Accelerometer-Based Human Abnormal Movement Detection in Wireless Sensor Networks

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ABSTRACT
Wireless sensor networks have become increasingly common in everyday applications due to decreasing technology costs and improved product performance. An ideal application for wireless sensor networks is a biomedical patient monitoring tool. Wireless patient monitoring systems improve quality of life for the subject by granting them more freedom to continue their daily routine, which would not be feasible if wired monitoring equipment were used. This paper explores an application of wireless biomedical sensor networks, which attempts to monitor patients for a specific condition in a completely non-invasive, non-intrusive manner. This non-invasive technique uses an accelerometer to determine if a person's arm movement is similar to that of a person suffering from a seizure. The effectiveness of the presented algorithm has been verified on test subjects and showed rare occurrences of false positives.

Categories and Subject Descriptors
J.3 [**Life and Medical Sciences**]: *Health.*

General Terms
Algorithms, Design, Experimentation, Human Factors.

Keywords
Wireless biomedical sensor network, Accelerometer, Movement detection.

1. INTRODUCTION
Wireless biomedical sensor network (WBSN) is an emerging field that leverages advancements in microelectromechanical sensor technologies and efficient wireless communication platforms in order to produce small, low cost and low power devices capable of monitoring patients for specific ailments or medical events. Well-defined standards such as IEEE 802.15.4 and ZigBee [10] have provided recent advances that are bringing deployments of WBSNs within reach. For example, a common concern with transmitting medical data is security. A patient's data should not be readable by anyone other than authorized parties. ZigBee and IEEE 802.15.4 have well defined encryption mechanisms that can be used to ensure data security.

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Even with recent advances, WBSN applications are not trivial to develop. Processing speed, memory, power consumption and data transmission capacity are major constraints that require careful design to meet without compromising system performance. The volume of data generated by conventional physiological signals complicates satisfying these constraints. Forwarding raw data to a nearby higher power PC is an option but only if battery life constraints of the device are removed. Much of the current body of literature for WBSNs relies on this type of off-line computation to detect events gathered from sensor data [9][1][2]. Wide scale WBSN adoption is unlikely until events can be detected in real-time on the patient device. This paper joins a body of literature that runs movement classification algorithms autonomously on sensor devices in real-time [4][7].

Our biomedical application of wireless sensor networks is based upon the premise that a small wireless node with an accelerometer is attached to a human wrist, like a wristwatch. This paper describes a threshold-based algorithm that uses this device to identify rapid shaking movements that usually accompany myoclonic, clonic and tonic-clonic seizures [5]. Upon detecting an abnormal event, the algorithm sounds an auditory alarm from the wrist-device and transmits an alarm message through a ZigBee wireless network to a patient monitoring station staffed by medical personnel.

2. Wireless Accelerometer Node Prototype
A small (1.75"x2.85"x1.00") wireless communication and accelerometer prototype was designed in order to develop the abnormal movement detection algorithm.

2.1 ZigBee Wireless Node
The smaller board with the antenna in Figure 1 is a standard radio communication module (RCM) in the Ember EM2420 based development kit. This board contains all of the hardware necessary to sustain wireless communication and execute basic computation that supports wireless sensor network applications. The Ember EM2420 radio communication module is primarily a pairing of the Ember EM2420 IEEE 802.15.4 RF Transceiver and the Atmel AtMega128L 8-bit microcontroller.

The larger board in Figure 1 contains the remaining facilities necessary to develop accelerometer-based abnormal movement detection algorithms. The significant components on the board are the following: Common 3V battery, Two momentary press buttons for programmable action and a 3-axis, 1.5g to 6g, 6mm x 6mm x 1.45mm accelerometer.

2.2 Accelerometer Functionality

The accelerometer selected for this project is the Freescale Semiconductor MMA7260Q device. This accelerometer has the ability to detect dynamic changes of acceleration in all directions by using independent X, Y, and Z axes. Each axis reports the current magnitude of acceleration with an analog voltage that is proportional to an acceleration "g-value" where "1g" is equal to the acceleration due to Earth's gravity. The g-value can be positive or negative with the 0g mapped to half of the accelerometer supply voltage.

