RestEaZe: Low-power Accurate Sleep Monitoring using a Wearable Multi-sensor Ankle Band

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Abstract

The well-recognized importance of adequate restful sleep for health and the high prevalence of disturbed sleep has produced wide-spread recognition of the clinical need and commercial potential for a practical cost-effective system to evaluate and support restful sleep at home. However, existing systems for sleep monitoring use wrist-worn devices that are shown to be inaccurate in measuring quality of sleep and ineffective as an aid for the diagnostic of sleep-related disorders such as RLS (Restless Leg Syndrome) and ADHD (Attention Deficit Hyper Activity Disorder). To address this gap in use of sensors in sleep medicine, in this paper, we present RestEaZe, a multi-sensor ankle band that can capture two leg movement phenotypes: Dorsiflexions that are correlated with sleep disorders such as RLS and ADHD, and Complex Leg Movements that are correlated with texture of sleep, namely sleep fragmentation and brief arousals. In this paper, we focus on the hardware and software architecture of the RestEaZe system, and present an algorithm that uses hierarchical sensing to reduce the power consumption of the ankle worn sensor. We show, through evaluation in the sleep lab and in the home setting that the RestEaZe system can last for 5 days on a single charge of a 400 mAh battery while collecting all the relevant leg movements.

Keywords: Sleep Monitoring, Wearable Sensors, Low-power sensor systems, Hierarchical Power Management.

1. Introduction

The well-recognized importance of adequate restful sleep for health and the high prevalence of disturbed sleep [1] has produced wide-spread recognition of the clinical need and commercial potential for a practical cost-effective system to evaluate and support restful sleep at home. The large number of existing at-home sleep recording system (MNaHS) devices attests to both the need and commercial potential but also the failure of any to meet the need. The more common sleep problems involve poor sleep habits, various idiosyncratic behaviors disrupting sleep, insomnia, circadian rhythms, and undiagnosed restless legs syndrome, low iron status and sleep apneas. Once identified, many can be managed through guided self-help; others need professional input. Evaluation of most requires repeated *multi-night* recordings given circadian rhythm effects, marked variability of events disturbing sleep [2] and desired intervention evaluation. The prevalence and significance of the problem require efforts to get wide public and consumer acceptance of using a system that could accurately identify significant sleep features, support appropriate self-help and provide triage for professional evaluation.

A wide range of MNaHS have been developed from bed pads to sound systems [3]. None of these systems aside from wrist worn monitors, have gained general commercial success for the following reasons: discomfort, sleep-room constraints, and limited accuracy [4]. Only wrist worn monitors have achieved wide commercial

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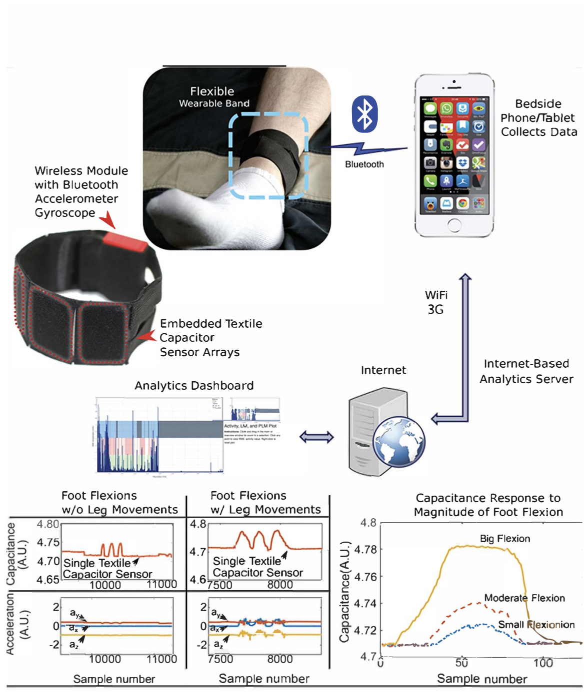


Figure 1: Prototype RestEaZe system. The system can distinguish foot flexions from other general leg movements. The system can also measure the amplitude of the foot flexions.

acceptance. These monitors, however, focus on “fitness for the fit” with sleep as an after-thought. Moreover, the data from existing commercial and professional wrist-worn systems are valid for group analyses but have very weak and sometimes not significant correlations across subjects indicating that there is limited value from these existing systems in obtaining significant measures for an individual. Moreover, the user could obtain essentially the same or better information from a sleep log. The claims that these monitors could identify sleep depth or stages have been discredited [5].

To address the above limitations, in this paper, we present RestEaZe, an ankle-worn band that captures leg movements during sleep. Recording from the arm while convenient, is inaccurate since it fails to identify features critical for sleep, for example, brief arousals. Moreover, arm movements are limited in drowsy waking before or during sleep and rarely show even basic sleep related movements [6]. In contrast, leg movements (LM) occur commonly in sleep providing a rich panoply of characteristics to be analyzed in relation to sleep biology and clinical sleep status. This is not surprising given the relevant neurobiology involving motor control in sleep, e.g. (1) active inhibition or reduction of LM during quiet restful sleep, (2) preparatory activation of LM with arousal/waking anticipating possible movement, and (3) activation or disinhibition of some sleep-related simple, repetitive movements primarily foot dorsiflexion noted as periodic limb movements in sleep (PLMS) [7].

