 0.2  $g$ , and the zero-crossing value is higher than a threshold of 15, this indicates a start of movement, and we would start counting the lasting time of this movement.
- 4) A moving event should last for more than 15 s, without stopping over 10 s between any action.
- 5) These values are set up by experiments.

Figure 2 shows a detected seizure, while the start and stop times were automatically detected by the algorithm mentioned above, and the seizure mark was set by the patient or his/her caregiver using the red mark button on the bracelet. However, there could be several (less than 2 times a whole day) seizures that failed to be extracted by the algorithm mentioned above, due to the patient not pressing the mark button in time after having a seizure, and may have some unstable actions before he/she press the button. In these

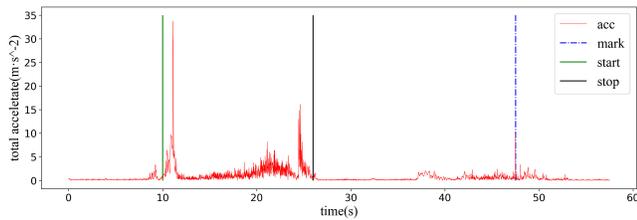


Fig. 2. Detected movement, the start and stop time of a movement are shown in green and black, which were automatically detected by the algorithm. The blue line showed when the patient or his/her caregiver used the mark button, indicating it was a seizure event.

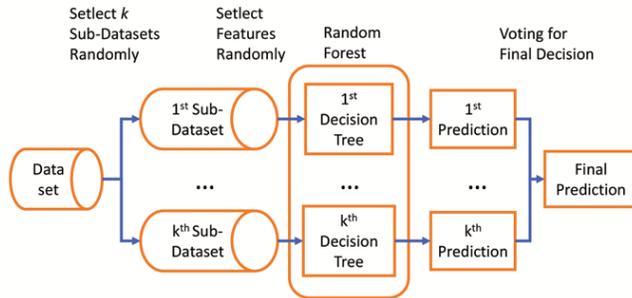


Fig. 3. The process of building a RF classification.

circumstances, extra movements would be recognized as seizures, and we would check and delete the wrong labels and re-mark the right seizure movements.

In total, we have extracted 5341 normal movements and 379 seizures, among which 527 normal movements and 242 seizures happened at night. In this way, all seizure events and normal moving events are preserved, and data without movements are discarded.

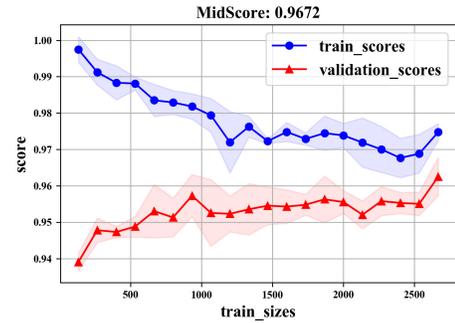
#### D. Feature Extraction and Selection

Different features have been investigated for classification, such as mean, maximum, minimum, median, standard deviation, and inter quartile range [7]. As a preliminary study, we selected some time-domain features to describe each event and evaluated those features to select the most useful ones to build the classification model.

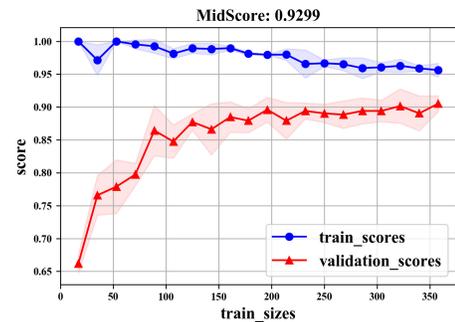
For each dimension of the whole 11-D data ( $ax, ay, az, gx, gy, gz, q0, q1, q2, q3, acct$ ), we calculated minimum, maximum, mean, variance, interquartile range, and the lasting time of the movement. Then the best features are selected by a filter feature selection called analysis of variance. If a  $Pvalue < 0.05$ , we admit that the values of the extracted feature are significantly different between seizure and non-seizure movements. All features with  $Pvalues < 0.05$  were incorporated into a multivariate model.

