Volume 6, Issue 9, September 2016 ISSN: 2277 128X

International Journal of Advanced Research in Computer Science and Software Engineering

Research Paper

Available online at: www.ijarcsse.com

An Android App for Epilepsy Seizure Detection

Tran Tri Dang

Faculty of Computer Science and Engineering, HCMUT – VNU-HCM, Vietnam

Abstract— Epilepsy is a common neurological disorder and can affect people of all ages. Detecting epilepsy seizure early when it happens, especially in a home setting, can help prevent serious health issues that can occur as consequences of the seizure. However, it is not easy to deploy such solutions to families because of the expensiveness and complexities of related medical equipment. To overcome this problem, in this paper, we propose an algorithm for detecting epilepsy seizure that can be implemented and installed on mobile smart phones, provided that these devices are attached to patients' hands. In particular, the algorithm uses phones' acceleration sensors to decide if there are seizure jerking movements or not. The decision making are based on some thresholds, which are obtained empirically. We also implemented a prototype app on Android operating system to experiment and evaluate the proposed algorithm. Experiment results show some potentials of this app with regard to high detection rate and acceptable false positive rate.

Keywords— Seizure detection, jerking movement detection, epilepsy seizure, Android app, personal health care

I. INTRODUCTION

Epilepsy is one of the most common neurological disorders and can affect people of all ages. Epilepsy patients having un-controlled emotions and behaviours when their neuronal activities are disturbed. These anomalous brain signals can lead to seizure. Because there are many types of abnormal brain activity, there are also many types of seizure.

Different seizures produce different symptoms on epilepsy patients. For example, the generalized tonic-clonic seizure creates unconsciousness, convulsions, and muscle rigidity. Knowing what kind of seizure is happening is a necessary step to provide appropriate treatment to patients. In these situations, electrical signals of the patient's brain are required to identify the correct epilepsy seizure. However, this data is not easily obtained, especially in home environment. Therefore, to provide health care support to epilepsy patients, alternative data is needed.

When an epilepsy patient is experiencing seizure, one of the most common symptoms displayed is jerking movement. Although not all seizures create jerking movements, recognizing these activities from other normal activities is a useful step in provide treatment at home. Furthermore, jerking movements can be detected using popular and cheap devices, making it one of the right data sources to deploy health care support to a wide range of epilepsy patients, especially ones live in poor areas.

One popular and cheap, yet powerful enough, device type that can be used as equipment to detect epilepsy patient's jerking movements is smart phone. In particular, any smart phone with built-in acceleration sensor is capable to become such an equipment. In addition, another benefit of using smart phone to provide health care support to epilepsy patients is we can utilize its available storage and communication capabilities effectively. Using stored medical records, such as symptoms and prescription history, can helps health professional diagnose easily and provide better treatment. With built-in communication system, notification messages can be sent to responsible people in urgent events, such as when the patient is unconscious and cannot do anything.

In this paper, we describe our work on developing a smart phone app to support epilepsy patients and their care givers. This app consists of two main components: the first component is responsible for detecting jerking movements, and the second component is in charge of interfacing between the app and the end user. The operating system we use to develop this app is Android. Android is used because of its large number of users and also its open nature. But it should be noted that the jerking movement detection algorithm is platform independent. So, in the future, this work can be extended to other operating systems as well.

The rest of the paper is structured as follows. In Section 2, we provide related works to our research. In Section 3, we propose an algorithm to recognize jerking movements. Section 4 presents the implementation details of our app. Experiment settings and results are discussed in Section 5. And finally, we conclude our work in Section 6.

II. RELATED WORKS

According to the National Institute of Neurological Disorders and Stroke, there are many types of seizure in epilepsy patients [1]. These seizures are results of the abnormal electrical activities of the brain. As a result, the most accurate method of detecting seizure is to monitor and analyze the electrical signals of the patients' brain. In particular, that is to look for abnormal patterns in the brain activities from Electroencephalogram (EEG) data.