The goal of RestEaZe is to use leg movements to characterize sleep in the home at a cost lower than sleep labs. The RestEaZe system is illustrated in Figure 1. The ankle band provides measurements from four separate sensors: 3-D accelerometer, gyroscope, magnetometer, and an array of textile capacitive sensors. These sensors allow RestEaZe to use machine learning algorithms to calculate leg orientation and characterize leg movements. Figure 1 shows that the capacitance sensor detects foot dorsiflexion and can distinguish them from other complex leg movements using the inertial sensors. These two types of leg movements can then be used to calculate measures unique to the leg and also those previously determined from the arm such as sleep efficiency, sleep fragmentation, and brief arousals. For the system to be useful in the home and for large cohort studies, however, it is important that the ankle band can capture the relevant data at low power consumption and can last on a single charge for several days. This first paper on RestEaZe, therefore, focuses on the sensor system and algorithms designed to make the system low power and usable.

Research contributions: The design, implementation, and evaluation of the RestEaZe system presents the following novel research contributions.

- **Multi-Sensor Ankle Band for Monitoring Sleep:** We present the use of flexible textile-based capacitive sensor arrays and inertial sensors built into ankle bands for sleep quality analysis. Our sensors can sense two types of movements using a single point measurement system: (1) Foot flexions whose periodicity can be used to help diagnose restless leg syndrome, ADHD in kids, and insomnia [8]; and (2) Complex Leg Movements that can be used to determine texture of sleep (e.g, brief arousals). We have developed analytics that use these movements to determine restful/restless sleep, brief arousals and sleep fragmentation, and sleep efficiency. The focus of this paper, however, is not on the development of the sleep measures but on the design of a low power system development for longitudinal sleep monitoring studies in a home setting.
- **Hierarchical Sensing for low-power consumption:** We present a system that uses a machine learning algorithm on data from the low power capacitive sensor arrays to predict when relevant movements are likely to occur, and then wakeup other energy hungry sensors such as the gyroscope, accelerometer, and magnetometer. The algorithm is low overhead and can be implemented on the micro-controller system with relevant optimizations.
- **Prototype development and evaluation:** We have prototyped a fully functional RestEaZe ankle band. We have performed a thorough evaluation both in the context of a sleep lab (on four subjects) and in-home settings on eight subjects. We have obtained relevant IRB approval to perform these studies. In our evaluation, we show that the RestEaZe band can accurately capture relevant sleep measures while lasting for more than 5 days on a single battery charge.

2. Need for RestEaZe

Restless sleep is a major problem in our society affecting productivity, health and quality of life for adults and learning ability of children. The leg movements characterizing restless sleep uniquely mark sleep quality and several medical conditions. However, capturing the complexity of these leg movements in sleep requires sophisticated sensors and analytics, currently limited to sleep laboratories. Leg movements during sleep can be divided into Complex Leg Movements during Sleep (CLMS) and Periodic Leg Movements of Sleep (PLMS), the classic periodic dorsiflexion of the foot at the ankle produced by activation of the anterior tibialis muscle. The significance of these two movements differ. CLMS patterns reveal texture and severity for sleep-behavioral intervention; PLMS reveal possible medical conditions such as restless legs syndrome (RLS), sleep apnea, and REM behavior disorder. Both need to be measured. The standard PLMS measure uses muscle activity (EMG) from electrodes secured to the skin in a costly and limited access sleep lab. There is no simple ambulatory way to accurately record leg EMG in the home. Alternative activity measures fail. A new method enabling simple ambulatory PLMS and CLMS measures is required for sleep characterization.

In this paper, we present a novel enabling system called RestEaZe that combines the following two components: (1) textile-based non-rigid capacitive sensors arrays for measuring foot flexions (PLMS), a 9-axis IMU for measuring leg movements (CLMS) and leg position, built into a small, non-intrusive, low-cost, wireless ankle-worn unit. This system rather than recording the standard PLMS leg muscle activity using EMG, records the very specific effect of that muscle activity, i.e. foot flexion. The system, illustrated in Figure 1, is the only single point measurement system that can distinguish foot flexion from other leg movements; (2) an analytic engine that uses the measured foot flexions, leg movements, and leg positions to calculate reliable PLMS and CLMS indices and features, described in the next sections. The system has an optional backend providing sophisticated analytics for relating movement features with medical conditions. This backend provides sleep indices, activity visualizations and logs for the consumer. The smartphone

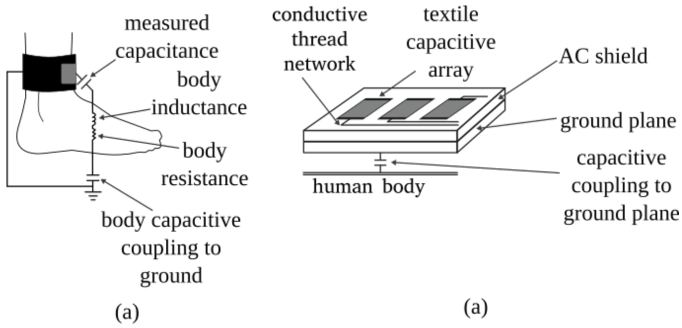


Figure 2: (a) The figure illustrates the equivalent electrical circuit which allows capacitive measurements. The user is coupled into the ground which allows for more sensitive measurement of motion by the capacitive sensors. (b) The figure shows the construction of the sensor array. The bottom layer allows for coupling the user into the system ground. The middle layer shields the capacitive sensors on the top layer from the user's body directly underneath the sensors. Conductive threads connect the various layers to the capacitance sensing IC.

