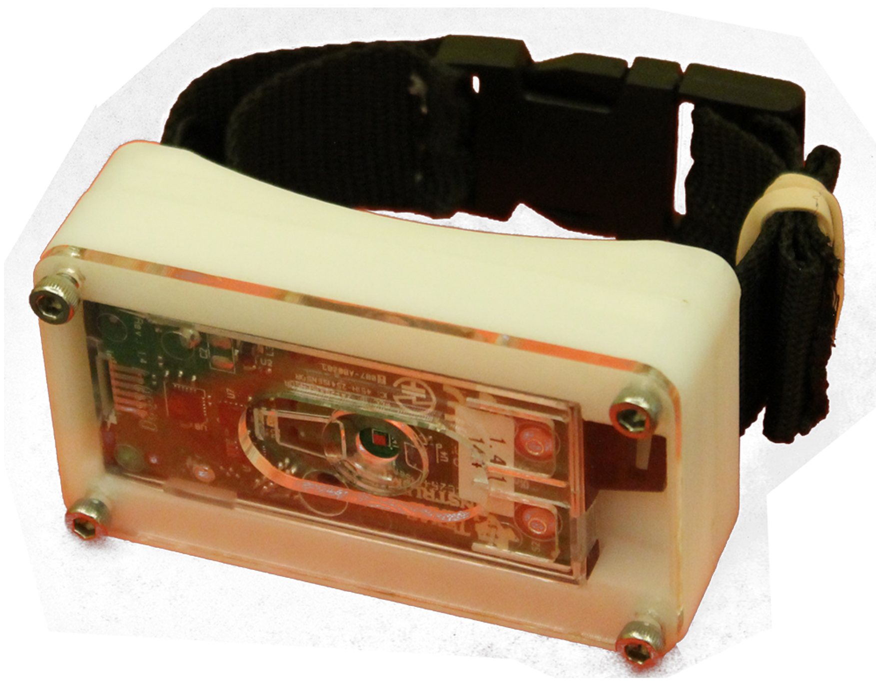
NightOwl

A real-time, wearable, nighttime seizure notification and reporting system



CS 6235 (Fall' 14) Project Final Report

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Table of Contents

1 Introduction 3
2 Related work 4
3 The NightOwl System 4
3.1 System Architecture 4
3.2 Features of the NightOwl Android Application 5
3.3 Building a custom sensor 5
4 Pilot Study 7
4.1 Neurology training videos 7
4.2 Mock seizures data collection 8
4.3 Seizure Detection 8
5 Results 10
5.1 Manual thresholds 10
5.2 Support Vector Machine (SVM) 10
6 Discussion 10
7 Future work 11
7.1 Service Model 11
7.2 Stand-alone device 11
7.3 Increase battery life 11
7.4 Support four sensors 11
8 Conclusion 12
9 References 13

1 Introduction

Many patients with epilepsy have uncontrolled seizures at night that go undetected and unreported while they are sleeping (85%) [1,3]. Epileptic seizures often impact a person's motor activity [7], with periods of repetitive, uncontrolled shaking. This presents two sets of problems. First, nighttime seizures can be particularly dangerous [2] for patients as caregivers are often asleep at night and are therefore less able to respond for keeping patients safe. Second, neurologists rely on patients or caregivers to report the number and duration of seizures [5,6] for prescribing and adjusting medication [4], however this information is not available to them when nighttime seizures go undetected.

Therefore we propose a real-time, wearable system called NightOwl for detecting nighttime seizures, notifying caregivers and reporting seizures in a "seizure diary" log for clinicians.[1] NightOwl includes a pair of wrist-worn, Bluetooth enabled inertial devices that stream live accelerometer measurements to a nearby Android phone for recognizing seizure events. The app issues an audible alarm for notifying caregivers and simultaneously logs the date and time of seizure events in a "seizure diary" for sharing with clinicians.

