Accelerometer-Based Human Abnormal Movement Detection in Wireless Sensor Networks

T. Ryan Burchfield and S. Venkatesan
Computer Engineering Program
University of Texas at Dallas
Richardson, Texas 75080
{timothy.burchfield@student., venky@}utdallas.edu

Abstract— **Wireless sensor networks have become increasingly common in everyday applications due to decreasing technology costs and improved product reliability. An ideal application for wireless sensor networks is a biomedical patient telemetry-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 biomedical wireless sensor networks, which attempts to monitor patients for specific conditions 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 or acute brain injury causing loss of consciousness or coma. The results of the presented algorithms have been verified on test subjects and showed few occurrences of false positives. In future tests, automatic calibration based upon false positives will further reduce the occurrence of errors for a given test subject. The algorithm developed proved to be versatile enough that other applications such as fragile shipment monitoring required no major modifications.**

I. INTRODUCTION

Wireless biomedical sensor network (WBSN) is an emerging field that leverages advancements in microelectromechanical systems (MEMS) sensor technologies and reliable wireless communication algorithms in order to produce small, low cost, low power and reliable devices capable of monitoring patients for specific ailments or medical events. One major consideration that has been addressed in recent advancements is battery life of the wireless patient monitoring device. As in cell phones, the battery in wireless devices tends to be the largest necessary component. Therefore, one way to decrease the size of a device is to reduce battery size, which is only feasible if the power consumption of the device is also lowered. Recent products such as TI MSP430 series microcontroller and TI/Chipcon CC2420 ZigBee compliant RF transceiver draw a maximum of 280µA and 18.8mA respectively. The current demand of the transceiver can be further minimized by utilizing a well-defined network infrastructure that allows duty cycling of the transceiver.

Well-defined standards such as IEEE 802.15.4 and ZigBee [1] have also 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.

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. For example, a two lead ECG recording digitized by a 12 bit analog to digital converter at a common 500Hz sample rate generates about 12kb of data per second. At this data creation rate, a standard 8MHz, 8KB memory microcontroller is not capable of running alarm triggering diagnostic algorithms in real-time. Forwarding the data to a nearby higher power PC is an option, only if battery life constraints of the device are removed. Much of the current body of literature for WBSNs relies on the data forwarding approach, or off-line computation, to detect events gathered from sensor data [2][3][4]. Wide scale WBSN adoption is unlikely until events can be detected in real-time on the patient device. This paper seeks to join a body of literature that runs monitoring algorithms autonomously on sensor devices in real-time [5][6].

We now consider the traits that make a WBSN network good. WBSNs are most beneficial when the sensors selected to monitor patient condition are small, non-invasive devices that request no lifestyle change from the wearer. Device configurations that do not meet these recommendations are likely to fall astray due to lack of compliance from patients who are unwilling to periodically stop their current activity to untangle wires or participate in a measurement when the probability of an actual problem event is small. It has been shown that, in general, patient compliance decreases over time in situations requiring significant lifestyle changes due to medical procedures [7]. We shall label devices that meet these recommendations to enhance compliance as "non-intrusive".

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. The accelerometer provides instantaneous measurement of acceleration (caused by a person's movements) that is currently acting on the device. In this configuration, the accelerometer with accompanying algorithms can be used to classify the subject's movement into one of a few categories. This paper focuses on two threshold-based algorithms, which attempt to identify movements that are potentially harmful or indicative of immediate danger to a patient. The first algorithm seeks to identify rapid shaking movements that usually accompany myoclonic, clonic and tonic-clonic seizures [8]. Automated, quick seizure detection has the capability of alerting medical personnel when the patient is not physically capable of requesting help. The second algorithm is designed to generate an alarm when a patient has sustained an extended period of inactivity, potentially indicative of coma onset or loss of consciousness triggered by an acute brain injury. Like shaking movements, detecting inactive periods also has the potential to alert medical personnel to a problem more expediently than other means. Upon detecting an abnormal event, both algorithms sound an auditory alarm from the wrist-device and transmit an alarm message (with necessary patient identification) through a ZigBee multi-hop wireless network to a patient monitoring station staffed by medical personnel.