#### E. Model Estimation and Validation

In this study, we used a random forest (RF) classifier, which is composed of an ensemble of decision trees, and a voting strategy is employed for the final prediction. Figure 3 shows the process of building an RF classification. RF



(a) RF Model performance on overall data



(b) RF Model performance on night data

Fig. 4. Learning curves of RF for epileptic seizure detection. The blue line with round spots shows the accuracy of training, and the red line with triangle spots shows the accuracy of validation, while the shadow around the line shows the range of accuracy of the 3-fold cross-validation.

uses a bootstrap method, which is a resampling technique, to randomly select  $N$  samples from  $N$  original training samples, and the  $N$  selected samples here could be repeated. If we repeat this operation for  $k$  times, we would get  $k$  new training sets, and each new training set would have  $N$  samples. In this study, we have  $m_{all}=56$  features in each sample, and the maximum number of features that could be used in every leaf should be set as  $m_{try}$  ( $m_{try} < m_{all}$ ). Then RF builds  $k$  decision trees for these  $k$  new training sets. Those  $k$  decision trees would have  $k$  predictions, including “seizure” and “normal movements”. At last,  $k$  predictions would vote for the final prediction. Advantages of the RF classification are the possibility of training the model with an imbalanced data set (most data are normal movements and few are seizures) and the flexibility to adjust the model with an increasing amount of data.

There are three parameters to be tuned for RF model, the number of decision trees  $k$ , the maximum depth  $d$  of each tree, and the number of features ( $m_{try}$ ) each leaf could use. More trees would result in better performance, but at the same time, it would lead to higher calculating cost and likely overfitting the model. Increasing  $m_{try}$  generally improves the performance of the model as at each node now we have a higher number of options to be considered. However, this is not necessarily true as this decreases the diversity of individual trees, which is the specialty of RF. A larger  $d$  makes the model more prone to capturing noise in training data. Thus, for an optimal solution the parameters  $k$ ,  $d$ , and

$m_{try}$  have to be tuned to minimize the tradeoff between detection sensitivity and precision.

Figure 4 shows the performance in the model building process of RF model on overall data and night data. For the overall model and the night model building step, we used a 3-fold cross validation approach to test the temporary performance. Then we calculated a *Midscore* to describe the mean accuracy score of training and validation in model building step as:

$$Midscore = \frac{mean_{train} + std_{train}}{mean_{validation} - std_{validation}} \quad (2)$$

where  $mean_{train}$  and  $mean_{validation}$  are the mean accuracy of training and validation, while  $std_{train}$  and  $std_{validation}$  are the standard deviation of training and validation accuracy scores. The *Midscore* reaches 96.72% for the overall model and 92.99% for the night model.

### III. RESULTS

The performance is characterized in terms of sensitivity and the positive predictive value (PPV) of the system.

We used 30% overall data (1602 non-seizure events and 114 seizures) to test the trained RF model of overall seizure detection. In the meanwhile, we used 30% night data (161 non-seizure events and 70 seizures) for night seizure detection.

The result of night detection shows that the RF model based on home collected data could correctly identify 61 out of 70 night seizures (mean sensitivity 88.01%) and 153 (95.03%) out of 161 non-seizure events with a false alarm rate (FAR) of 0.23/24h (8 false alarm from 3 patients). The PPV of 88.33% further shows the efficacy of the night seizure detection system. The validation results for overall seizure detection shows that a total of 87 out of 114 night seizures (mean sensitivity 75.91%) seizure events were detected and 1591 (99.31%) of 1602 non-seizure events were classified correctly with a FAR of 0.13/24h (11 false alarm from 4 patients), and the PPV was 88.90%.

We compared our RF model with some other classifiers and we found that our RF model performed better than K Nearest Neighbors, Support Vector Machine, and Logistic Regression with higher sensitivity and higher precision.

### IV. DISCUSSION AND CONCLUSIONS

In this work, the data collection method used in the home was designed, and the practicality of this method was investigated and proved. Especially, the RF modeling approach was used to classify imbalanced datasets of normal movements and epileptic seizures. Moreover, different kinds of normal movements were involved in this study. The experimental results show that the RF approach is capable of characterizing epileptic seizures during day and night, with an accuracy rate of 96.59% and 92.43%, and the PPV values are 88.90% and 88.33%. Missed seizures could be caused by small amplitudes. The proportion of seizures is different in day and night, so there is a necessity to build a night seizure detection model separately.