Figure 1: NightOwl overview (Right) seizures are detected and an audible alarm is issued for notifying parents sleeping in a nearby room (Left) seizures are reported in a "seizure diary" for sharing with clinicians.

[1] This effort is a new initiative that and is not funded or associated with existing research at Georgia Tech.

2 Related work

There has been a long history of efforts to detect seizures that involve motor movement; however to date no studies have been conducted in home settings. Motor changes can often be detected using wearable inertial sensors. Many of the most successful systems use one or more accelerometers for detecting repetitive motion [9].

In recent years Cuppens et al [8] instrumented patients with accelerometers for detecting hypermotor seizures (precision 60.0%, recall 95.2%). This work inspired much of our efforts; however the analysis was completed offline and did not notify caregivers. In our work we adopted several features from Cuppens et al [8] but performed analysis online using low-cost, commodity android hardware for supporting seizure notification and reporting.

3 The NightOwl System

The NightOwl system consists of a Bluetooth-enabled TI SensorTag that is worn on the patient's wrist and transmits live accelerometer data a nearby Android phone. An Android app monitors this incoming data for 1) detecting periods of intense repetitive, "seizure-like" motion, 2) notifying caregivers with an audible alarm and 3) reporting seizures in a "seizure diary" for informing clinicians, Figure 1.

Here our initial goal was to detect generalized tonic-clonic type seizures that are characterized by periods of muscle stiffening full body convulsions as these would likely be the most feasible for us to detect with one ore more wearable accelerometer devices.

3.1 System Architecture

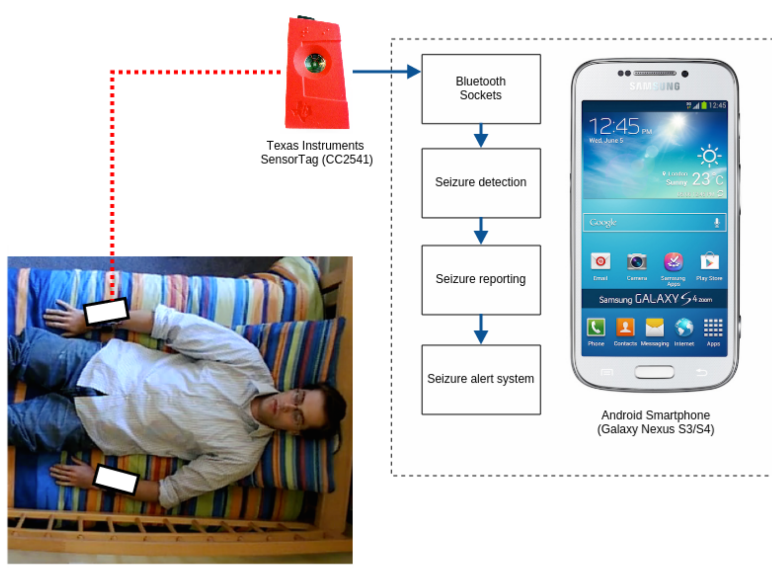

Figure 2: The SensorTag transmits accelerometer measurements to the NightOwl app. The app detects seizures and 1) issues an audible alert to a nearby caregiver's and 2) logs occurrence in a "Seizure Diary"