The abnormal movement detection philosophy can be extended to more types of dangerous events, like human fall detection [2][3][5][6]. It should be noted that the events that can be detected by an accelerometer paired with the algorithms discussed within this paper could be accurately detected with conventional medical technologies such as EEG. However, conventional technologies are intrusive to a person's lifestyle, with many wires and possibly requiring surgical implantation, so they are not scalable monitoring solutions for general populations. The accelerometer-based event detection scenarios discussed here are especially advantageous in nursing home, assisted living or managed healthcare environments where there is typically a high patient to medical staff ratio, and a mass deployment of said technology will require no lifestyle change from the patient wearer.

II. 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 algorithms. Figure 1 is a picture of the prototype that was strapped to testers' wrists in order to test the devised algorithms.

A. 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. Ember Corporation has developed a ZigBee compliant networking stack for this radio communication module that provides an API interface for application developers to simplify wireless communication tasks such as network formation, route management and general data transmission.

The abnormal movement detection algorithms will require specific functionality from the microcontroller. The most important characteristics of this prototype, using the Atmel microcontroller, are the following:

- 8Mhz clock rate
- 4KB internal data memory
- 10-bit analog to digital converter (ADC), with 7 available channels on the EM2420 RCM

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:

- Easy to buy 3V battery with an average 4-day life
- Two momentary press buttons for programmable action upon user input
- Pin-outs for signal I/O and debugging
- An auditory buzzer (hidden underneath RCM board)
- A 3-axis, 1.5 to 6 "g", 6mm x 6mm x 1.45mm accelerometer (hidden on the under side of the brown board)

The board prototype here is an example of design over-kill in order to guarantee sufficient facilities exist for this and future experiments. Stage two development devices will not require as large a footprint caused by the I/O pins and generic battery.

B. Accelerometer Functionality

Abnormal movement detection is facilitated by an analog accelerometer, which is a sensor that varies an output voltage with a direct correlation to the magnitude of acceleration in a given direction. Since a change in acceleration is inherent to movement, the accelerometer provides information about the movements to which it is subjected.

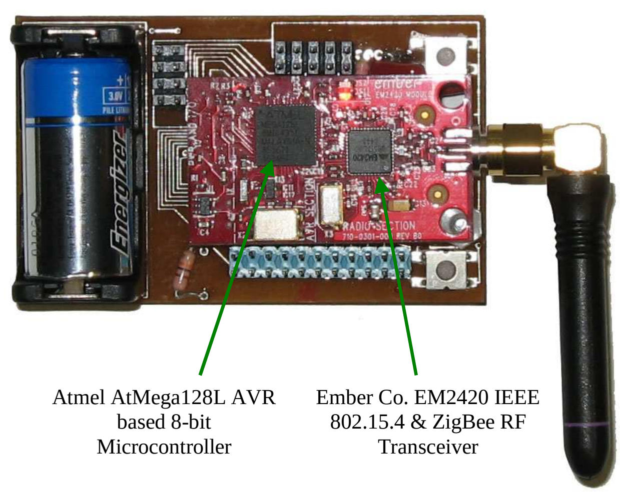

Figure 1. Wireless accelerometer platform prototype

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 (Figure 2). Each axis reports the current magnitude of acceleration with an analog voltage that is mathematically converted to a "g-value" where "1g" is equal to the force of Earth's gravity. The g-value can be positive or negative with the "0g" location centered at half of the accelerometer supply voltage. In our prototype, the supply voltage is 3.0V that leads to a "0g" location at 1.5V.