© 2016, IJARCSSE All Rights Reserved

Because EEG provides the most accurate data source for seizure detection, it is used widely by researchers for that purpose. In paper [2], the authors developed a classifier for seizure onset detection. In order to train the classifier, the patients' EEG data is recorded in both seizure and non-seizure situations. These data is then inputted to a modified nearest-neighbour algorithm to learn the parameters. When experimenting with 12 patients, the resulting system has a seizure onset detection rate of 100% with an average delay of 9.35 seconds after onset. The false alarm rate of the system is acceptable, which is only 0.02/h. Furthermore, because of the small computational load, the detection algorithm can produce results in real time. In another work, EEG data is used not only to detect epileptic transient events but also to classify them into one of four categories: epileptic spikes, muscle activity, eye blinking activity, and sharp alpha activity [3]. Association rule mining is utilized for the detection and classification. The overall technique includes four stages as follow: at the first stage, transient events are detected; then, in the second stage, transient events are clustered and features are extracted; the third stage involves features discretization and features subset selection; and finally, in the fourth stage, association rule mining is used to classify transient events. When the system was evaluated with 25 EEG recordings, in which 12 are normal and 13 are epileptic, the best accuracy obtained was 87.38%. The outcomes of transient events are then used for spike detection and assessment, which can be useful to the neurologists in the diagnosis of epilepsy. EEG data is also used with many other techniques, such as artificial neural network [4], genetic algorithm [5], and multilayer perceptron [6], to detect seizures. In paper [4], the authors use time-frequency analysis to segment EEG signals. The EEG segments are then fed into an artificial neural network for epileptic seizure classification. In paper [5], both linear and nonlinear models are used for seizure detection. To make the processing more efficient, principle component analysis are used together with genetic algorithms. In paper [6], the authors represent EEG signals by means of rational functions and rational discrete short-time Fourier transform is used for feature extraction. Consequently, the coefficients of the rational discrete short-time Fourier transform become the inputs of the classifier, which is a multilayer perceptron.

Although EEG data is accurate in epileptic seizure detection and prediction, it is not easily collected in a home setting. As a result, researchers are looking for alternative data sources that can be captured and processed by popular and cheap devices. At the moment, one of these possible data sources is acceleration data generated from movements of epilepsy patients. Although not all seizures can be recognized with acceleration data, this data can, at least, provides a mean to detect motor seizures at the epilepsy patients own home, and therefore sends on time warnings to care givers.

In paper [7], the authors developed 4 time-frequency and time-scale methods to detect myoclonic seizures from acceleration data. The reason why myoclonic seizure is chosen as the detection target is because of all motor seizures, 74% of the them consists of at least one myoclonic element. The methods that are developed include: the short-time Fourier transform, the Wigner distribution, the continuous wavelet transform, and a newly introduced model-based matched wavelet transform. The 4 methods are then evaluated with real patient data. Data from 15 patients are used for training, and data from 21 patients are used for testing. The paper experiment result demonstrates that acceleratory data can be used to detect myoclonic seizures.

Because of the programmable capability of smart phones, as well as the falls of their prices, smart phones are used not only for seizure detection but also for general epilepsy health care support. In paper [8], the authors evaluated the applications of mobile phones in the day to day care of epileptic patients. The users of these applications are classified into 2 groups: epilepsy patients/care givers and health professionals. For each group, different requirements are needed from the supporting apps. The result of [8] can serve as a general guideline for designers when developing smart phone apps for epilepsy support and treatment.

In a similar research, some applications on smartphones that are used in seizure management are surveyed [9]. The authors studied existing apps on the big smartphone platforms, including iPhone, Android, Blackberry, Windows Mobile and Nokia-Symbian. In this work, only apps that are related to seizure management and not aimed exclusively at health professionals are included. The authors found 28 such apps. There are 2 features every app has to support: patient education and self-monitoring. Patient education is meant to provide patients with useful information related to their situations, while self-monitoring helps patients to track their own health in time.

The most relevant work to ours is presented in [10]. In this work, the authors developed an algorithm, called Seizario, on mobile smart phone which is capable of both seizure detection and fall detection. Like our proposed technique, this technique also use acceleratory data for seizure detection. However, its data processing and decision making algorithm is different from ours.

III. SEIZURE DETECTION

The main objective of the proposed seizure detection algorithm is to recognize when an epilepsy patient has seizure. To achieve that objective, it needs to be able to differentiate between the patient's normal state and her seizure state. In particular, we consider the patient's jerking movements as indications for seizures. As such, our technique can recognize myoclonic and clonic seizures [11].

Jerking movements can be detected using acceleratory data collected in real-time from a smart phone attached to a patient's body (in our case, the patient's hand). Although it is not convenient for the patient to bring a smart phone from time to time, it is still acceptable because of the small size of these devices these days and other utilities they can provide like playing music, news article, entertainment, etc. Furthermore, wearable smart devices are becoming popular, and they run the same operating systems as smart phones do. So, there is no restriction in deploying our technique to these platforms in the future.