3.2 Features of the NightOwl Android Application

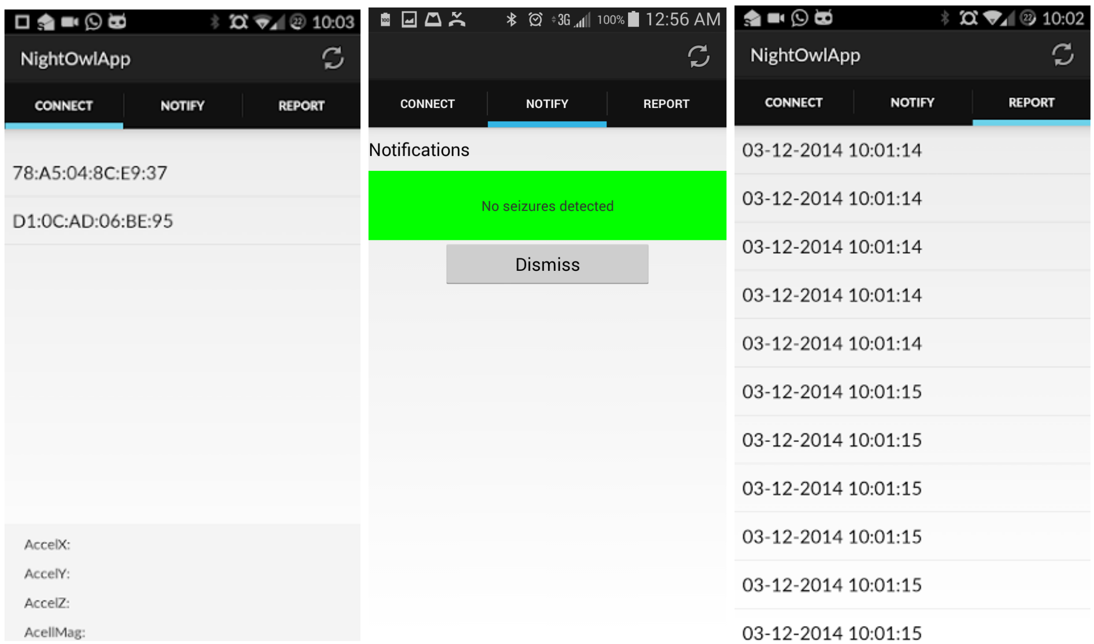

Figure 3: Features of the app: From L-R: The connections tab, the alarm notifications tab, the reports tab

The Android app is designed from a very minimalist and functional point of view, with three tabs: Connect, Notify and Report. Their functions are explained below:

1. **The Connect Tab:** This tab displays all available and switched-on SensorTags or our experimental device in the vicinity. The user may simply click on the appropriate ID of the device to start receiving data from it.
2. **The Alarm Notifications Tab:** When a seizure is detected according to the algorithms described later in this report, a loud alarm is generated which can then be turned off by pressing the Dismiss button in this tab.
3. **The Reports Tab**: Whenever a seizure is detected, the exact timestamp of the occurrence is logged here for the purpose of diagnosis by doctors.

3.3 Building a custom sensor

TI SensorTag's battery life was limited to 2-4 hours. This led us to build a custom sensor with the goal of extending battery life to 12 hours for recording detecting seizures over the course of an entire night.

Our motion sensor was prototyped by interfacing an MMA8452Q accelerometer and an nrf8001 Bluetooth Low Energy (BLTE) chip to an Arduino Uno. The programming for the Arduino was done using the Arduino IDE. We also designed a PCB using EagleCAD and used the circuit mill at GVU's Prototyping Lab.