3. Signal Processing

The algorithm for abnormal movement detection requires a set of data processing operations that interpret the voltages generated by the accelerometer and then convert them into interpretable data. These operations are described at depth in Burchfield and Venkatesan [3]. The goal of these operations is to generate a single smoothly changing curve that represents the recent activity level of the test subject. The algorithms use a sample rate of 20Hz.

The smooth curve is generated by first converting measured voltages into g acceleration values as defined by the accelerometer specification [6]. In order to reduce memory and processing requirements the next step combines the g acceleration value for each axis into a single value by using the root-mean-squared (RMS) method for taking the magnitude of a vector. Following RMS computation, the absolute difference from the previous sample is calculated as Δg_rms. Finally, the average of the Δg_rms values taken over the last 1 second is computed. 1-second was chosen because it allows new movement trends to manifest quickly in the algorithms' input and temporary, erroneous values are sufficiently diluted by the rest of the samples.

4. Rapid Shaking Detection (RSD) Algorithm

The RSD algorithm consists of two major conditions that are required in order to trigger an alarm based upon a person's movements. The first criterion is that the movement shall be of sufficient magnitude. This is to ignore non-seizure-like shaking movements such as using a pencil eraser on paper or head scratching. The second condition is an elevated activity level for a prolonged duration of time. This second condition proves to be necessary in order to eliminate false alarms caused by brief violent movements such as a jump, or the repetitive acceleration jolts caused by walking up or down stairs. The details of these conditions are discussed in the following two sections. A sample average Δg_rms graph is provided in Figure 2 to aide explanation. This two alarm threshold concept was originally proven to be effective at detecting specific events in ECG recordings by Langley et al [8].

4.1 Alarm Criteria – Drastic Movement

The drastic movement condition of the RSD algorithm is implemented with two threshold values, Gmin and Tmin. Gmin has been empirically set to an average acceleration change of 0.9g per sample (50ms period). The Tmin value has been empirically set to 750 ms (15 consecutive samples). Together, the Gmin and Tmin values ensure that the accelerometer detects an average acceleration change greater than 0.9g for duration no less then 0.75s in order to satisfy the drastic movement condition. The time at which this condition becomes satisfied has been labeled in the Figure 2 plot.

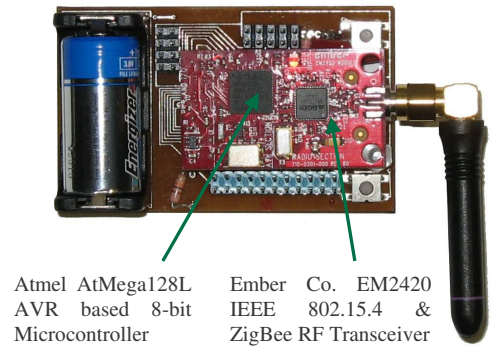

Figure 1. Wireless accelerometer platform prototype

4.2 Alarm Criteria – Sustained Movement

The sustained movement condition of RSD algorithm is implemented in a manner similar to that of the drastic movement condition. A more frequently exceeded g threshold value of Gthresh is used to signify that the test subject is exhibiting an elevated activity level. The value selected for Gthresh is 0.5, which corresponds to, on average, half a g of acceleration change per sample. The corresponding time threshold is implemented differently for the sustained movement condition. The sustained movement condition is considered satisfied if the average change in g value exceeds Gthresh for TsCountThresh or greater non-consecutive samples. Non-consecutive examples are required in this case because this condition was engineered in order to identify periods of elevated activity. Rapid shaking movements indicative of the onset of a seizure may experience brief (order of milliseconds) lulls that would cause the algorithm to reset unnecessarily in a consecutive count model. Thus, counting non-consecutive threshold crossings places less emphasis on the magnitude of the acceleration change and more emphasis on the movement trend. Since non-consecutive threshold crossings are counted, a reset condition must be specified for the threshold cross counter. The threshold cross counter is reset to zero after a sufficient period of inactivity, defined to be Tthresh samples with an average value below Gthresh. We chose Tthresh to be 60 resulting in 3 seconds of unsuspicious activity from the subject. The relevance of the sustained movement condition to the overall algorithm is displayed in Figure 2.