The algorithm we developed is based on this basic observation: when there are jerking movements, the recorded acceleration values obtained from the smart phone sensors go through big changes. By analyzing these changes'

© 2016, IJARCSSE All Rights Reserved

amplitudes, with regard to the time period in which changes happen, we can decide whether there are jerking movements or not. Fig. 1 displays acceleration data values in 2 cases: walking (left) and having jerking movements (right).

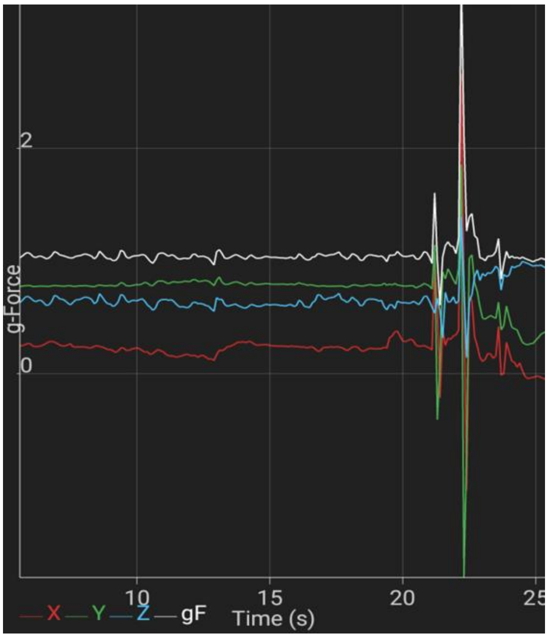

Fig. 1 Acceleration data values in time when walking (left) and having jerking movements

To further refine the proposed algorithm, we also borrow the ideas from the research papers [12] and [13]. To be more specific, we define 2 thresholds g_{thres} and g_{min}, both of which are limits that acceleration values changes must be bigger than to trigger notification of seizures. But g_{thres} and g_{min} have different roles in the detection algorithm. g_{thres} is used to exclude seizure-like activities such as hand shaking from real seizures. Usually, the changes in acceleration values for these activities are smaller than the changes generated by jerking movements. So, by tuning g_{thres}, we can control the false positive rate that is caused by recognizing wrongly normal actions as seizures.

On the other hand, the second threshold g_{min} is used to eliminate strong but short movements, such as jumping or waking up stairs. These movements can produce data that make the detection algorithm falls if it only use the first threshold. Note that this second threshold g_{min} is used together with a time period value T_{min}. T_{min} is the shortest interval in which acceleration changes must always exceed g_{min} if these acceleration values are actually generated by seizure activities.

A. Acceleration change calculation

Below is the detailed description of the detection algorithm, assuming the values of g_{thres} and g_{min} are already decided. Smart phone accelerator sensors provide 3 independent components of the patients' acceleration data: g_x, g_y, and g_z.
The magnitude of the acceleration is therefore is given as

$$g_{rms} = \sqrt{g_x^2 + g_y^2 + g_z^2}$$

By reading acceleration values continuously, the change amplitudes can be calculated as:

$$\Delta g_{rms} = g_{rms\_current} - g_{rms\_last}$$

Because of the limits of hardware sensors, reading current acceleration values usually gives high change magnitudes even for slight movements. To overcome this issue, the read values are averaged first before used to make decision. The average calculation is depended on the sampling rate. According to paper [12], a sampling rate of 20Hz is reasonable. If the sampling rate is too high, then the change amplitudes are almost near zero per sample, plus the storage requirement is larger; on the other hand, if the sampling rate is too low, then the change magnitudes will be very high. When the sampling rate is n, the formula to get average acceleration change in one second is given as:

$$\Delta g_{rms\_avg} = \left(\sum_{i=0}^{n} \Delta g_{rms\_i} \right) / n$$

B. Jerking movements detection

The seizure detection algorithm starts with checking whether the average acceleration change exceeds the first threshold g_{thres} or not. If that condition is met, the detection algorithm enters the second phase. In this phase, the average acceleration change has to maintain a minimum value of g_{min} continuously in a time period T_{min} in order to raise a seizure event. If the average acceleration change falls below g_{min} during T_{min}, the algorithm starts over again. Fig. 2 is an example chart depicting the average acceleration change in time when there is a seizure event.