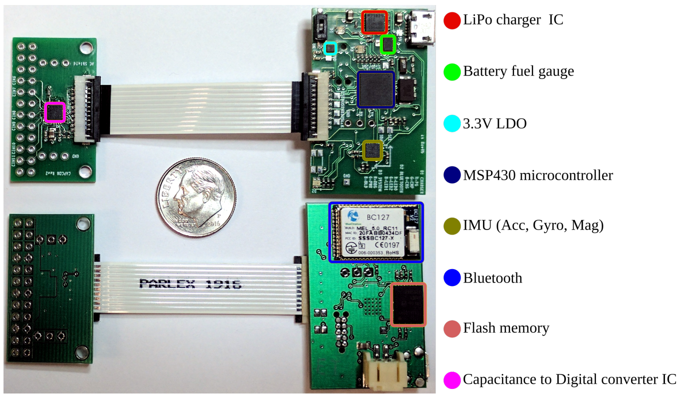


Figure 3: Capsense system consists of an MSP430FR5969 micro-controller, BC127 Bluetooth 4.0/BLE module, N25Q 512 MBit flash memory, MPU9250 accelerometer/gyroscope/magnetometer (IMU), and battery charging/monitoring chips. The daughter board contains the AD7147 capacitance to digital converter chip.

and ankle band unit allow the user to evaluate and possibly modify his restless sleep and optionally discuss results with his doctor. The same system with extended backend support allow the doctor to determine the nature of restless sleep, its severity and possible associated medical condition.

Another key attribute of our system (which is not part of this paper) is the inference of brief arousals during sleep which is a primary assessment for restful sleep producing alertness the next day. Sleep assessment examining restful sleep and health outcomes had initially focused on total sleep time. As sleep medicine advanced our understanding of the texture of sleep, it became apparent that for restful, healthy sleep the continuity of sleep (uninterrupted sleep) was almost as important as total sleep time. An excessive number of brief micro-arousals fragmenting sleep even without reduction in total sleep time produces decreased alertness [9, 10, 11], impaired mood and executive function, and mental flexibility [10, 11]. Similar results have been reported from animal studies showing frequent brief arousals without loss of total sleep time impaired maze learning [12]. Measuring wake and brief arousals disrupting sleep is seen as important as measuring total sleep time for evaluation of restful sleep. The rich panoply of sleep LM characteristics associated with arousal provide a putative measure of arousal and waking.

3. Hardware System Description

For capturing sleep quality measures, we have developed a fully functional custom sensing platform called RestEaZe. It comprises a multi-sensor ankle band which is depicted in Figure 4. The band is intended as a single point measurement system for capturing leg movements during sleep, and capture other attributes such as sleep position. The band has three textile capacitive sensors sewn in and are connected to a custom embedded system motherboard called Capsense using embroidered conductive fibers. The Capsense board houses a MSP430 micro-controller, inertial measurement unit (IMU) with accelerometer, gyroscope and magnetometer, Bluetooth module, flash memory and various battery charging/monitoring chips. This system connects with a flat-flex connector to a daughter board which contains the capacitance measurement circuit. The capacitive plates, made of conductive fabric, are sewn onto a non-conductive pleather band and connected to a routing layer. In order to shield the routing layer, an AC shield layer made of conductive fabric sits in between the capacitive sensor array and the routing layer. Finally, the ground layer sits beneath the routing layer. Sheets of non-conductive satin cloth are used to prevent any of the conductive layers from electrical shorting. The conductive thread network on the routing layer is made of silver-plated thread and is stitched by an embroidery machine. The embroidered traces connect to the Capsense daughter board by hand sewing. Because of wear and tear, conductive thread/layers fray and can form undesirable micro-connections. This construction minimizes the chance of this happening thereby increasing the reliability of capacitive measurements.

The Capsense system employs a modular and sewable friendly form factor, with a hardware architecture that supports low power sleep monitoring. The modular overview of the Capsense system hardware is illustrated in Figure 3. The whole system is powered by one rechargeable 400 mAh lithium polymer battery which can be charged from the on-board USB connector. When the system is connected to a charger, the charge management IC switches the system power source from the battery to USB. In this way, the system can operate normally while the battery is charging. The RestEaZe system can operate in two modes: (1) serial streaming mode; and (2) flash storage mode.

Streaming mode: In the serial streaming operating mode, the system can collect data for 20 hours on a full charge. Another device, such as a PC or smart phone has to maintain a Bluetooth connection to the ankle band to collect data streamed from the band. In addition to data packets, the band also periodically sends status packets that contain information such as battery and sensor status.

Flash mode: When the system operates in flash storage mode, instead of sending data packets over Bluetooth, the system writes data to flash memory. At the default sampling rate of 25 Hz, up to 14.6 hours of data can be stored on the 512 Mbit chip without compression. At the end of a data collection session, a `STOP` command followed by a `START_DUMP` puts the system into a mode in which data is read from the flash, assembled into data packets and sent over Bluetooth to the PC or smart phone. In addition to data packets, flash status packets are sent to help the end device track the progress of the flash dump. For example, a night's worth of data (typically eight hours), will take close to 30 minutes to offload from the band.

Capacitive sensing: A unique component of our system in an array of textile capacitive sensors built into the ankle band. This sensing technique is based on the principle of parallel plate capacitor, where the conductive fabric and the user's body serve as two plates of a virtual capacitor (see Figure 2 for the equivalent electrical circuit for our system). Change in distance between the capacitive sensors and the user's body produces a change in capacitance that can be used to classify the type of motion or serve as a wakeup trigger. The capacitive sensors (and the sensing circuit) is ultra-low power (consuming few micro-watts of power) and can capture any movement in the vicinity of the plates. Hence, they are used to capture both periodic leg movements and the complex leg movements and can act as a low power wakeup sensor for the more energy expensive IMU. Therefore, the capacitors in conjunction with the IMU behave as a hierarchy of sensors and the power consumption of the system can be optimized by keeping the higher power sensor asleep most of the time. The capacitive sensors, on the other hand, are on all the time and whenever they detect a movement, it wakes up the IMU for data collection from the capacitive sensors and the IMU.