5. Dynamic Thresholds and Calibration

We are currently working various improvements to this algorithm. One such improvement is the design of an auto-calibration mechanism that varies the RSD algorithm thresholds for a given test subject based upon their movement history. This implementation also accepts false-alarm feedback from the wearer using the momentary press buttons on the prototype board. For RSD alarms, this calibration reviews the recent average change history in order to determine which condition, drastic movement or sustained movement, was the last to be satisfied. Then the count threshold or the average voltage change threshold for the corresponding condition is adjusted.

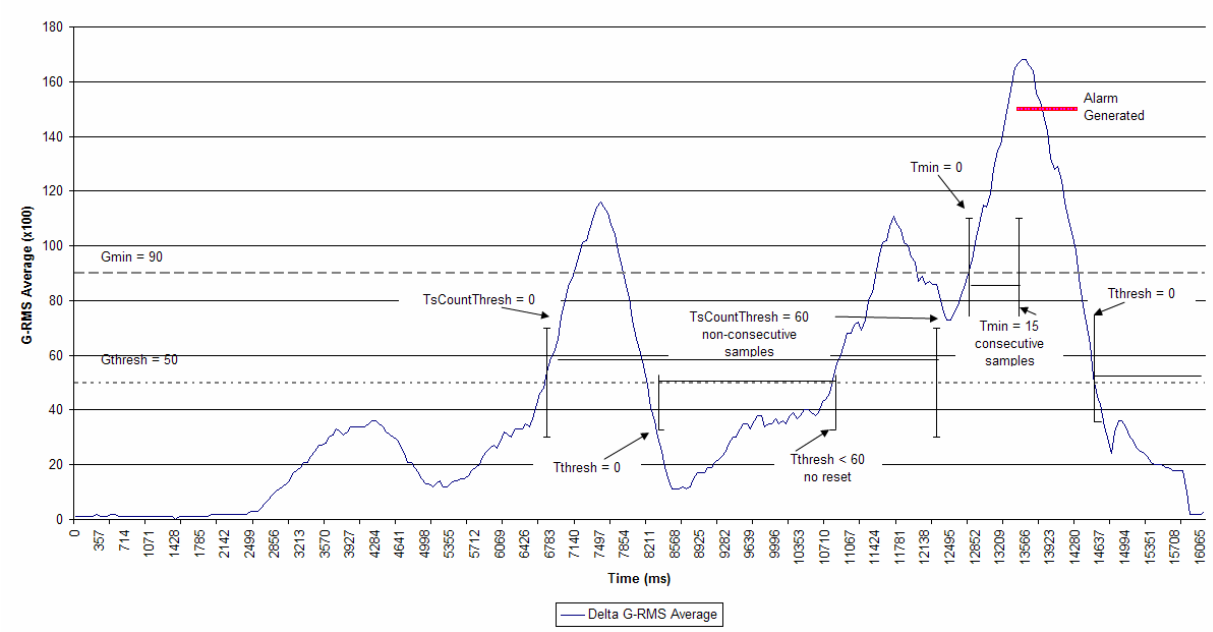

Figure 2. RSD threshold configuration

6. Results

Testing the abnormal movement algorithm is a challenge because the targeted movement has a low occurrence rate among the population. Furthermore, there is a lack of medical resources at our institution to complete a thorough clinical study. However, the algorithms can be evaluated to determine the frequency of false positives triggered during normal movement. This aspect of algorithm testing has been extremely successful. Even when attempting to trigger false positives with normal but exaggerated movements, the RSD algorithm generates rare alarms. Since no test data was available from a subject who had a seizure while wearing the prototype device, several testers were asked to wear the device and emulate seizure-like shaking to the best of their ability. The RSD algorithm was able to detect each person's suspicious movements with no need for individual calibrations. The next step in testing is to begin longer duration trials with more test subjects in order to obtain statistical measure of the algorithm's success.

7. Conclusion

Wireless sensor networks show great promise for biomedical monitoring applications. In this paper, an application of wireless sensor networks has been developed to detect abnormal human movements that could be indicative of a serious health danger. Our algorithm is beneficial because it runs in real-time on low power, embedded microcontroller devices and is non-intrusive to the patient's life so patients are less likely to become non-compliant with the monitoring.

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