Compared to epileptic seizures detection, the classification of seizure types is more challenging due to the limited number of training data and subjects. A limitation of this study is that only convulsive seizures can be detected by motor sensors because some seizures are not clearly visible in ACC and ANG signals, and the measurement of the EMG and other signals might be useful. As a result, in our further study, we would use wearable PPG, EMG, and ECG monitoring devices to contribute to more kinds of seizures, such as non-convulsive seizures. Furthermore, few patients were involved in this study, and we would include more patients to make the system more sensitive and accurate.

In conclusion, the results show that our study is useful for the automated detection of convulsive seizures based on home collection methods using ACC and ANG, and it would make a promising contribution to a complete wearable multi-sensor seizure detection system.

### REFERENCES

- [1] L. Chang, Progress in epidemiological investigation of epilepsy in china, *Journal of International Neurology and Neurosurgery* 39 (002) (2012) 161–164.
- [2] A. Neligan, G. S. Bell, S. D. Shorvon, J. W. Sander, Temporal trends in the mortality of people with epilepsy: A review, *Epilepsia* 51 (11) (2010) 2241–2246.
- [3] C. Harden, T. Tomson, D. Gloss, J. Buchhalter, J. H. Cross, E. Donner, J. A. French, A. Gil-Nagel, D. C. Hesdorffer, W. H. Smithson, M. C. Spitz, T. S. Walczak, J. W. Sander, P. Ryvlin, Practice guideline summary: Sudden unexpected death in epilepsy incidence rates and risk factors, *Neurology* 88 (17) (2017) 1674–1680.
- [4] S. Beniczky, I. Conradsen, P. Wolf, Detection of convulsive seizures using surface electromyography, *Epilepsia* 59 Suppl 1 (2018) 23–29.
- [5] J. van Andel, C. Ungureanu, R. M. Aarts, F. Leijten, J. B. A. M. Arends, Using photoplethysmography in heart rate monitoring of patients with epilepsy, *Epilepsy & Behavior* 45 (2015) 142–145.
- [6] S. Beniczky, T. Polster, T. W. Kjaer, H. Hjalgrim, Detection of generalized tonic-clonic seizures by a wireless wrist accelerometer: A prospective, multicenter study, *Epilepsia* 54 (4) (2013) e58–e61.
- [7] G. T. Borujeny, M. Yazdi, A. Keshavarz-Haddad, A. R. Borujeny, Detection of epileptic seizure using wireless sensor networks, *Journal of medical signals and sensors* 3 (2) (2013) 63–68.
- [8] K. Cuppens, P. Karsmakers, A. Van de Vel, B. Bonroy, M. Milosevic, S. Luca, T. Croonenborghs, B. Ceulemans, L. Lagae, S. Van Huffel, B. Vanrumste, Accelerometry-based home monitoring for detection of nocturnal hypermotor seizures based on novelty detection, *IEEE Journal of Biomedical and Health Informatics* 18 (3) (2014) 1026–33.
- [9] K. Cuppens, L. Lagae, B. Ceulemans, H. S. Van, B. Vanrumste, Detection of nocturnal frontal lobe seizures in pediatric patients by means of accelerometers: a first study, in: 31st International Conference of the IEEE EMBS, Minneapolis, Minnesota, USA, 2009, pp. 6608–6611.
- [10] S. Kusmakar, C. K. Karmakar, B. Yan, T. J. O'Brien, R. Muthuganapathy, M. Palaniswami, Automated detection of convulsive seizures using a wearable accelerometer device, *IEEE Transactions on Biomedical Engineering* 66 (2) (2019) 421–432.
- [11] T. M. E. Nijsen, R. M. Aarts, P. J. M. Cluitmans, P. A. M. Griep, Time-frequency analysis of accelerometry data for detection of myoclonic seizures, *IEEE Transactions on Information Technology in Biomedicine* 14 (5) (2010) 1197–1203.
- [12] T. M. E. Nijsen, R. M. Aarts, J. B. A. M. Arends, P. J. M. Cluitmans, Automated detection of tonic seizures using 3-d accelerometry, in: 4th European Conference of the International Federation for Medical and Biological Engineering, Vol. 22, Berlin, 2009, pp. 188–191.
- [13] M.-Z. Poh, T. Loddenkemper, C. Reinsberger, N. C. Swenson, S. Goyal, M. C. Sabtala, J. R. Madsen, R. W. Picard, Convulsive seizure detection using a wrist-worn electrodermal activity and accelerometry biosensor, *Epilepsia* 53 (5) (2012) e93–e97.
- [14] J. B. A. M. Arends, Movement-based seizure detection, *Epilepsia* (2018) 30–35.