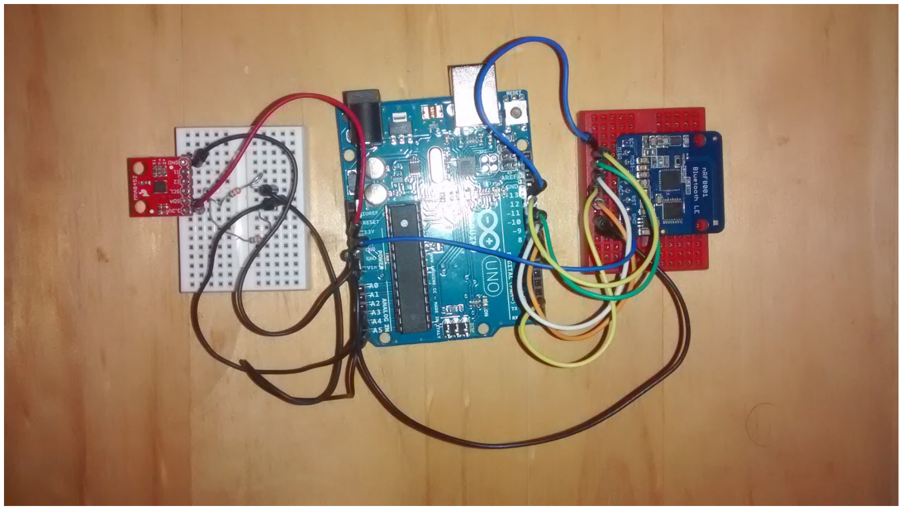

Figure 4: Breadboard setup. The Arduino Uno (centre) is flanked on the left by the MMA8452Q accelerometer and on the right by the nrf8001 BTLE chip.

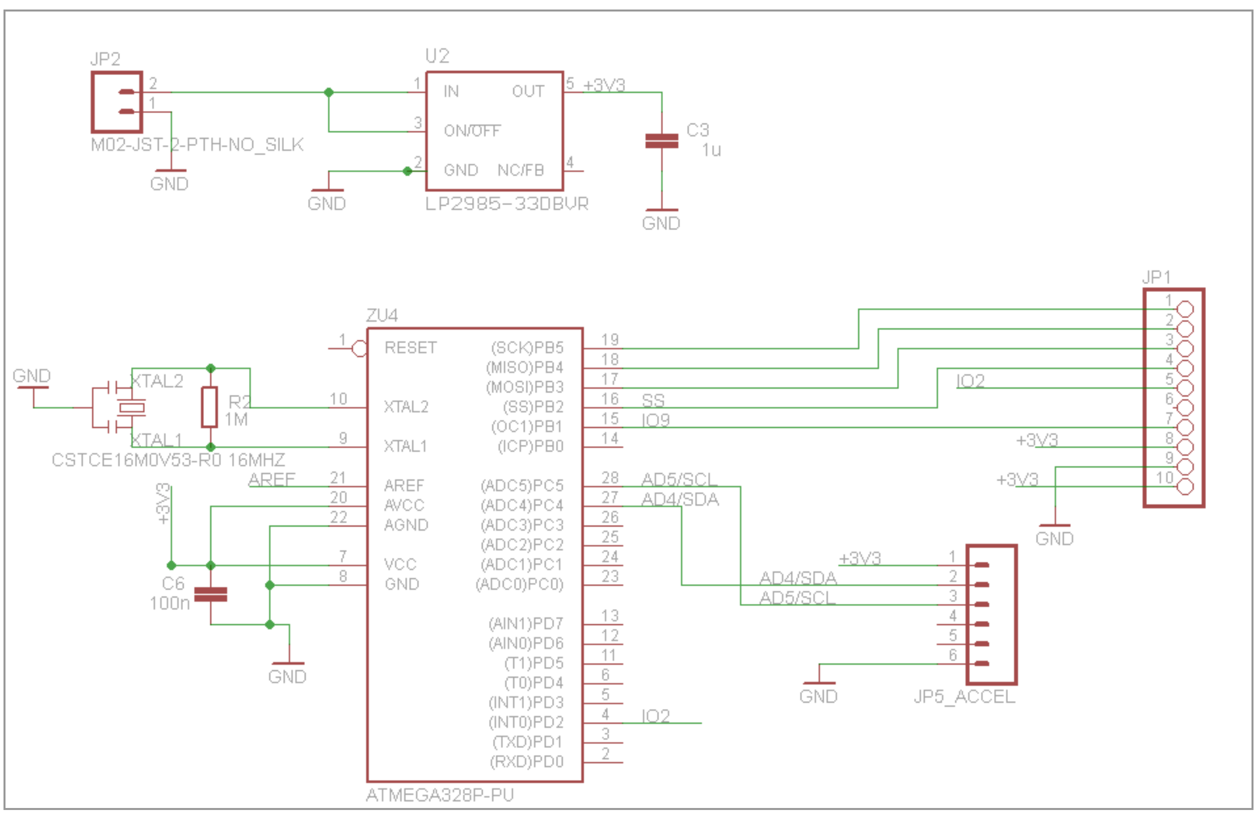

Figure 5: EagleCAD schematic diagram of our PCB showing the Arduino microcontroller (lower-left) interfaced with a Bluetooth module and accelerometer (middle and bottom right).

