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Detection of Nocturnal Epileptic Seizures Using Wireless 3-D Accelerometer Sensors

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***Abstract*—The aim of this paper is to provide a lightweight approach for early detection of nocturnal epileptic seizures using data from wireless 3-D accelerometer sensors. We use the exponentially weighted moving average algorithm to forecast the current value of the accelerometer measurement, and when the difference between measured and forecasted values is greater than the dynamic threshold on any axis, a notification is transmitted to the base station, which maintains a sliding window of received notifications. When the filling ratio is greater than a predefined threshold, an alarm is triggered by the base station. The proposed approach is intended to improve the performance of existing mobile health detection systems based on the analysis of electroencephalogram (EEG). To reduce their false alarm rate, we seek to correlate detection results from 3-D accelerometer with other physiological parameters through a majority voting. Our experimental results on real dataset collected from the epileptic patient show that our proposed approach is robust against temporal fluctuations and achieves a high level of detection accuracy, which in turn proves the effectiveness of this approach in enhancing the reliability of existing detection approaches based on EEG signal analysis.**

***Index Terms*—3-D accelerometer, Epileptic Seizure Detection, EEG, Anomaly Detection, EWMA, Wireless Sensors Networks**

I. Introduction

Epilepsy is neurological disorders caused by chronic dysfunction of the brain and its susceptibility to generate unprovoked and unpredictable seizures. They are unexpected, sudden and not explained by an immediate causative factor. Between 0.5% and 1% of the population is suffering from this dysfunction, where in 70% of cases, we can treat these crises using available therapy (anticonvulsant). For the remaining 30%, the surgery should be considered to remove the epileptogenic area [1].

These people are usually isolated during the night and vulnerable to several physical injuries or asphyxia due to a blocked airway after swallowing their tongues. It is often risky during the night (i.e. isolated) where the patient cannot call for help. The nocturnal seizure may pass unnoticed by family or healthcare professionals and may cause several medical complications or death. It requires an automatic detection of epileptic seizure to trigger an alarm for assistance.

The electroencephalogram (EEG) has an important role in the diagnosis and the detection of epileptic seizure which usually creates clear abnormalities in the EEG. Several approaches have been proposed for the detection of epileptic seizure through the analysis of EEG signal [2], [3]. However, the similarity between epileptic seizure features and some of the background noise (such as eye blinks and other eye movements, etc.) provokes false alarms and reduces the reliability of such monitoring systems. The sensitivity of existing detection systems is 30-35% [4] for tonic-clonic seizures and less for the other types.

Generalized epileptic seizure involves the entire brain and produces bilateral motor symptoms usually with loss of consciousness. Therefore, seizures often produce random limb and chest movements. Using accelerometer (ACC) sensor is a relevant solution to quickly detect epileptic seizure and raise an alarm for family (or surrounding persons) to limit the seizure's consequences. This will enhance the reliability of existing monitoring systems based on EEG analysis, through correlation and majority voting with raised alarms by ACC sensors.

Wireless ACC sensor is used to capture motion in 3-D axis and transmit the collected data to a local computing station such as Smart-Phone, tablet or computer. The autonomous aspect of these wireless sensors is one of their major advantages since they are able to perform treatments on collected data in real time and send only relevant information. They are able to perform distributed lightweight data processing adequate with their constrained resources (e.g., processor, battery, memory).

In this paper, we propose a solution to improve the reliability of wireless monitoring systems for the detection of epileptic seizures through the use of ACCs. The proposed approach is based on two steps: Exponentially Weighted Moving Average (EWMA) to forecast the current measurements, and the difference between measured and forecasted values. To distinguish between normal movements and those induced by epileptic seizures, a sliding window is used to absorb temporal fluctuations. The purpose of this approach is to provide online analysis and in-network detection for underlying motor seizures.

The use of Wireless Body Area Networks (WBANs) as mobile Health (mHealth) monitoring system for epileptic seizures detection might improve the detection through monitoring and analysis of many physiological parameters, such as EEG, electromyogram (EMG), electrocardiogram (ECG), SpO2, Galvanic Skin Response (GSR), etc. The electrical discharge during epileptic seizure affects the muscles, respiration rate and heart rate (or ECG). The temporal and spatial correlation of 3-D ACC data with other physiological

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parameters will improve the detection accuracy and reduce the false alarm rate. In this paper, we focus only on in-network seizures detection using 3-D ACC data to provide complementary information to improve the performance of exiting systems. We use three ACC sensors positioned at wrist, leg and chest of the monitored patient in order to find the optimal place for ACC and to achieve maximal detection.