External synchronization: When collecting data in a sleep lab, we have to be able to synchronize our data with data produced by the sleep lab's polysomnograph (PSG) hardware. RestEaze outputs a pseudo-random binary waveform to a GPIO port. This port is then connected to a custom PCB board which contains a voltage divider and snaps which are compatible with standard EMG electrodes. This pseudo-random pattern is recorded by PSG and the band so that we can synchronize the two systems.

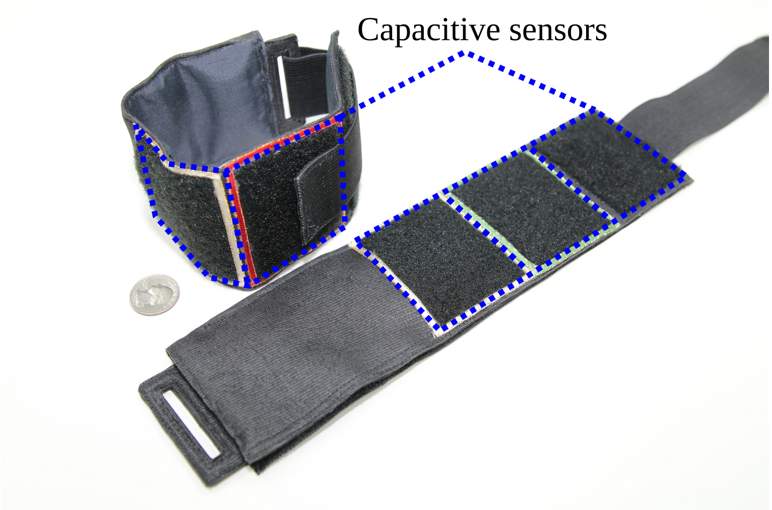


Figure 4: The RestEaZe ankle band. The band comprises textile capacitive sensors built into the ankle band and a data collection board which houses a IMU, Bluetooth module, micro-controller, and charging circuitry.

Module	Sleep power	Active power
micro-controller	<1 mW	<1mW
flash	110 μW	11.6 mW
capacitive sensor	7.0 μW	3.5 mW
bluetooth	19.5 mW	51.0 mW idle, 57.9 mW TX
IMU	30 μW	26.2 mW

Table 1: Power consumption of individual modules that constitute the Capsense platform.

Practical implementation challenges: Capacitive sensors are sensitive to various sources of noise. Additionally, interfacing a PCB to fabric has been a challenge. We tried several ways of connecting the capacitive sensors to the capacitance-to-digital (CDC) conversion IC. Originally, the CDC chip was on the main compute board that clamped onto cloth backing that had sewn conductive thread terminals. Over time, the clamps would tear up the conductive thread and the connection between the CDC and sensors would break. Also, noise from other components on the PCB affected capacitive sensor readings. In the current iteration, we designed a small and easily sewable daughter board which contains the CDC chip, and breakout through-holes for connecting capacitive channels to sensors by hand sewing the daughter board to the embroidered traces. The Capsense daughter board contains the CDC chip and breaks out 6 capacitive channels. This has been a reliable solution with some bands reliably collecting over a dozen nights of data (see Figure 5).

4. Software System Description

We performed several software optimizations at the RestEaZe band to collect data from multiple sensors in a synchronized fashion.

Sensor reading: The IMU has an internal sampling rate of 1 kHz for the accelerometer/gyro and we sample this sensor at 25 Hz. The Capacitance-to-Digital conversion IC (CDC) as an internal sampling rate of 250 kHz and we also sample this sensor at 25 Hz. Since the sensors are sampling asynchronously, we generate a system tick every 40 ms using a combination of a built-in real time clock and timer to sample the CDC. We use a 32 kHz crystal as the reference clock for these circuits. The crystal we are using has a frequency tolerance of 20 ppm, so the worst case drift is 1.152 sec over 8 hours. The IMU is configured

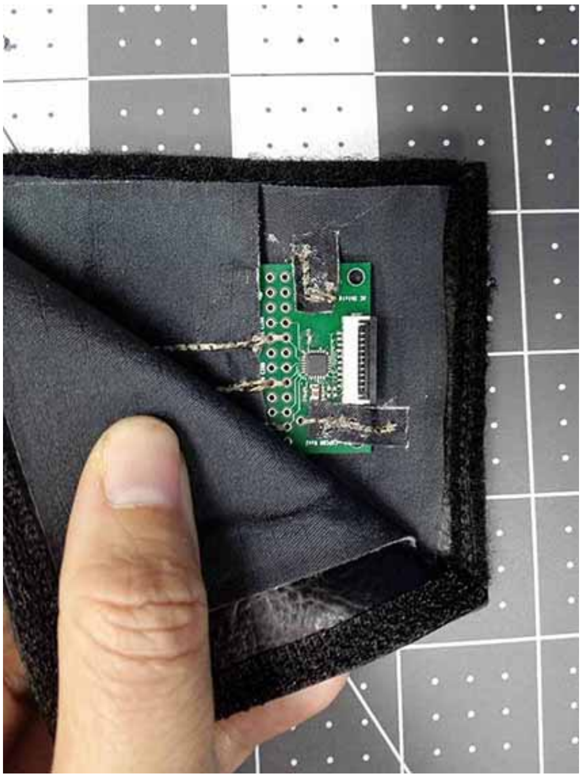


Figure 5: Conductive threads connected to ground, shield and capacitive sensors connect to Capsense daughter board in the RestEaZe band.

to produce a hardware interrupt, and we record the time of this event relative to the last system tick using capture/compare hardware built into the micro-controller.