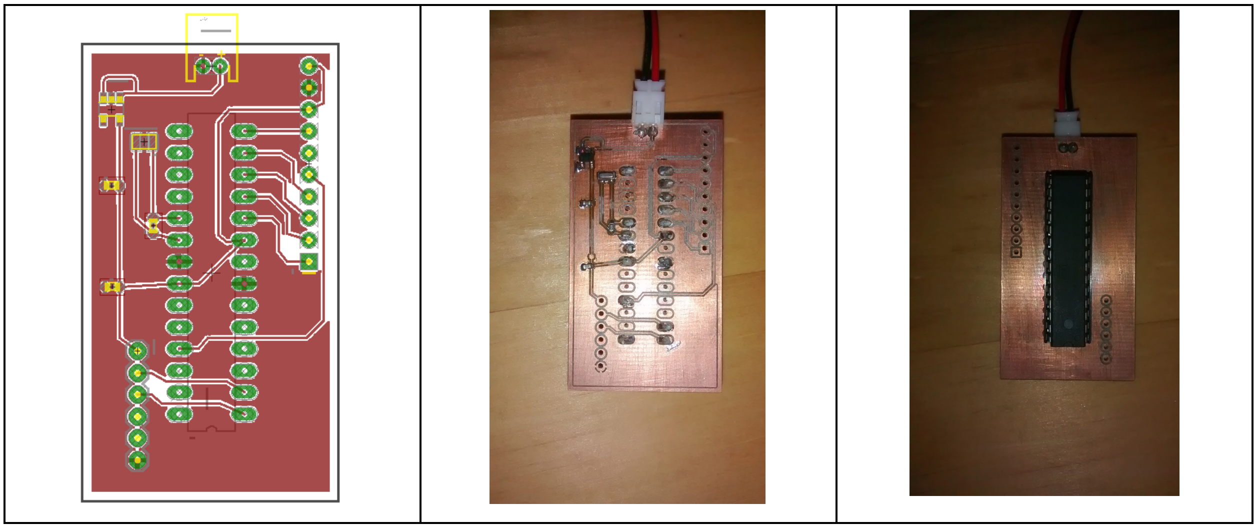

Figure 6, L-R: The EagleCAD board layout of our PCB, the front and back of the finished PCB (showing microcontroller)

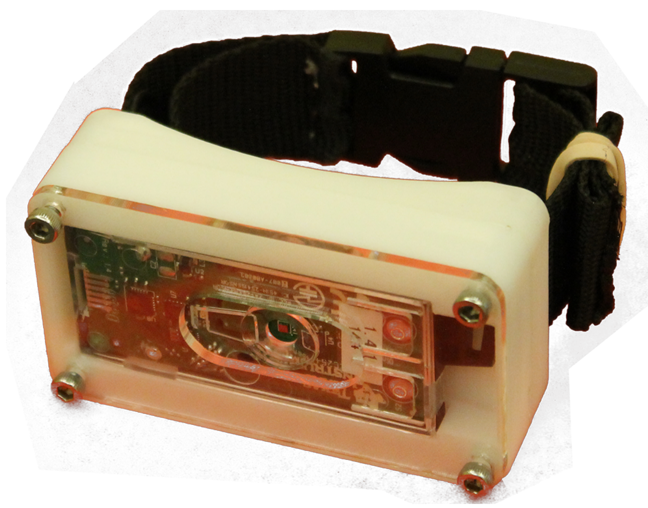

Figure 7: The 3-D printed wristband with TI SensorTag enclosed

4 Pilot Study

4.1 Neurology training videos

To begin we reviewed training videos that visually described a wide range of seizure patterns. From these videos, we got an idea of what seizures really look like. This helped us immensely in chalking out a plan of action for the project. These videos gave us the idea to design a 3-D printed wristband that can be securely fastened to the patient's limbs. We also took inspiration from the opinions of doctors who were interviewed in designing our Android app interface, retaining only the essential data required for their diagnostic purposes.

