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Detection of Epileptic Seizure Using Wireless Sensor Networks

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ABSTRACT

The monitoring of epileptic seizures is mainly done by means of electroencephalogram (EEG) monitoring. Although this method is accurate, it is not comfortable for the patient as the EEG-electrodes have to be attached to the scalp which hampers the patient's movement. This makes long-term home monitoring not feasible. In this paper, the aim is to propose a seizure detection system based on accelerometry for the detection of epileptic seizure. The used sensors are wireless, which can improve quality of life for the patients. In this system, three 2D accelerometer sensors are positioned on the right arm, left arm, and left thigh of an epileptic patient. Datasets from three patients suffering from severe epilepsy are used in this paper for the development of an automatic detection algorithm. This monitoring system is based on Wireless Sensor Networks and can determine the location of the patient when a seizure is detected and then send an alarm to hospital staff or the patient's relatives. Our wireless sensor nodes are MICAz Motes developed by Crossbow Technology. The proposed system can be used for patients living in a clinical environment or at their home, where they do only their daily routines. The analysis of the recorded data is done by an Artificial Neural Network and K Nearest-Neighbor to recognize seizure movements from normal movements. The results show that K Nearest Neighbor performs better than Artificial Neural Network for detecting these seizures. The results also show that if at least 50% of the signal consists of seizure samples, we can detect the seizure accurately. In addition, there is no need for training the algorithm for each new patient.

Key words: *2D accelerometer, epilepsy seizure detection, K Nearest-Neighbor, neural network, wireless sensor network*

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INTRODUCTION

Epilepsy is one of the most common neurological disorders, affecting almost 60 million people all over the world. Most of the affected people can be treated successfully with drug therapy (67%) or neurosurgical procedures (7%-8%). Nevertheless 25% of the affected people cannot be treated by any available therapy.[1] For refractory patients who continue to have frequent seizures, it has been shown that intensive monitoring with electroencephalogram (EEG) and video over a long period, contributes to the management of daily care and the adjustment of drug therapy.[2] The long-term monitoring with EEG and video can be very unpleasant for patients, and analyzing large amounts of EEG/video-data is very labor intensive for medical personnel. Furthermore, this method cannot yet be applied in real-time procedures.

All the above-mentioned factors have made it necessary to look for sensors that are patient friendly and can be used for a reliable automatic detection of epileptic seizures. One of these sensors is the accelerometer. Accelerometers are used in many medical research areas for activity recognition.[3-5] For instance, in Parkinson's disease, studies aim at distinguishing pathological (periods of hypokinesia, bradykinesia and dyskinesia) and normal movements.[6,7]

Here, we focus on motor signs since epileptic seizures are often accompanied by motor signs. With accelerometry (ACM), only seizures that express themselves in movements or disturb normal movement patterns can be detected. The results in reference[8] demonstrate that 3D ACM is a valuable sensing method for seizure detection. The authors in reference[9] propose an algorithm based on HMM for seizure detection. As in reference[9], in reference[10] the patient movements are modeled with Hidden Markov Models and Bayesian analysis of the signal is performed. Algorithm of seizure detection in reference[9] is without adaptation to patient but this problem is overcome in reference[10]. About nocturnal epileptic seizure, reference[11] focuses on the distinction between seizure moves and nocturnal moves. Sensors are therefore attached on a patient and the authors propose to detect period with motor activities.

Long-term home monitoring can provide the neurologist an objective measure of the number of seizures that a patient can have during the day. Also in some of the

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heavy epileptic attacks the patient needs medical care after or during the seizure. Human body movement can be monitored through a wireless network composed of inertial sensors. Reference [12] presents the development of Wagyromag (Wireless Accelerometer, GYROscope, and MAGnetometer), a wireless Inertial Measurement Unit (IMU) composed of a triaxial accelerometer, gyroscope and magnetometer. The authors describe a seizure detection system based on Wireless Sensor Network (WSN) that can determine the location of the patient when a seizure is detected and sends an alarm to hospital staff or the patient's relatives.

Proposed System

In this paper, we introduce a system based on WSN that provides a continuous monitoring without limiting the freedom and privacy of the patients. The main goal is to distinguish between data with and without seizure movement.