The rest of this paper is organized as follows. Section II reviews relevant related work and different existing approaches for epileptic seizures detection. Section III presents our proposed approach for body motion and ACC data analysis to detect epileptic seizures. In section IV, we present our results from experimental evaluation. Section V contains concluding results and some perspectives for our future work.

II. Related work

Medical Wireless Sensor Networks (WSNs) offer a continuously remote monitoring of patients [5]. Wireless sensors are able to collect various vital signs, such as heartbeat, pulse, oxygenation ratio, ECG, EEG, EMG, etc. Several approaches for epileptic seizures detection [6], [7] using WSNs have been proposed to replace the conventional wired EEG through the use of tiny and lightweight devices. Authors in [8] compare classification results using Naïve Bayes, K-Nearest Neighbors (k-NN), Decision Tree (C4.5), Logistic Regression and Artificial Neural Networks (ANN). They found that ANN achieves the best performance, and this result has confirmed in [6].

Various methods to detect motor manifestations observed during seizures via magnetic or inertial sensors have been proposed in [9]–[11]. Many devices for epileptic seizure detection are available in the market and able to alert parents and caregivers when attack begins [12]–[14]. These sensors are able to extract relevant information from subject's movements and to distinguish seizure from normal body motions. Another approach in [15] is based on triaxis (3-D) magnetometer to assess in real-time recorded movement and detect such as sitting/standing up position. Authors in [16] investigate the optimal placement of accelerometers for detecting a range of everyday activities.

Furthermore, the characterization of movements due to neurological causes was also studied using accelerometers for the detection of hand tremors for patients suffering from Parkinson [17]. A model is formulated in [18] for arm movements during myoclonic seizures.

As epilepsy seizure induces salvation, involuntary and uncontrolled movements, seizure detection using ACC signals was proposed and applied on animals [19], [20] or on patients [21]. Authors in [20] propose a three-state finite state machine to detect seizure activities using 1-axis ACC. Authors in [22] propose a seizure detection approach based on three 2-D accelerometer positioned on the right arm, left arm and left thigh. They use ANN and k-NN to distinguish seizures movements from normal movements. The detection accuracy of their proposed approach depends on the parameter k in k-NN.

Authors in [23] present another approach to detect nocturnal seizures in pediatric patients using accelerometers attached to the extremities. The data classification is achieved using non-parametric estimate of the probability density function of normal movements and a static threshold. The training phase does not require any seizures. Authors in [24] use 3-D accelerometer to detect seizures and to distinguish with normal body motion. They apply four time-frequency and time-scale methods: Short Time Fourier Transform (STFT), Wigner Distribution (WD), Continuous Wavelet Transform (CWT) and Model-based Matched Wavelet transform (MOD). They found that CWT and MOD achieves better detection accuracy than STFT and WD. Authors in [25] analyze the efficiency of epileptic seizures detection using 3-D ACC, without limiting the detection to nocturnal seizures, since the patient may be in motion.

The use of accelerometers attached to the body has been investigated as possible detection method for epileptic seizures. Authors in [21] use 5 ACCs to detect seizures with different features. Authors in [26] propose an approach to detect nocturnal seizures using 2 ACCs attached to wrist and ankle. The sensitivity of their system is 91,67% and the specificity is 83,92%. Authors in [27] use three 3-D ACCs positioned on the wrists and the head of the patients and their system achieves 80% of sensitivity and 95% of specificity. Therefore, the performance of monitoring system highly depends on the position of accelerometers.

In this paper, we aim to develop a lightweight method for in-network detection of epileptic seizures with high detection accuracy, low false alarms and low detection delay. The proposed system also performs distributed processing to minimize power consumption by the transmission of normal measurements.

III. Proposed Approach

To ensure early detection of epileptic seizure, we consider a real deployment scenario, where three wireless 3-D ACC sensors are positioned on wrist, leg and chest. These sensors are used to acquire patient movements in real time as shown in figure 1.