4.2 Mock seizures data collection

Mock seizures were collected at the AwareHome as a starting point for our seizure detection algorithms. Team members were instrumented with wrist worn TI SensorTags and instructed to enact both seizure and nonseizure motions. Each motion was timestamped such that we had a collection of "seizure" and "nonseizure" events, Figure 8.

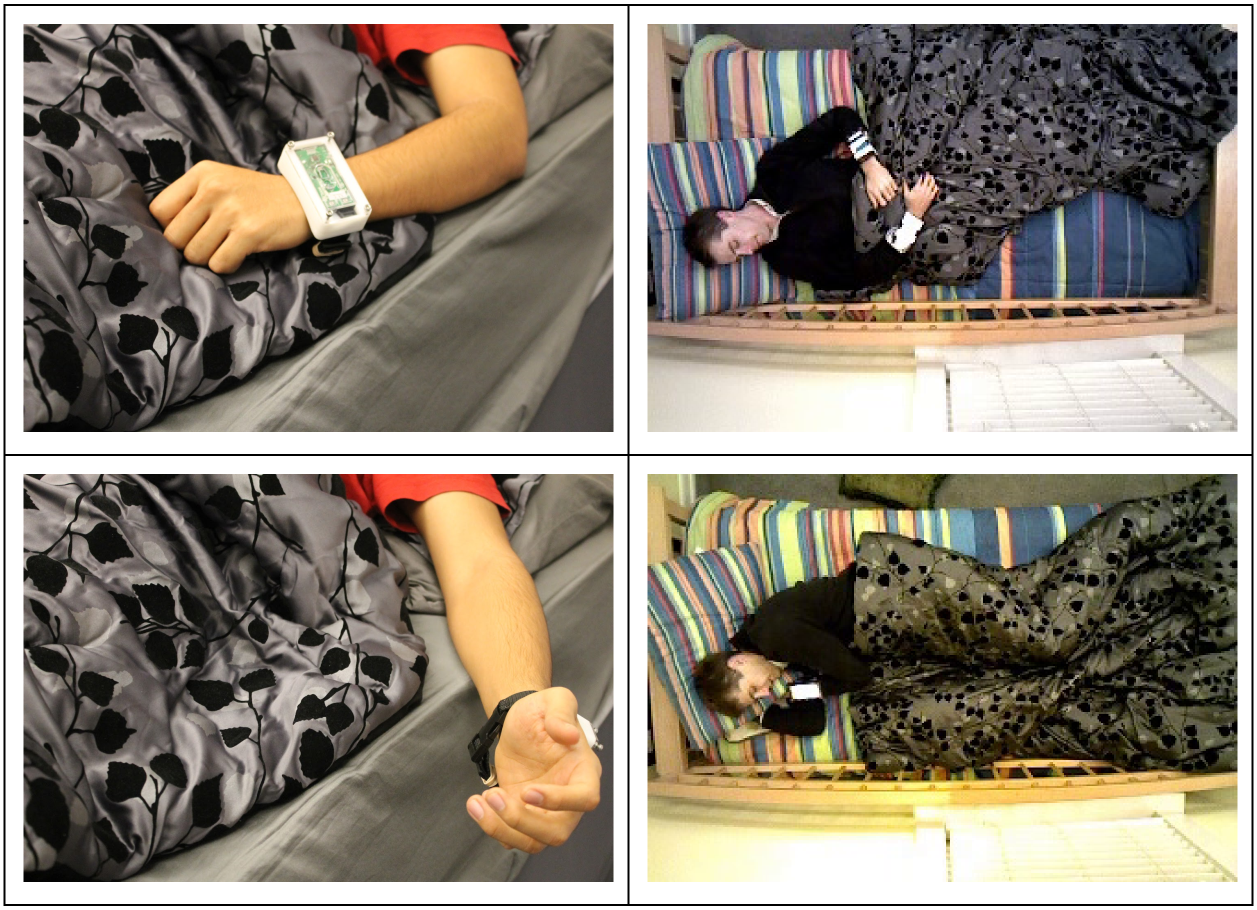

Figure 8: Mock seizures recorded at the Georgia Tech AwareHome

4.3 Seizure detection

Next we developed software for analysing accelerometer measurements and detecting intervals of intense, repetitive seizure-like motions. This called for creating a set of features.

We employed the following seizure detection algorithm:

1. We identified periods of intense convulsions in a time interval of 1 seconds.

2. Calculate the value of each of the following features proposed by Cuppens et al. [8] to be sufficient to determine a seizure event. All features are represented by the following equations.

- **Eqn. 1**: To calculate the maximum of magnitudes of each of the accelerometer channels per limb - left limb and right limb.
- **Eqn. 2**: To calculate the mean of means of all data samples per epoch (1-second intervals, in our case) per channel.
- **Eqn. 3**: To calculate the mean of standard deviations of all channels
- **Eqn. 4**: To calculate the sum of magnitudes of each of the accelerometer channels per limb - left limb and right limb.

$max_{magnitude} = max\left(\left\|XLeft_{1-3}(t)\right\|, \left\|XRight_{1-3}(t)\right\|\right)$, where the subscript 1-3 are each of the accelerometer channel (e.g x-channel, y-channel, x-channel)	eqn 1
$mean_{mean} = \frac{1}{6}\sum_{i=1}^{6}\frac{1}{n}\sum_{t=1}^{n}x_i(t)$, where *n* is the number of samples per epoch and *i* is the accelerometer channel index (e.g x-channel, y-channel, x-channel)	eqn 2
$mean_{std} = \frac{1}{6}\sum_{i=1}^{6}(\frac{1}{n-1}\sum_{t=1}^{n}(x_i(t) - y_i)^2)^{0.5}$	eqn 3