The general constraints and characteristics of the system are listed as follows:

- Flexibility: All external wirings can be removed to allow the subject under test move without restrictions
- Ease of use: The network protocol allows the sensor network to initialize itself in a highly *ad-hoc*, self-organizing manner
- Reliability: While data reliability is always important, it becomes a critical requirement for many applications, for example, in medical monitoring
- Biaxial acceleration measurement
- Rechargeable batteries
- Low power consumption
- Comfortability: The device has small size and low weight, and is able to be attached to different parts of patient's body.

There are two kinds of nodes in the network:

- Mobile sensor nodes which are placed on the body of patients
- Static nodes which are sited on fixed specific locations at the building.

The static nodes transport the collected data from mobile sensor nodes to a base- station. The base- station sends data to computer server through a USB cable. Recorded data will be processed and when a seizure is detected, static nodes can determine approximately the location of the patient and sends an alarm to hospital staff or the patient's relatives.

The analysis of the recorded data is based on artificial neural network (ANN) and K Nearest Neighbor (KNN) to recognize seizure movements from normal movements. Figure 1 shows the proposed system for epileptic seizure detection.

SEIZURE DETECTION METHOD

Data Collecting

Datasets from patients suffering from heavy epilepsy were used for the development of an automatic detection algorithm. In this system, three 2D accelerometer sensors were positioned on the right arm, left arm and left thigh of epileptic patients. Datasets were acquired from three patients suffering from severe epilepsy. The datasets of the epileptic patients were recorded during the day. We recorded 20 epileptic seizures.

Patients were asked to perform a sequence of everyday normal activities but were not told specially how to do them. Normal activities that we recorded included static activities such as reading, working with computer, brushing of teeth, and lying and dynamic activities such as walking. The sampling frequency of the accelerometer is 3 Hz. Figure 2 shows the pure output of accelerometers when sampling frequency is 3 Hz. It shows at first lying and then seizure signal. In this Figure the seizure has begun from 180 samples. Acceleration has been measured based on gravity ($g = 9.8\,m/s^2$).

For analyzing and detecting seizures from this huge data sequence, the best way is cutting the acceleration sequences

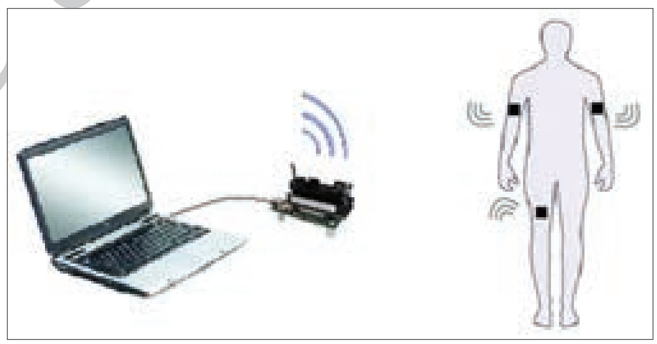

Figure 1: Proposed system for epileptic seizure detection

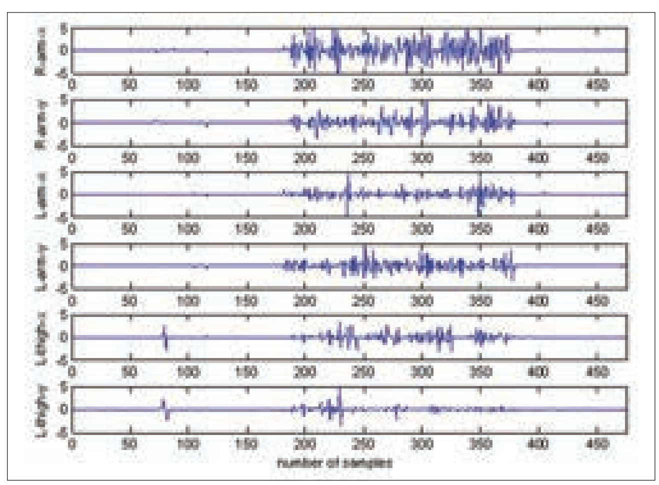

Figure 2: The pure output of accelerometers

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into many overlapping windows (segments) of the same length. For our data, the size of this window is considered 50 samples and it is repeated for every 25 samples. Since the sampling frequency is 3 Hz, we cut the data sequence every 9 seconds and analyzed this window of the ACM data to detect seizure. Figure 3 shows the acceleration data and overlapping window that located the signal.