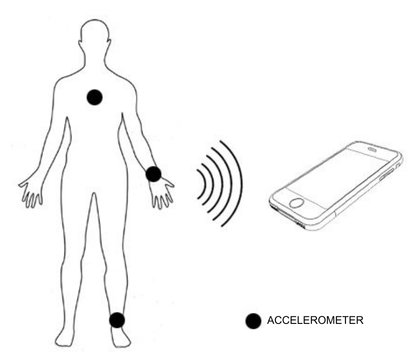

Fig. 1. 3 accelerometers for epileptic seizure detection

Let $X_i = \{x_{1,i}, x_{2,i}, \ldots, x_{n,i}\}$ denote the measured values by ACC_i. Usually, ACC sensor measurements are transmitted to the Local Processing Unit (LPU) every discrete time interval

T. The LPU can be any portable device, such as SmartPhone or Tablet. However, the energy consumed by sensor data transmission ranges from 10^3 to 10^4 times the energy used by computation. Furthermore, transmitting normal measurements that occur in the most of time is useless. Therefore to reduce the energy consumption of sensor by wireless data transmission, the seizure detection procedure is intended to work on the sensor, and only alarms are transmitted by sensors to the LPU when an anomaly is detected.

To achieve online detection and to reduce false alarms triggered by transient motions and temporal fluctuations, the LPU uses the filling ratio (R) of a sliding window before raising a medical alarm.

Each ACC sensor calculates the variance ($\sigma^2_{t,i}$) of the last k measured values and and uses the EWMA to predict the next value ($\hat{\sigma}^2_{t+1,i}$) based on the already registered activities. Afterward, the detection of divergence (or significant changes) between predicted and measured values is achieved through residual time series analysis and Z-score test.

Exponential smoothing is used for short-term forecasting by assuming that the next value of monitored attribute depends only on the current and the past values. The one step forecast of $\sigma^2_{t,i}$ is given in the following equation:

$$\hat{\sigma}^2_{t+1,i} = \alpha.(x_{t,i} - \mu_{t,i})^2 + (1-\alpha).\hat{\sigma}^2_t \qquad (1)$$

Where α is the weight (smoothing parameter) and must be between 0 and 1. $\hat{\sigma}^2_{t+1,i}$ is the predicted value for the variance by sensor ACC$_i$ at the instant $t+1$. The choice of weighting factor α controls the sensitivity of the EWMA forecasting procedure, where a large value of α (near to one) makes the procedure sensitive to recent changes or fluctuations. In our case, the choice of alpha is important to absorb the impact of small disruption and to reduce the false positive rate.

EWMA is considered attractive in terms of storage cost and computation complexity. To predict the current value, EWMA does not need to keep past measurements. It only uses the previous estimate and the current measurement. Figure 2 shows the forecasting procedure realized on the sensor, where the EWMA forecasting in equation (1) is used to predict the current value for the variance ($\hat{\sigma}^2_{t,i}$). As the sampling frequency must be greater than 20Hz to capture most human activities, many samples will be recorded by ACC in one second, and the variance of these values is calculated ($\sigma^2_{t,i}$). Afterward, the residual time series is used to measure the deviation between forecasted and measured values of variance:

$$R_t = \hat{\sigma}^2_{t,i} - \sigma^2_{t,i} \qquad (2)$$

The residual time series R_t follows a normal distribution with mean $\mu = 0$ and variance σ. The Z-score test is used to identify possible outliers (deviated values) as values falling outside the following range:

$$\mu - k \times \sigma^2 \leq R_t \leq \mu + k \times \sigma^2 \qquad (3)$$

A value of $k = 1.96$ allows the interval to contain 95% of values generated by gaussian distribution with the parameters μ and σ. μ is the mean and σ is the standard deviation of the residual time series. The p-value associated with 95% confidence level is 0.05. If the Z-score is between -1.96 and 1.96, the p-value is greater than 0.05 and the measurement is more likely generated by hypothesis H_0 (or normal hypothesis), otherwise, we reject the null hypothesis and we assume a change to anther hypothesis (H_1).