Configuration: The system is designed to be easily configured by a text based command system. The user can connect to the system over Bluetooth and submit commands to reconfigure the platform. We leverage the MSP430 FRAM capability for persistent memory storage to store configuration information that the system uses for initialization at boot time. This flexibility allows the platform to be used for other applications.

Low power operation: The default system configuration is aimed at data collection for analysis and does not leverage low power features of the various sensors and submodules. However, the system can be configured to put the Bluetooth, IMU, CDC and flash memory into low power modes. A summary of energy consumption between different operating modes can be found in Figure 9. A hierarchical sensing algorithm we developed takes advantage of this to extend battery life.

5. Hierarchical sensing

We use a hierarchical sensing system to optimize the power consumption of the RestEaZe band. As shown in Table 1, the capacitive sensor consume an order of magnitude lower power in active mode than the IMU and 20X less power than the Bluetooth module. Hence, if it were possible to detect a onset of a movement using just the capacitive sensor array, the IMU and the Bluetooth module can be kept in low power mode, and only woken up when an activity of importance is likely to occur. Therefore, the key challenge is to detect the onset of a complex leg movement or a periodic leg movement using the capacitors alone. Moreover, the algorithm needs to be light weight such that it can be implemented on micro-controller

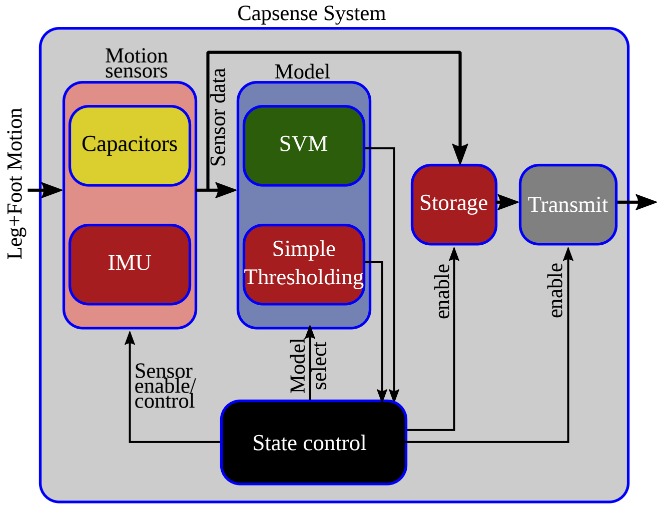


Figure 6: The Capsense system uses an SVM model to detection leg motion. The SVM model determines when to wake up the IMU for leg movement detection.

platform. To this end, we design a simple machine learning algorithm based on Support Vector Machines to predict the occurrence or absence of a movement using the capacitor data.

5.1. Machine Learning for Detecting Movement Onset

The key element in our machine learning algorithm is to determine an appropriate set of features on the capacitance data that can be used to detect a movement. We empirically determined the appropriate feature and kernel for our machine learning algorithm.

For our experimentation we used data collected on two pediatric patients, PED1 and PED2 (see Table 6). The movements in this data set was labeled by a trained technician. The ground truth for the complex leg movements was video data while the ground truth for the periodic leg movements (dorsiflexion) was EMG on the anterior tibialis. The unlabeled regions of the data were randomly partitioned and chosen as time periods with "no motion" label. This resulted in a total of 1508 distinct training data points. The predictor was tested against data from two patients, RZ0015 and RZ0016, that were not used to train the model (see Table 6). It successfully classified movements and in combination with a data reconstruction algorithm the restored signals had very high correlation to the original signals. An example of this can be seen in Figure 8.

We then calculate several statistical features such as mean amplitude, standard deviation of amplitude, skew, kurtosis and root-mean-square amplitude in a window. Once the features were calculated, an SVM model was trained for each combination of features. The accuracy of the models for each combination can be seen in Table 2. Although the combination of standard deviation and kurtosis yielded the highest score in this model, since the predictor had to be implementable on a micro-controller we have to be cognizant of other factors such as support vector size, computational complexity of the predictor and the computational complexity of calculating the feature. Hence, we chose the top feature, standard deviation to train the SVM.

In addition to the feature, the kernel used for the classification needs to be determined. Both RBF and linear kernels were tested along with varying C and gamma parameters using a grid search. The model is trained on the full development set. The scores are computed on the full evaluation set. The hyper-parameters tuned for highest precision can be found in Table 3. The hyper-parameters tuned for highest recall can be found in Table 4. The linear kernel with $C = 1000$ was chosen since it struck a good balance between accuracy, implementation complexity. Additionally, the size of the support vector was tuned by adjusting the number of features used to fit the model.