III. Signal Processing

Experiments indicate that a sample rate of 20Hz is ideal for reading accelerometer voltages. Given the average speed, and acceleration of human movements, a rate of 20 samples per second provides finely detailed information about a subject's motion. Higher frequency samples tend to saturate acceleration changes to near-zero change per sample and require more memory for data storage. Lower frequency samples saturate the average change per sample to be very high regardless of the subject's actual movement intensity.

Both of the devised algorithms for abnormal movement detection require a common set of data processing operations that interpret the voltages read from the ADC (generated by the accelerometer) and then convert them into interpretable data. The goal of these operations is to generate a single smoothly changing curve that represents the recent activity level of the test subject.

A. g Conversion

The accelerometer generates an analog voltage for each axis that is relative to the acceleration force (in g units) parallel to that axis. The selected accelerometer has an adjustable sensitivity range that allows for fine-grained data acquisition at low g levels or a more coarse-grained data acquisition at higher g levels. Since the abnormal movement algorithms require only a high-level picture of the wearer's movements, the accelerometer is configured for the course-grained (+/-) 6g range, which will adjust the output voltage of an axis, by 0.2V per g. In order to avoid the computation cost of floating point math on an 8-bit embedded microcontroller, the g-value is multiplied by 100, which generates two decimal places of precision. The formula for g conversion is

$$g\_value = 100 * [voltage_{measured} - (voltage_{source} / 2)] / sps,$$

where sps is samples per second, in our case 20.

B. Signal Aggregation

With three independent g-values computed, the next step in signal processing is to combine the values into a single value that will require less storage and computational resources from the microcontroller. As depicted in Figure 2, each accelerometer axis is represented by a vector in space, with the output voltage corresponding to its magnitude. The root-mean-squared method for taking the magnitude of a vector provides the desired global view.

$$g\_rms = \sqrt{g\_value_x{}^2 + g\_value_y{}^2 + g\_value_z{}^2}$$

C. Calculation for Δg_rms

The current `g_rms` value provides an instantaneous reading of the net acceleration that the accelerometer is experiencing. The abnormal movement detection algorithms require information about the change in acceleration; therefore, in this processing step the difference of the current sample is taken from the last sample.

$$\Delta g\_rms = |g\_rms_{current} - g\_rms_{last}|$$

D. Average Calculation

The final step of signal processing is to compute a running average of the Δ`g_rms` value of the samples occurring over a 1-second period. 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 within the last second such that sudden jumps in average value are minimized.

$$Avg\_\Delta g\_rms = (\sum_{i=1}^{sps} \Delta g\_rms_i) / sps$$

IV. 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. If either condition is not satisfied for a given accelerometer sample, no alarm is generated. 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. In order to implement this condition the algorithm shall require an upper threshold of activity that must be exceeded for some small threshold period. The second condition that shall be required to trigger an alarm in the RSD algorithm 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. This condition is implemented with a g threshold lower than that of the first condition, but a time threshold greater than the first condition. The details of these thresholds are discussed in the following two sections. A sample `Avg_Δg_rms` graph, with

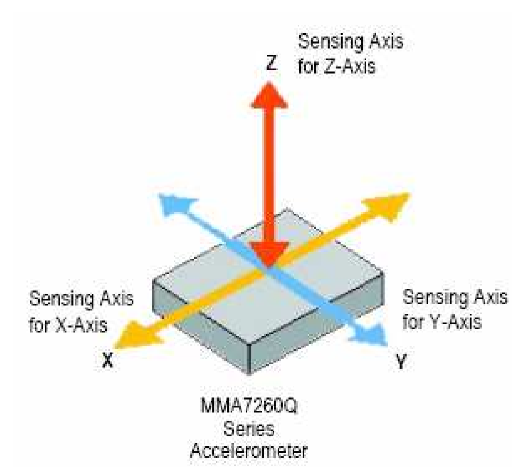

Figure 2. Accelerometer axis configuration [9]