Preprocessing

The output of an accelerometer attached to the human body consists of different components:

- Noise from sensor and measurement system
- Noise sources from the environment: (a) accelerations produced by external sources like vehicles; (b) accelerations due to bumping of the sensor or the body against other objects
- Noise sources from the body: (a) Muscle tremor; (b) Heart; (c) Respiration; (d) Blood flow
- Gravitational acceleration
- Acceleration due to movements of the body

In comparison to body movements, the noise from the sensor and measurement system can be neglected. All data used in this study were recorded while the patients were in their living environment, thus there were no accelerations produced by external sources.

When there is no movement, physiological perturbations, like respiration and heart rate and gravitational acceleration are visible in the signal. A preprocessing step is executed on the raw data for deleting these perturbations. To do that, we use a moving average filter. If the received signal is denoted as X(k), the filtered signal is given by following equation:

$$X_s(k) = X(k) - \frac{\sum_{l=-L}^{L} X(k+1)}{2L+1}$$

Where $X_s(k)$ is the output of the filter. 2 L + 1 is the size of the sliding window expressed in the number of samples, the filter length. We introduce a delay of LT in the flow of data. In practice T = 1/3, so for L = 2, the delay is 0.6 seconds.

Feature Extraction

The selection of discriminative features is the basis of almost all detection algorithms. The choice for certain features is based on the physiological phenomena that need to be detected.[13] In this way we should extract the features that help us to detect seizures. We used three features as follows:

- Variance measures the magnitude of a varying quantity in the signal. If $x_i = X_s(k)$, the variance of samples σ_i^2 can be calculated by:

  $$\sigma_i^2 = E\{|x_i - \bar{x}_i|^2\}$$

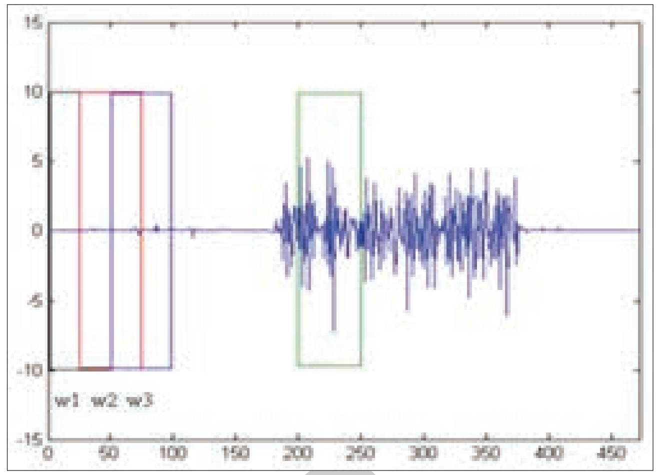

Figure 3: Acceleration data with overlapping windows

  Where $\bar{x}_i = E\{x_i\}$ is the average of samples

- Correlation is calculated between the two axes of each accelerometer. The correlation C_{ij} between *x* and *y* axes is given by:

  $$C_{ij} = E\{(x_i - \bar{x}_i)(y_j - \bar{y}_j)\}$$

  Where x_i and y_j are ACM input signals of *x* and *y* axes, respectively, so $\bar{x}_i = E\{x_i\}$ and $\bar{y}_i = E\{y_i\}$ are its mean.

  Energy is the sum of the squared discrete FFT (Fast Furrier Transform) component magnitudes of the signal. If the length of window is N, discrete FFT component magnitudes X_k of the signal and its energy E_s are given by:

  $$X_k = \sum_{n=0}^{N-1} X_s(n) e^{-j2\pi k \frac{n}{N}}, E_s = \sum_{k=1}^{n-1} X_k^2$$

  Energy parameter is used to discriminate sedentary activities from other activities.