$sum_{magnitudes} = \sum_{t=1}^{n}\left\|XLeft_{1-3}(t)\right\| + \left\|XRight_{1-3}(t)\right\|$	eqn 4

These features were then used to detect seizure-like motions both on the phone and on our mock seizure dataset. We evaluated two separate methods.

1) Experimental Thresholds - Next we selected threshold values for each of our features. From our experiments, we obtained the threshold value as 1.8, 0.2, -0.3 and 181.3 for Eqns 1 to 4 respectively. By setting appropriate thresholds we were able to detect seizures by comparing the metrics in Eqns. 1 to 4 with these thresholds. If the metrics exceeded their respective thresholds, a seizure was deemed to have been detected.

2) Support Vector Machine (SVM)
The features were used to train an SVM binary classifier. SVMs are "supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier" [10].

5 Results

The performance of our NightOwl system was evaluated against the mock seizure dataset. Measurements were chunked into 1 second time interval *epochs.* Each *epoch* was classified as "seizure" vs. "nonseizure" and compared against our ground truth labels.

5.1 Manual thresholds

The experimental thresholds that we selected resulted in a precision 21.0%, recall 97.96%.

5.2 Support Vector Machine (SVM)

Next we trained a support vector machine (SVM) binary classifier. This resulted in a precision 48.83%, recall 73.28% using a linear kernel.

6 Discussion

The resulting seizure detection was successful in that we were able to detect seizure patterns that would likely be associated with generalized tonic-clonic seizures.

The performance of our system was lower than expected, however this was likely due to our dataset. In addition to seizure events we also recorded typical sleep behaviors such as head scratching, rolling over and standing up to go to the bathroom. These behaviors made our classification much more difficult. "Head scratching" was often confused with seizure events. More subtle seizure events were often missed when using our threshold method.