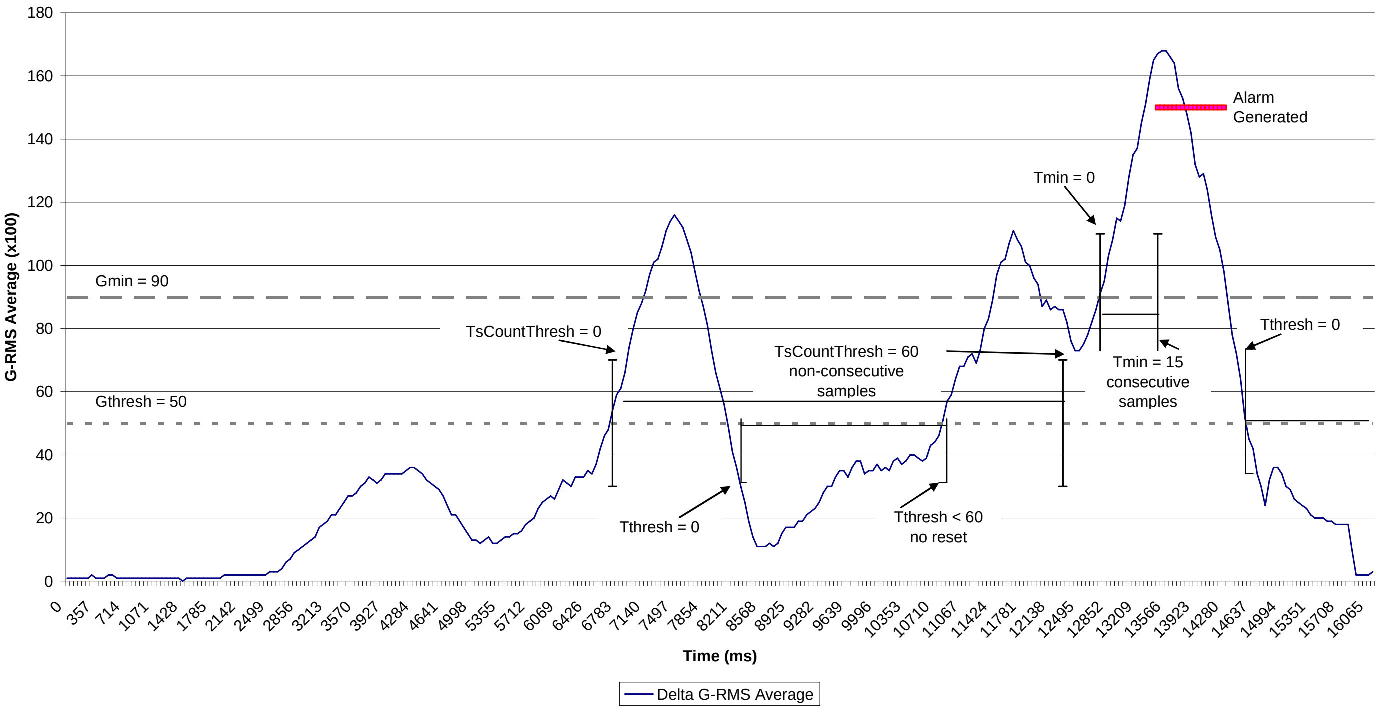

Figure 3. RSD threshold configuration

each threshold marked is provided in Figure 3.

The RSD algorithm borrows the two-condition alarm concept from Langley et al [10]. Langley et al. applied a similar algorithm, with dual conditions, to detect specific abnormal events in ECG recordings.

A. 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 a value of 90, which corresponds to an average acceleration change of 0.9g per sample (50ms period). The `Tmin` value has been empirically set to 15 consecutive samples. That corresponds to 0.75 seconds of data. Together, the `Gmin` and `Tmin` values designate that the accelerometer must detect 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 3 plot.