Choice of the Classifier

In our work, two classifiers were constructed to recognize seizure movements from daily activities. The first classifier is ANN and the second classifier is KNN.

ANN

The structure of the ANN classifier is shown in Figure 4. It consists of an input layer, a hidden layer, and an output layer $u = \{u_1, u_2, \ldots, u_r\}^T$ and $y = \{y_1, y_2, \ldots, y_h\}^T$ are the input and output vectors, respectively, where *r* represents the number of elements in the input feature set and *h* is the number of classes. Tangent sigmoid functions are selected as the activation functions *f* in the hidden and output neurons. In general, the back propagation learning algorithm (a gradient descent optimization method) is used to train the ANN. However, it is known that the gradient descent learning method is subject to slow convergence and local minima.[14]

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Levenberg-Marquardt backpropagation is one of the best solutions for neural network training.[14] A multilayer perceptron with a hidden layer of 15 nodes and with Levenberg-Marquardt backpropagation as the training algorithm was used in the ANN classifier.

KNN

This rule classifies x by assigning it to the label which is the most frequently represented among the *k* nearest samples; in other words, the KNN query starts at the test point and grows a spherical region until it encloses k training samples, and labels the test point by a majority vote of these samples. The criterion of distance in KNN classification is the Euclidean distance that is given by the following equation.

$$d_E = [(x - m_i)^T (x - m_i)]^{1/2}$$

where x is a test point and m_i is a training sample.

Network Topology

There are several architectures that can be used to implement WSN applications, including star, mesh, and star-mesh hybrid. Each topology presents its own set of challenges, advantages, and disadvantages. The topology refers to the configuration of the hardware components and how the data are transmitted through that configuration.

XMesh is a full featured multi-hop, *ad-hoc*, mesh networking protocol developed by Crossbow,[15] for wireless network. An XMesh network consists of nodes that wirelessly communicate to each other and are capable of hopping radio messages to a base station where they are passed to a central server. The hopping effectively extends radio communication range and reduces the power required to transmit messages. By hopping data in this way, XMesh can provide two critical benefits: improved radio coverage and improved reliability. Two nodes do not need to be within direct radio range of each other to communicate. Xmesh provides to support both Zigbee standards (802.15.4) and advanced mesh networking. XMesh provides a TrueMesh networking service that is both self-organizing and self-healing. In Figure 5 is presented the diagram for XMesh network.

We have implemented this WSN in a three-floor building that has 16 rooms in each floor.

Hardware Requirement

We have implemented this system with our wireless sensor nodes, Motes, developed by Crossbow Technology. The device is built upon the IEEE 802.15.4 standard and has an 8-bit Atmel ATmega microcontroller. It uses the Chipcon CC2420, ZigBee ready radio frequency transceiver designed for low-power and low-voltage wireless communication in the 2.4 GHz unlicensed ISM band.[15]

For the purpose of seizure detection, we use MTS310 sensor board. MTS310 has a variety of sensing modalities including an accelerometer two-axis device. Figure 6 shows an MICAz Mote and an MTS310 sensor board.[16]

Locating the Patient

As mentioned above, the static nodes have an interface role between mobile sensor nodes and base-station. Also, location of each mobile node can be determined by the closest static node. So the location of static nodes must be