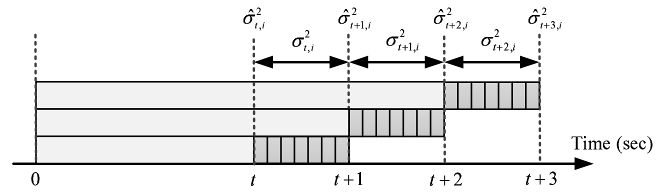

Fig. 2. Predicted and measured values of variance

When significant statistical change is detected on any of the three axis, a notification (or an alarm) is triggered and transmitted to the LPU, which maintains a sliding window of w counters to combine data ACCs placed at different locations. Each counter in the window represents a time slot, and increments for each received alarm from used ACCs as shown in figure 3. When the Filling Ratio (FR) is greater than predefined threshold $FR > h$, an alarm is triggered by the LPU.

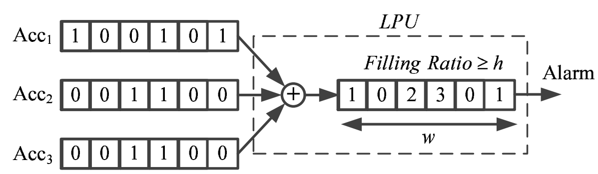

Fig. 3. Window containing alarm counters

Algorithm 1 contains the pseudo code of two implemented functions: the first runs on each ACC, and the second on the LPU. As the proposed approach is distributed, the forecasting procedure using EWMA and the Z-score testing on residual time series are achieved on the sensor. The final decision for seizure detection alarm is done on the LPU.

IV. Experimental results

In this section, we present our experimental results using data collected from the epileptic patient by three ACCs placed on the wrist, the leg and the chest. Many 3-D accelerometers tools are freely available for iPhone from the APP store. The collected data from tri-axial accelerometers positioned on chest, leg and wrist are presented in figures 4, 5 and 6 respectively. The sampling frequency of the ACC signals is 100 Hz.

The collected data are analyzed on the ACC sensor where only raised alarms are transmitted to the LPU. However, given the strong correlations of the three axes in the collected values, we will focus only on the X-axis in the rest of this paper. The same goes for Y-axis and Z-axis. The variations of measured

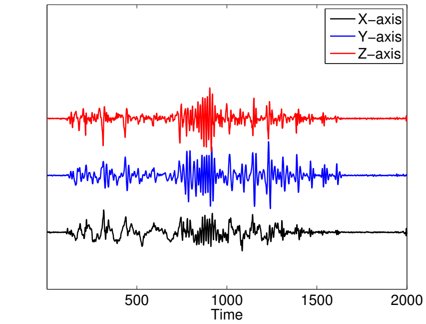

Fig. 4. Data from ACC placed on the chest

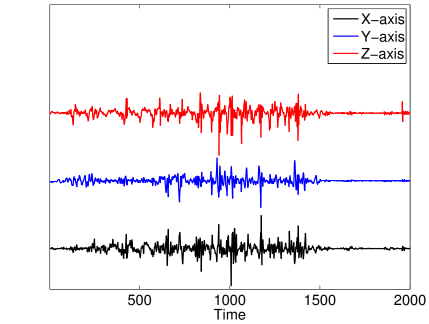

Fig. 5. Data from ACC placed on the leg

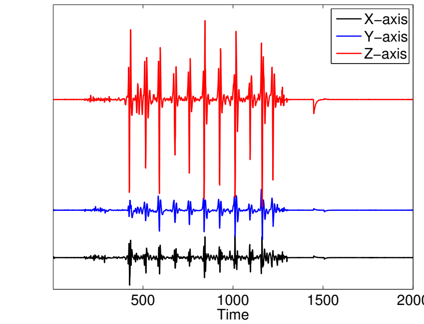

Fig. 6. Data from ACC placed on the wrist

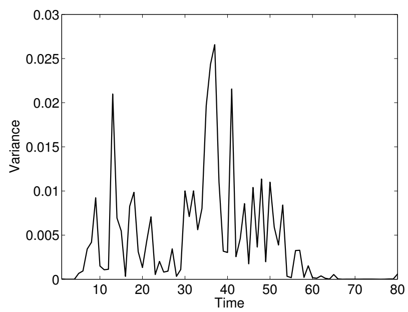

Fig. 7. Variance of X-axis data (Chest)