B. 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` was 50, 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, which is defined to be `Tthresh`, 60, samples with an average value below `Gthresh`. This equates to 3 seconds of unsuspicious activity from the subject. The relevance of the sustained movement condition to the overall algorithm is displayed in Figure 3.

V. INACTIVITY DETECTION ALGORITHM

The accelerometer demonstrates the versatility of non-conventional medical sensors and their applicability to the biomedical realm. In this section, we describe a simple algorithm that utilizes the accelerometer to identify periods of extended inactivity. Periods of extended inactivity are identified by setting two thresholds, similar to those used in the RSD algorithm. `TooCalmThreshCount` is the minimum number of consecutive samples that are required to have `G_RMS_Delta` less than `TooCalmThresholdGRMSDelta` in order to trigger an alarm for prolonged inactivity. `TooCalmThresholdGRMSDelta` has been empirically set to half a g change from the previous sample. Due to extreme variations in activity levels of monitored patients, the `TooCalmThreshCount` parameter will have to be individually calibrated for every patient. For testing purposes, the algorithm has been verified with a value that corresponds to 50 minutes of consecutive samples less than `TooCalmThresholdGRMSDelta`.

VI. CALIBRATION

The authors are currently working various improvements to this collection of algorithms. One such improvement is the design of an auto-calibration mechanism that varies the RSD and inactivity detection 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. Experimental analysis will be required to determine which threshold should be incremented, and the incremental value to be used. This experimental process is currently underway by the authors.

VII. RESULTS

Testing the abnormal movement algorithms is challenging because the targeted abnormal movements have 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 no 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 knowledge and ability. The RSD algorithm was able to detect each person's suspicious movements with no need for individual calibrations. This indicates the proposed algorithm's capability to distinguish suspicious movement from regular movement. 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.

The inactivity detection algorithm has been tested for smaller durations of time in order to prove the concept. A test subject was asked to lie still for 15 minutes and the threshold for lack of movement (`TooCalmThreshCount`) was lowered to 10 minutes. After 10 minutes, the alarm was properly triggered and transmitted to the base station. Future improvements to this algorithm include the addition of context awareness such as posture (sitting, standing, lying down) recognition similar to those methods developed in [2][3][4][6] but with a focus on real-time processing and results.

VIII. ALGORITHM EXTENSABILITY

The RSD algorithm presented in this paper bears the attribute of extensibility. The same basic threshold-based structure can be used to identify many other patterns of movements. For example, the prototype in the RSD experiments has been applied to a new problem of fragile shipment monitoring. In fragile shipment monitoring, we seek to provide a way to monitor fragile shipments for mishandling in order to determine the time of abuse and the party responsible for such abuse in case of damage liability.

For this type of event monitoring, we consider three event types: 1) Instantaneous impact of excessive g-force, 2) Prolonged exposure to excessive vibration, 3) Excessive tilt. The first type of event is easily detectable by a single comparison of each accelerometer sample to a threshold value. The RSD algorithm is also capable of detecting this type of event when the sample frequency is increased and the applicable thresholds are modified. The RSD algorithm is a perfect match for detecting events of the second type because prolonged events of excessive vibration closely resemble the rapid shaking movements detected by the algorithm. According to our investigation, no commercially available products provide detection for this type of event. Finally, the thresholds used in the RSD algorithm are easily modified per the manufacturer guidelines for a given product in order to define the unacceptable forces for a package. The remaining event type for mishandling is detectable using standard tilt calculations from the accelerometer documentation [11]. Reusable products are commercially available to recognize event types 1 and 3.

Current low-cost damage indicators such as the ShockWatch shock and tilt indicators are mechanical devices that produce a visible, physical change when they have been subjected to g-forces or tilt in excess of a maximum that is pre-configured for each product. The downside to these devices is that they are not able to record the time of the damage and are generally one-time use products.