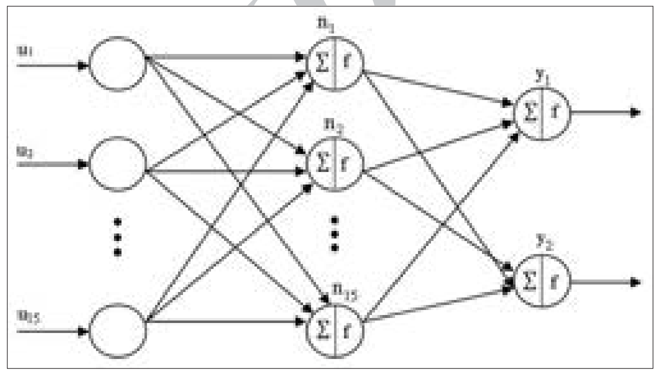

Figure 4: structure of artificial neural network

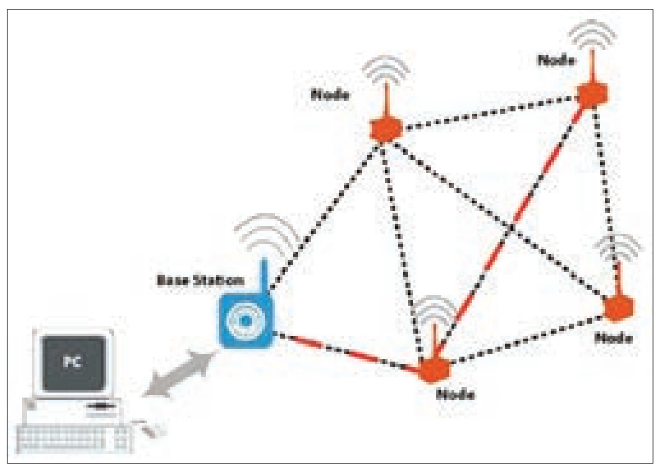

Figure 5: X Mesh network diagram

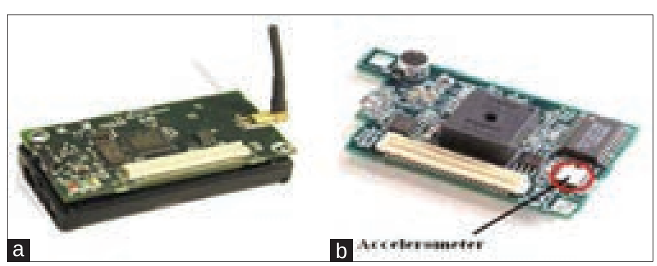

Figure 6: (a-b) MICAz mote, MTS310 sensor board

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Table 1: Performance of ANN classifier for seizure detection

	Number of marked seizure	Number of detected seizure	Number of false alarm
Patient# 1	7	6	1
Patient# 2	9	7	0
Patient# 3	4	4	2

ANN – Artificial neural network

Table 2: Performance of KNN classifier for seizure detection

	Number of marked seizure	Number of detected seizure	Number of false alarm
K=1	20	18	3
K=3	20	20	2
K=5	20	20	0

KNN – K Nearest Neighbor

chosen such that at any time, a mobile node connects to one and only one static node, since each mobile node is localized by the nearest static node. Although a large radio range for the nodes increases the power consumption and decreases the accuracy for localizing the mobile nodes, it helps to cover a building with fewer static nodes. So, we should set a trade-off between the number of nodes and radio range for them.

We set the node's power on 316 μW. In this power, the radio range of nodes is 30 m in a line of sight area and we can cover a building using eight static nodes.

EXPERIMENTAL RESULTS

The proposed system in this research can be used for patients living in a clinical environment or at their home, where they do only their daily routine. We could detect seizures from normal activities such as walking. The analysis of the recorded data is based on the ANN and KNN to recognize seizure movement from normal movement. When we classified datasets of the three patients by ANN to detect epileptic seizures, we obtained the results shown in Table 1.

As can be seen in the table, three seizures have not been detected and we have obtained three false alarms. Sensibility in this system is 85%.

Then we used KNN to classify the datasets and detect seizures. The results of using this classifier with $k = \{1, 3, 5\}$ are shown in Table 2.

Table 2 shows that for k = 1 two seizures have not been detected and three normal activities have been detected as seizures. For k = 3 we have only two false alarms. But for k = 5 no seizure has been missed by the system and we have no false alarm. So KNN algorithm has produced better results than ANN.

DISCUSSION AND CONCLUSION

One of the most interesting applications of WSN is health monitoring. In this paper we introduced a monitoring system based on WSN for detection of epilepsy seizures. This system can be used for patients living in a clinical environment or at their home, where they do only their daily routine. Our system can determine the location of the patient when a seizure is detected and sends an alarm to hospital staff or the patient's relatives. Since our sensors are wireless, the subject under test can move without restrictions. In addition, because of the small size of the sensor nodes, they are wearable for patients. Our experimental results showed that 5 Nearest Neighbors provides better results than the ANN classifier. Furthermore, there is no need for training the algorithm for each new patient.

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