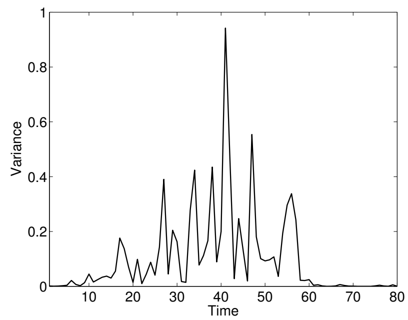

Fig. 8. Variance of X-axis data (Leg)

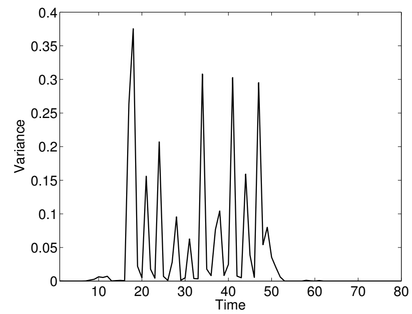

Fig. 9. Variance of X-axis data (Wrist)

Algorithm 1 Proposed algorithm

function ONSENSORPROCESSING(none)
    if $(window.size() == W_0)$ **then**
        $\sigma_t^2 \leftarrow window.variance()$
        $R_t \leftarrow \hat{\sigma}_{t,i}^2 - \sigma_{t,i}^2$
        if $\left(R_t < (\mu - k\sigma^2) \text{ or } (R_t > \mu - k\sigma^2)\right)$ **then**
            Transmit the value 1 to LPU
        end if
    else
        window.add(data)
    end if
end function
function ONLPUPROCESSING(Alarm)
    window.add(Alarm)
    if $(Window.FR() \geq h)$ **then**
        Raise an alarm for seizure detection
    end if
end function

variance, for window size of 25 time slots on the sensor, are presented in figures 7, 8 and 9.

Figure 10 shows the variation of measured and predicted values of data variance from ACC placed on the wrist of the monitored person. During seizure, patients usually suffer from involuntary and uncontrolled behavioral symptoms, and thus inducing a deviations between measured and predicted values of the variance. As the seizure begins at time instant $t = 40$, we can notice in figure 10 the deviations between both (expected and measured data variance). The residual time series (R_t) associated with the difference between measured and predicted values is displayed in figure 11.

The Z-score test is used to detect deviation in the residual time series. Figure 12 shows the variations of the Z-score, as well as the chosen threshold with $(k = 1.96)$. 95% of the data should be inside the interval $[\mu - 1.96.\sigma, \mu + 1.96.\sigma]$. It is important to note that the three sensors measure data of different intensity. Since the position of the ACC has an impact on the motor seizure detection, such as the variations of measurements from chest ACC were smaller and less significant than those obtained from ACCs on the leg (or ankle) and the wrist as shown in the variation of the variance in figures 7, 8 and 9. In fact, the detection operation is obvious in ACC data positioned on ankle and wrist, but the variation is low in data from the chest's ACC sensor.

The raised alarms (or detect seizures) by the LPU are shown in figure 13 for a filling ratio of 10% and a window size $w = 60$ time slots. There is no significant difference in the detection accuracy when considering a filling ratio (as shown in figure 3) with value greater or equal to 2, i.e. at least 2 sensors detect and notify the seizure to the LPU. In contrast, the difference between single and multiple ACC detection highly increase the false alarm rate. It is important to find the optimal position of ACCs to detect seizure. ACCs positioned on ankle and wrist provide a good data variation in contrast to chest, where variations can not be clearly distinguished.

To conduct performance analysis, we begin by analyzing the impact of the parameter α on the predicted values of

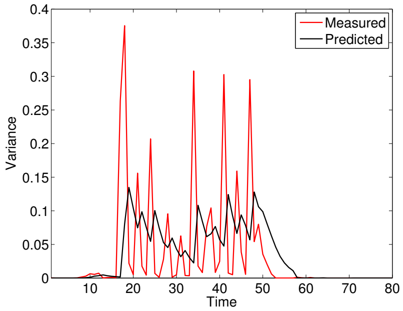

Fig. 10. X-axis data variance (Wrist)

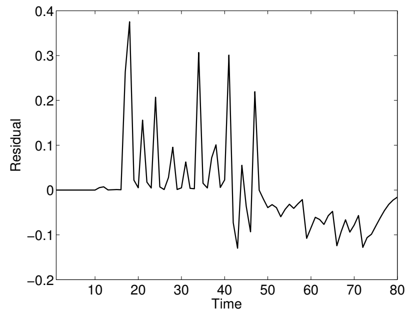

Fig. 11. Residual ($R_t = \hat{\sigma}^2_{t,i} - \sigma^2_{t,i}$)