In addition we chose to maximize recall at the cost of precision (e.g false alarms are permissible but we do not want to miss seizures). Due to the limited time that was available at our disposal as a group, we were able to conduct the tests only with one sensor and for one limb. The app supports multiple devices anyway, one possible future work could be to try and repeat the experiment with four sensors - one for each limb of the patient.

Our contributions in this project are threefold:

1. First, we developed an Android app that listens to incoming inertial data from a sensor and performs real-time data analysis in order to determine whether or not a seizure has occurred. And in case a seizure event is detected, it raises a loud alarm to alert caregivers in the vicinity and also logs the timestamps of seizure occurrence for the purpose of diagnosis by doctors.

2. Secondly, we designed and developed a custom Arduino-based motion sensor that transmits accelerometer data over Bluetooth. We also developed an initial version of the printed circuit board design using GVU's Prototyping Lab as well as a 3-D model of a wristband to enclose the final PCB (that includes a battery as well).

3. Thirdly, we interfaced the custom sensor to the NightOwl app and enabled the app to listen to multiple sensors at a time.

In addition to the above documented results, we also have two short video clips demonstrating the working of our app:

1. http://youtu.be/yqXYiTq7Tfw
2. https://www.youtube.com/watch?v=2HYT9BUP-DY

7 Future work

We believe that NightOwl has the potential for becoming a commercial product. The following are a list of next steps that we would pursue for extending and refining aspects of our system:

7.1 Service Model

Many devices contain accelerometers and onboard computing capabilities. Instead of supplying our own SensorTag or custom accelerometer devices, we could consider providing our seizure detection software as a service for enabling users to use sensors that they already own. For example the Apple Watch contains accelerometers that could be used as an alternative to our dedicated SensorTags.

7.2 Stand-alone device

In practice a stand-alone device may be required for reducing interoperability issues and simplifying deployment. For example vendor specific Bluetooth issues may complicate our development process and some users be discouraged by having to download software to a personal mobile phone. Instead we could replace the smart phone with a known dedicated device that would be more stable for us to debug and evaluate. For example the low-cost Raspberry Pi could be used to perform the number crunching and linking to the Internet. In turn this may reduce chances of human error (e.g forgetting to run the app).

7.3 Increase battery life

Increasing battery life beyond 8 hours will be essential for detecting seizures during a typical night. The custom device that we're developing will have a battery life beyond 12 hours. The first step was to our breadboarded prototype to PCB. Issues with a linear regulator slowed our progress, and 1-2 additional weeks would be needed for addressing this issue and connecting our larger battery pack. If successful this could be a viable product for the healthcare market.

7.4 Support four sensors

Many types of seizures are characterized by motion on a single side of the body (e.g the left arm and left leg may "jerk" at the same rate during a partial seizure). These changes may be helpful for improving the accuracy of our seizure detection. In this case we were only able to afford two sensors; however in the future we'd like to support four sensors for instrumenting both arms and legs.

8 Conclusion

Epileptic seizures often impact a person's motor activity [7], with periods of repetitive, uncontrolled shaking. These motor changes can often be detected using wearable inertial sensors. We have implemented a proof-of-concept system called NightOwl for detecting seizures, notifying caregivers and reporting seizures in a "seizure diary" log for clinicians.

To summarize, we have developed an experimental Bluetooth-enabled motion sensor that transmits its on-board accelerometer data over Bluetooth and interfaces with our Android app which in turn performs real-time seizure detection and issues alerts when seizures are detected. We have also interfaced TI SensorTag devices with our Android app.

This project has been a very rich learning experience. We as a group have learnt quite a lot about Android programming, prototyping (both 3-D modelling and breadboarding) as well as PCB design using EagleCAD. Besides the technical aspects, we were rewarded with a very enjoyable exercise in teamwork and collaboration. There were many challenges we had to overcome, but we constantly strived to better ourselves by coming up with solutions at the right time. Overall, this project has been the highlight of the CS 6235 course and something that all three of us really enjoyed working on as a team.

9 References

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