Table 2: Comparison of models calculated from different combinations of features: {kernel: 'linear', C: 1000}

Avg	StdDev	Skew	Kurtosis	RMS	TP	TN	Accuracy
F	T	T	F	F	0.85	0.86	85.67
F	T	F	F	T	0.93	0.78	85.33
F	T	F	F	F	0.82	0.88	85.27
F	T	T	T	F	0.83	0.88	85.14
F	T	T	T	T	0.90	0.78	84.16
F	T	F	T	F	0.78	0.90	83.87
T	T	F	T	F	0.90	0.77	83.59
T	T	F	F	F	0.92	0.75	83.56
F	T	F	T	T	0.88	0.77	82.29
T	T	T	F	F	0.94	0.71	82.22
T	T	T	T	F	0.96	0.68	81.35
F	T	T	F	T	0.87	0.75	81.06
T	T	T	T	T	0.92	0.69	80.47
T	T	F	T	T	0.93	0.66	79.47
T	T	T	F	T	0.94	0.64	78.85
T	T	F	F	T	0.94	0.62	77.90
F	F	F	T	F	0.97	0.20	57.14
T	F	T	T	F	0.72	0.43	56.34
T	F	T	F	T	0.24	0.88	56.10
F	F	F	F	T	0.22	0.88	55.92
F	F	T	T	T	0.82	0.31	55.89
F	F	T	T	F	0.97	0.15	54.82
T	F	T	T	T	0.61	0.48	54.77
F	F	F	T	T	0.64	0.45	54.04
T	F	F	T	F	0.48	0.59	53.57
T	F	T	F	F	0.20	0.85	52.75
T	F	F	F	F	0.68	0.38	52.68
T	F	F	T	T	0.50	0.55	52.64
F	F	T	F	F	0.00	1.00	51.00
F	F	T	F	T	0.23	0.77	50.78
T	F	F	F	T	0.40	0.61	50.61

Table 3: Best parameters tuned for precision: {kernel: 'linear', C: 1}

class	precision	recall	f1-score	support
no	0.91	0.96	0.93	2018
yes	0.72	0.53	0.61	401
avg / total	0.88	0.89	0.88	2419

Table 4: Best parameters tuned for recall: {kernel: 'rbf', C: 100, gamma: 0.001}

class	precision	recall	f1-score	support
no	0.95	0.94	0.94	2018
yes	0.69	0.74	0.72	401
avg / total	0.91	0.90	0.90	2419

Table 5: Implemented SVM: {kernel: 'linear', C: 1000}

class	precision	recall	f1-score	support
no	0.84	0.84	0.84	439
yes	0.85	0.85	0.85	467
avg / total	0.84	0.84	0.84	906

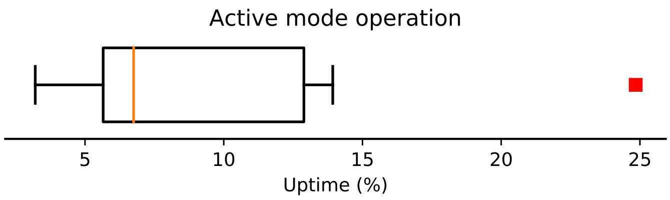


Figure 7: Percentage of time spent in active mode for two subjects (0,1) of nine nights total.

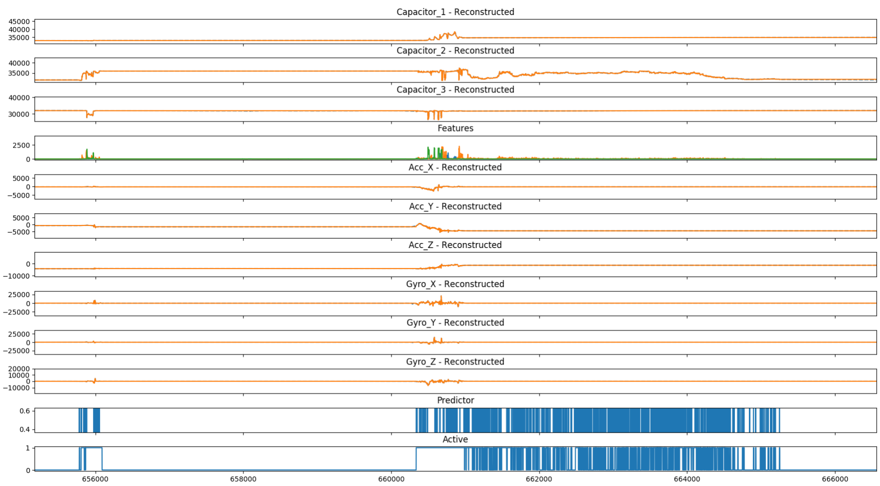


Figure 8: Using motion predictor on RZ0015 data to generate a synthetic reconstruction of right leg data with a correlation of 0.99 for each IMU axis. In this instance, the IMU would be active 13.56 % of the total time.

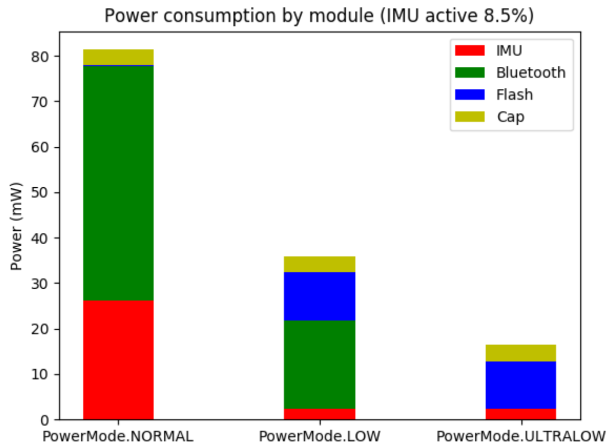


Figure 9: Power consumption breakdown by different system modules in different modes of operation. PowerMode.NORMAL: IMU is always on, using Bluetooth to transmit data, conventional operation. PowerMode.Low: IMU is idled and woken up by machine learning predictor, Bluetooth is in sleep mode, flash is used to store data. PowerMode.ULTRALOW: IMU idled and woken up by machine learning predictor, Bluetooth is turned off using a relay, flash is used to store data.