1) Low-Power Implementation

A low-power implementation of accelerometer sensors with the RSD algorithm would utilize a TI MSP430 family microcontroller, Freescale MMA7261QT +/-10g tri-axial accelerometer, and a push button activated RF transceiver (TI CC1050) that is only powered on in order to get or set parameters, thus conserving battery power. In this configuration, the complete device would draw less then 1mA current under normal operation. Thus, an easily available battery could power the system for an estimated 1,500 hours, which exceeds standard overseas freight times of three to four weeks. Upon receiving the package the device simply needs to have the transceiver activated via push button then the event history can be recorded with the timestamp of the event. The number of events that can be stored is widely variable depending upon the required program size and flash memory available on the MSP430 selected.

Hardware cost of this low-power monitoring platform totals about $20, when ordering component quantities 1k-10k. The $20 investment is then completely reusable unlike most of the currently commercially available products. Finally, manufacturers typically desire the use of fragile shipment monitoring devices when the product in the shipment is of particularly high value. In this case, the elimination of their liability in the case of a single failure will pay for hundreds to thousands of the reusable sensors.

IX. SUMMARY

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 algorithms are advantageous because they run in real-time on low power, embedded microcontroller devices and are non-intrusive to the patient's life so patients are less likely to object or become non-compliant with the monitoring. The inexpensive hardware and non-invasive detection techniques make such applications viable and desirable in nursing home and other managed healthcare institutions. The algorithm has also proven to be easily extensible to other non-medical applications as evidenced by the fragile shipment monitoring system.

X. REFERENCES

[1] ZigBee Alliance. 12/01/06. ZigBee-2006 specification.

[2] M. J. Mathie, B. G. Celler, N. H. Lovell and A. C. Coster, "Classification of basic daily movements using a triaxial accelerometer," *Med. Biol. Eng. Comput.,* vol. 42, pp. 679-687, Sep. 2004.

[3] F. R. Allen, E. Ambikairajah, N. H. Lovell and B. G. Celler, "Classification of a known sequence of motions and postures from accelerometry data using adapted Gaussian mixture models," *Physiol. Meas.,* vol. 27, pp. 935-951, Oct. 2006.

[4] J. Boyle, M. Karunanithi, T. Wark, W. Chan and C. Colavitti, "Quantifying Functional Mobility Progress for Chronic Disease Management," *Engineering in Medicine and Biology Society, 2006.EMBS'06.28th Annual International Conference of the IEEE,* pp. 5916-5919, 2006.

[5] J. Chen, K. Kwong, D. Chang, J. Luk and R. Bajcsy, "Wearable sensors for reliable fall detection," *Conf. Proc. IEEE Eng. Med. Biol. Soc.,* vol. 4, pp. 3551-3554, 2005.

[6] D. M. Karantonis, M. R. Narayanan, M. Mathie, N. H. Lovell and B. G. Celler, "Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring," *IEEE Trans. Inf. Technol. Biomed.,* vol. 10, pp. 156-167, Jan. 2006.

[7] N. H. Miller, M. Hill, T. Kottke and I. S. Ockene, "The Multilevel Compliance Challenge: Recommendations for a Call to Action: A Statement for Healthcare Professionals," *Circulation,* vol. 95, pp. 1085-1090, February 18. 1997.

[8] Epilepsy.com. (2004, 07/26/04). Type of seizures : Epilepsy.com. 2006(11/05), Available: http://www.epilepsy.com/epilepsy/types_seizures.html

[9] Freescale Semiconductor. (2006, 02/2006). MMA7260Q 3-axis accelerometer: Technical data.

[10] P. Langley, E. J. Bowers, J. Wild, M. J. Drinnan, J. Allen, A. J. Sims, N. Brown and A. Murray, "An algorithm to distinguish ischaemic and non-ischaemic STchanges in the holter ECG," in 2003, pp. 239-242.

[11] M. Clifford and L. Gomez, "Measuring Tilt with Low-g Accelerometers," vol. 2007, pp. 8, 05/2005. 2005.