© 2016, IJARCSSE All Rights Reserved

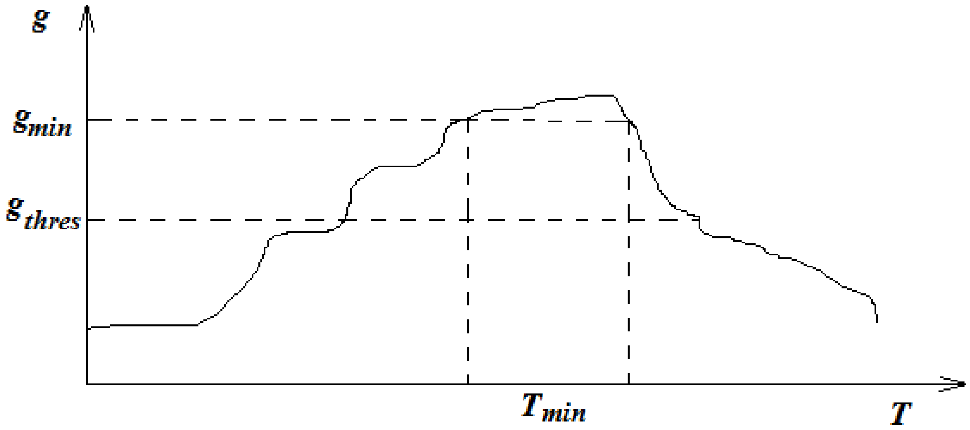

Fig. 2 Average acceleration change in time when there is a seizure event

The seizure jerking movements detection algorithm is given in the flowchart of Fig. 3.

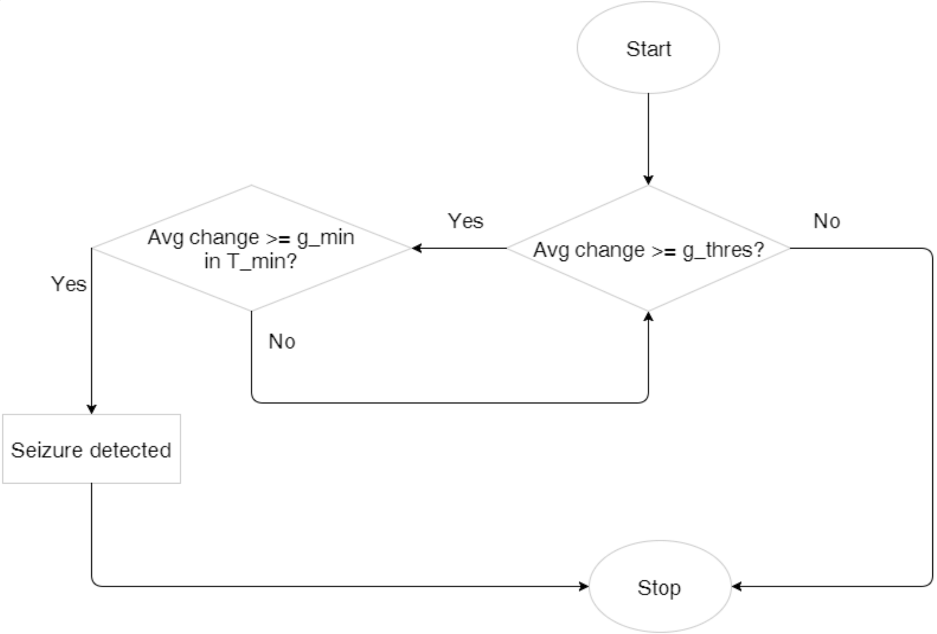

Fig. 3 Seizure jerking movements detection algorithm

IV. IMPLEMENTATION

A. User interface

Based on the proposed detection algorithm, we develop a prototype mobile app on Android OS to experiment and evaluate our approach. Besides the detection implementation, the app also includes a simple user interface to help patients and their care givers record seizure and medication history. In addition, we also store general information about epilepsy and epilepsy treatment in the app to make these knowledge easily accessible for the users. However, we have not yet evaluated the usability of this app in this paper. The main user interface of our app is displayed in Fig. 4.

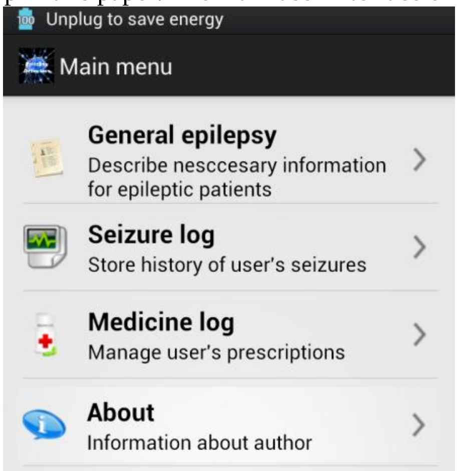

Fig. 4 The main user interface of our prototype app

B. Reading acceleration sensors

Android based devices have built-in sensors that can be used to measure devices' properties such as orientation, motion, etc. These sensors can return raw data with high precision and accuracy. There are 3 broad categories of sensors: motion sensors, environmental sensors, and position sensors [14]. For the purpose of this research, we concentrate on motion sensors only.