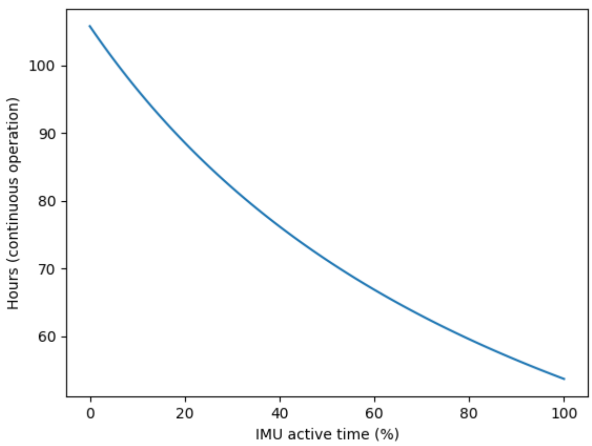


Figure 10: When operating in ultra low power mode, the bands estimated total continuous operation decreases as the IMU is turned on more often.

ALGORITHM 1: Main loop for low power operation

```
IMU_on = FALSE;
repeat
    if (IMU_on == TRUE) then
        readIMU();
    end
    readCDC();
    ring_buffer_insert_CDC_data();
    if (IMU_on == TRUE) then
        ring_buffer_insert_IMU_data();
        if (CDC_buffer_is_full() == TRUE) then
            acc_std_dev = calc_acc_std_dev();
            if (acc_std_dev < 10.0) then
                IMU_on = FALSE;
                power_imu_off();
            end
        end
    else
        cap_std_dev = calc_cap_std_dev();
        if (CDC_buffer_is_full() == TRUE) then
            motion = predict_motion();
            if (motion == TRUE and cap_std_dev > 1.0) then
                IMU_on = TRUE;
                power_imu_on();
            end
        else
            IMU_on = FALSE;
        end
    end
until TRUE;
```

Implementation: Capacitive measurements are inserted into a six element ring buffer. Since the smallest movement we want to measure is 0.5 seconds, our sample window is half of that. Every time the ring buffer fills up, the standard deviation of the measurements is calculated and submitted to the predictor. If the predictor classifies the feature as a movement, the system is switched into the mode where the IMU is turned on and sensor measurements are written to flash. While the system is in the high power mode, the accelerometer values are inserted into a six element buffer and when the buffer is full the standard deviation of the accelerometer values is calculated. If the standard deviation is above an experimentally derived threshold, the system continues in high power mode.

The Support vector is 93 elements long. The predictor was implemented in C and since the micro-controller did not contain a floating point unit, we used a fixed point math library provide by Texas Instruments in order to be able to execute the predictor within the 40 ms window set by the required sampling rate. Algorithm 1 describes the algorithm implemented on the micro-controller.

Data reconstruction: Since the data from the IMU is collected intermittently and our sleep quality analysis algorithm requires a uniformly sampled data stream, the sensor data must be processed to conform to this. The reconstruction algorithm is *sample and hold* with the accelerometer data filtered with a localized median filter with a window size of 5 (see Figure 11 for an example). The filter is used when the system transitions from low to high power state since sometimes the accelerometer data exhibits spurious spikes. The gyroscope, however, did not show spikes, so only sample and hold is used. Over the course of five nights, a band with the regular firmware and a band with the low power firmware were worn on the right leg. The data from the low power band the the regular band was analyzed through our sleep quality algorithm and

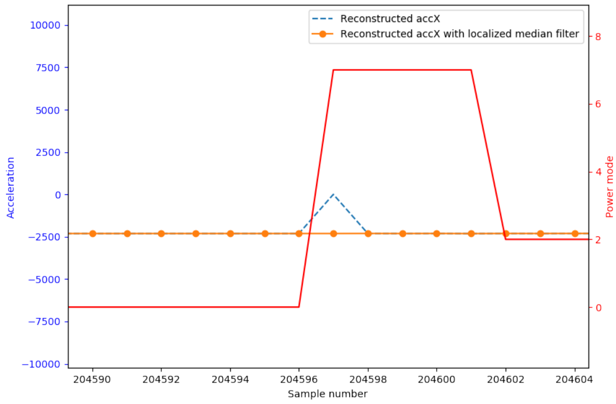
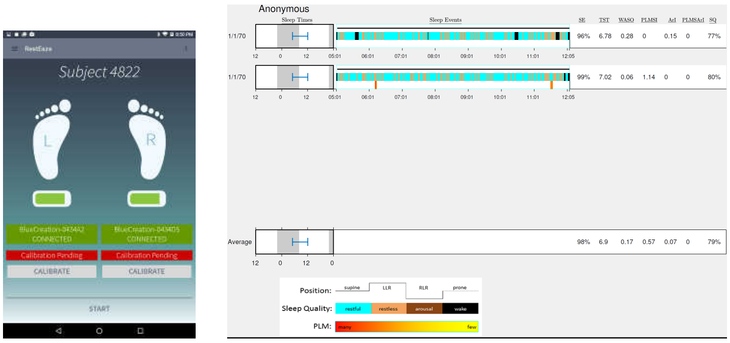


Figure 11: During transitions from low power to high power modes, the accelerometer sometimes produces spurious data. A localized 5 point median filter is used to remove these spikes.



(a) (b)

Figure 12: (a) The figure shows the home screen of our Android app that interfaces to the Capsense system. (b) The figure shows an output from a subject as an output of the backend analytics.

matched closely.