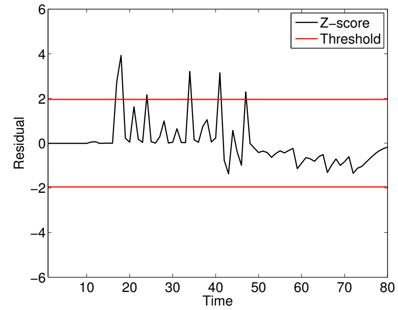

Fig. 12. Z-score and threshold

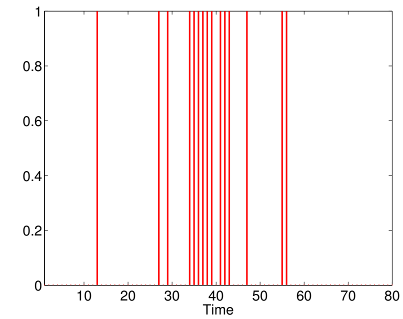

Fig. 13. Raised alarms

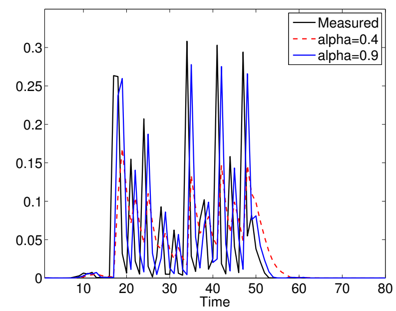

Fig. 14. Impact of weighting factor (α)

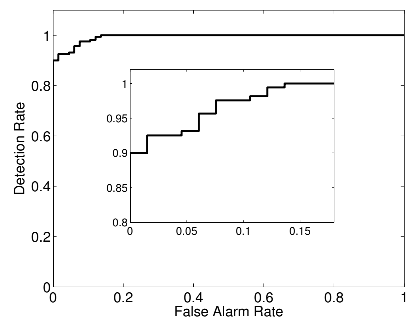

Fig. 15. ROC

variance. Figure 14 shows the impact of weighting factor on the prediction of variance. Choosing a value of α near to 1, the predicted time series becomes more sensitive to the new values and their fluctuations. We use $\alpha = 0.3$ to have a regular smoothing of data and to minimize the errors of variance forecasting by giving more weight to past values. This allows the forecasting to adapt to normal movements and to distinguish them from suspicious movements.

To evaluate the performance of the proposed approach, we use a synthetic data set containing 100 seizures at different time instants and we apply our algorithm to study the impact of the threshold h or the filling ratio at the detection accuracy. We used the ROC (Receiver Operating Characteristic) curve to show the impact of h on the True Positive Rate (TPR) given in equation 4 and the False Positive Rate (FPR) given in equation 5.

$$TPR = \frac{TP}{TP + FN} \times 100\% \tag{4}$$

Where TP is the number of true positives, and FN is the number of false negatives. FPR is defined as the ratio of incorrectly detected seizures:

$$FPR = \frac{FP}{FP + TN} \times 100\% \tag{5}$$

Where FP is the number of false positives and TN is the number of true negatives. Figure 15 shows the ROC for the proposed approach where the detection probability reaches 100% for a FAR of 13%. The ROC proves that it is possible to distinguish normal activity from epileptic seizures.

V. Conclusion

In this paper, we proposed an approach for automatic detection of epileptic seizures. The approach aims at enhancing the detection accuracy and reducing the false alarms of existing WBAN systems used to detect seizures. It is based on the change point detection in the variance of ACC data to detect seizures.

To reduce energy consumption by sensor data transmission, a distributed detection mechanism is applied on each sensor and only notifications are transmitted to the LPU when a change is detected. The LPU uses the filling ratio of the sliding window to take a final decision to trigger an alarm. We applied our proposed approach on real dataset in which we synthetically inject several seizure motor at different time instants in order to evaluate the performance of our approach. Our experimental results show that our proposed approach is able to achieve a good detection accuracy, with low false alarm rate and with low detection delay.

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