Among other things, motion sensors give us acceleration forces along 3 physical axes (x, y, z). The returned values are in the form of multi-dimensional arrays. The Java class SensorEvent is used to present a sensor event and it also holds information about the event, such as sensor's type, time-stamp, and sensor's data. In case of acceleration data, SensorEvent will store TYPE_ACCELEROMETER as its sensor type, and SensorEvent.values[0], SensorEvent.values[1], and SensorEvent. values[2] will store acceleration forces along the x, y, and z axes respectively. Fig. 5 displays the coordinate system used by the Android acceleration sensor (and other motion sensors).

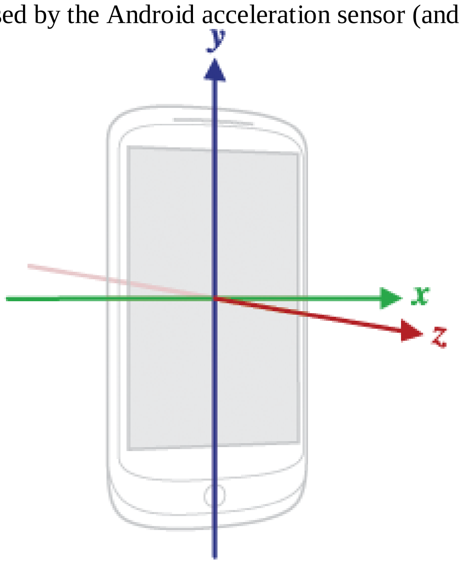

Fig. 5 Coordinate system of the Android acceleration sensor [14]

V. EXPERIMENT

A. Experiment settings

At the time of this writing, we were not able to invite real epilepsy patients to participate in our experiment. Therefore, we decided to use a simulation condition instead. In particular, we ask 5 volunteers join our tests. For these tests, at first, we give them a brief introduction about epilepsy seizures and let them watch videos of epilepsy patients having jerking movements. Then, we request them to mimic these behaviours while holding an Android smart phone, with our app installed, in their hands. The acceleration data generated in these cases is labelled as seizure. We also ask them to perform other activities like waking, standing, etc., with the smart phone in their hands too, to produce acceleration data for normal cases.

We use the acceleration data for seizure and normal cases, obtained as described above, to evaluate our detection algorithm. For this evaluation, we assume a fixed value of T_{min} is appropriate, as suggested in [12]. So, a value of 750ms is chosen for T_{min}. On the other hand, the values of g_{thres} and g_{min} are adjusted in each round of test.

B. Experiment results

The values of g_{thres} are running from 20mg to 80mg and the values of g_{min} are running from 60mg to 120mg. For each pair of (g_{thres}, g_{min}), all recorded acceleration data is fed into the detection algorithm. The detection results are compared with the respective data labels to measure the detection rate and false positive rate. We arrange the performance results based on detection rate; and for 2 results with the same detection rate, the result with smaller false positive rate is consider better.

In overall, we achieve the best performance of 95% detection rate and 6% false positive rate when g_{thres} = 60mg and g_{min} = 75mg. However, the best performance for each volunteer is different and obtained at different values of g_{thres} and g_{min}. Table I displays the best performance of each volunteer and the appropriate values of g_{thres} and g_{min} when the performance is reached.

Table I Best performance of each volunteer and the respective G_{THRES}, and G_{MIN} values

Id	Detection rate	False positive rate	g_{thres}	g_{min}
1	100%	5%	60mg	75mg
2	95%	8%	55mg	80mg
3	95%	3%	60mg	70mg
4	95%	5%	65mg	80mg
5	90%	0%	50mg	75mg

© 2016, IJARCSSE All Rights Reserved

From the result of this experiment, it is clear that threshold values for each patient should be set individually to achieve the best possible outcome. However, because this app is targeted at real patients, it is difficult to obtain training data in advance. This is an open problem that we may try to solve in the future.

VI. CONCLUSIONS

In this paper, we have proposed an algorithm for seizure jerking movement detection on mobile smart phones. The algorithm uses acceleration data that can be easily obtained by sensors equipped in popular smart phones. We also implemented a prototype app on Android platform to evaluate our work. Experiment results show that our app can recognize seizure with high detection rate and at an acceptable false positive rate.

There are some remained issues this work has not solved yet. The first one is testing this app with real dataset. As stated previously, we only invite normal people to join our experiment and ask them to mimic seizure jerking movements after watching sample videos. Acceleration data generated in this way may be different with real seizure jerking movement data. As a result, experiment results may not reflect real situations. The second issue in this work is our assumption about the fixed position of the smart phones. These devices are assumed to be hold in the patients' hands continuously. Although this assumption is not very practical for a long time period, it is still acceptable when a small duration is considered, e.g. some minutes. And holding these phones in small durations does not affect the detection rate in any way. Furthermore, with the increasingly growth of wearable smart devices, implementing our algorithm in device like smart watches just makes this assumption natural.

ACKNOWLEDGMENT

This research is funded by Ho Chi Minh City University of Technology – Viet Nam National University Ho Chi Minh City under grant number T-KHMT-2015-32.

REFERENCES

[1] (2016) National Institute of Neurological Disorders and Stroke (NINDS) website. [Online]. Available: http://www.ninds.nih.gov/disorders/epilepsy/epilepsy.htm

[2] H. Qu, and J. Gotman, "A patient-specific algorithm for the detection of seizure onset in long-term EEG monitoring: possible use as a warning device," *IEEE Transactions on Biomedical Engineering*, vol. 44, no. 2, pp. 115-122, 1997.

[3] T. Exarchos, A. Tzallas, D. Fotiadis, S. Konitsiotis, and S. Giannopoulos, "EEG transient event detection and classification using association rules,"*IEEE Transactions on Information Technology in Biomedicine*, vol. 10, no. 3, pp. 451-457, 2006.

[4] A. Tzallas, M. Tsipouras, and D. Fotiadis, "Epileptic seizure detection in EEGs using time–frequency analysis," *IEEE Transactions on Information Technology in Biomedicine*, vol. 13, no. 5, pp. 703-710, 2009.

[5] S. Liang, H. Wang, and W. Chang, "Combination of EEG complexity and spectral analysis for epilepsy diagnosis and seizure detection," *EURASIP Journal on Advances in Signal Processing*, 2010.

[6] K. Samiee, P. Kovács, and M. Gabbouj, "Epileptic seizure classification of EEG time-series using rational discrete short-time Fourier transform," *IEEE Transactions on Biomedical Engineering*, vol. 62, no. 2, pp. 541-552, 2015.

[7] T. Nijsen, R. Aarts, P. Cluitmans, and P. Griep, "Time-frequency analysis of accelerometry data for detection of myoclonic seizures," *IEEE Transactions on Information Technology in Biomedicine*, vol. 14, no. 5, pp. 1197-1203, 2010.

[8] L. Ranganathan, S. Chinnadurai, B. Samivel, B. Kesavamurthy, and M. Mehndiratta, "Application of mobile phones in epilepsy care," *International Journal of Epilepsy*, vol. 2, no. 1, pp. 28-37, 2015.

[9] P. Pandher, and K. Bhullar, "Smartphone applications for seizure management," Health Informatics Journal, vol. 22, no. 2, pp. 209-220, 2016.

[10] A. Helmy, and A. Helmy, "Seizario: novel mobile algorithms for seizure and fall detection," *In 2015 IEEE Globecom Workshops*, 2015, pp. 1-6.

[11] (2016) WebMD magazine. [Online]. Available: http://www.webmd.com/epilepsy/guide/types-of-seizures-their-symptoms

[12] T. Burchfield, and S. Venkatesan, "Accelerometer-based human abnormal movement detection in wireless sensor networks," *In Proceedings of the 1st ACM SIGMOBILE International Workshop on Systems and Networking Support for Healthcare and Assisted Living Environments*, 2007, pp. 67-69.

[13] P. Langley, E. Bowers, J. Wild, M. Drinnan, J. Allen, A. Sims, N. Brown, and A. Murray, "An algorithm to distinguish ischaemic and non-ischaemic ST changes in the Holter ECG," *In IEEE Computers in Cardiology*, 2003, pp. 239-242.

[14] (2016) Android Developer website. [Online]. Available: https://developer.android.com/guide/topics/sensors/sensors_overview.html

© 2016, IJARCSSE All Rights Reserved