Smart phone application: For this system to be useful for non-technical users, we developed an Android application. It allows a user to pair with the bands, calibrate sensors, and start/stop data collection with minimal instruction. The main screen of the application is shown in Figure 12. Battery meters for each band serve to alert the user when they are on low battery. The application can be configured to switch the band between streaming and flash storage modes. Finally, the application supports storing the collected data locally or uploading data to a backend server. These modalities of operation cover several use cases necessary for sleep research. Long term studies for instance necessitate that the system be used at subjects homes without the guarantee of Internet access and without the possibility of assistance from a technician. Figure 12 (a) shows a screen shot of the smartphone application.

Extracting sleep measures: The multi-sensor data is analyzed by our custom written data analysis software to extract sleep quality measures such as the number of complex leg movements, number of periodic leg movements, number of arousals during the time, wake after sleep onset duration, and sleep efficiency. The analytics underlying the calculation of these metrics is beyond the scope of this paper, but we have verified the accuracy of these metrics with standard PSG (polysomnograph) tagging. Figure 12 (b) shows an example report generated by our backend analytics.

Table 6: Demographics of the subjects we evaluated RestEaZe on in the sleep lab.

Patient	Age	Sex	Disorder	Active %
PED1	10	male	ADHD	4.45
PED2	16	female	ADHD	8.64
RZ0015	60	female	insomnia	0.71
RZ0016	69	female	RLS	18.92

6. Evaluation

The RestEaZe system comprise the ankle bands, a smartphone application, and backend analytics to calculate sleep quality metrics. These metrics can be used to assess the quality of sleep, texture of sleep, and can be used as an aid for diagnostics of sleep related disorders. The goal of this paper is to present the hardware and software architecture of the RestEaZe system and present algorithms that make the system low power and usable. Hence, our evaluation focuses on the following key questions.

- What is the average power consumption of RestEaZe when applied on a wide variety of subjects, i.e., subjects with sleep-related disorders, and healthy subjects that may or may not experience disrupted and fragmented sleep?
- Can the RestEaZe system, with its low power consumption, provide the same quality of data as an always-on RestEaZe system?

6.1. Experimental Setup

To answer the above questions, we perform our system evaluation in two phases. In the first phase, we use RestEaZe in a sleep lab in conjunction with polysomnograph (PSG). In a PSG session, we collect a variety of other physiological data on a subject such as EEG, EKG, respiration rate, blood oxygen level, and EMG for muscle groups on the leg. Additionally, we record the entire sleep session using a IR camera. The data from the RestEaZe band is tightly synchronized with data from the proprietary PSG system using a pseudo-random sequence generated by the band which is fed into the PSG data collection module using an auxiliary input port. For the sleep lab studies, we recruit four subjects, 2 adult subjects and 2 pediatric subjects. The demographics and sleep related disorder experienced by each subject is described in Table 6. For the sleep lab evaluation, our RestEaZe bands are always-on. The sleep lab data analysis provides us clinically valid ground truth on arousals (EEG), periodic leg movements (dorsiflexions measured by EMG on the anterior tibialis muscle), and complex leg movements (video). Using this ground truth data, we have validated the efficacy of our analytics (not part of this paper). A trained technician scored the PSG data for event start time, event duration, body position (supine, prone, left/ride side), leg state (crossed/uncrossed), leg position (right/left on top), flexion, and complex leg movement (toe wiggling, foot jolts, etc). We run trace-based simulations to evaluate the efficacy of our power management system. This data set constitutes the ground truth of labeled PSG and RestEaZe data for building a model. In both subjects data sets, the total leg movement time constituted less than 10% of the total sleep time—pointing to the need for an effective power management strategy.

To demonstrate the efficacy of the power management system, we further perform 8 nights of in-home evaluation on 8 different subjects. The age of the subjects ranged from 20-35 and included six males and two female subjects. The subjects wore two RestEaZe bands, one on the ankle and the other just above the ankle on the same leg for a night. One of the bands had the power management algorithm implemented on the micro-controller, while the second band was always-on. The bands could not be placed on top of each other since that would interfere with capacitive sensing. Due to this arrangement, the axis of the IMUs between the two bands were unlikely to line up perfectly. We discuss this limitation in the next section. The average recording session lasted 7.5 hours with a standard deviation of 1.3 hours.

Table 7: Demographics of the subjects we evaluated RestEaZe on in-home data collections. This table shows the mapping between patient and experiment ID which is used in other figures.

Patient	Sex	Experiment ID
0	male	exp8
1	female	exp12
2	female	exp20
3	male	exp18
4	male	exp19
5	male	exp21
6	male	exp22
7	male	exp24

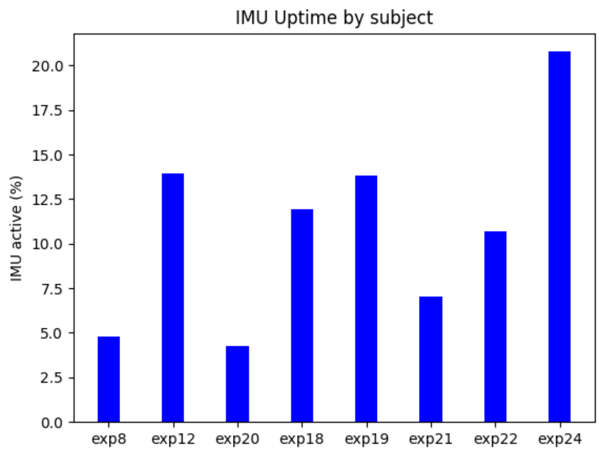


Figure 13: Percentage of time spent in active mode for eight different subjects.

6.2. RestEaZe Energy consumption

We use two metrics to evaluate the energy consumption of the RestEaZe system: (1) Total uptime that RestEaZe sensors (apart from the capacitors) was on during an overnight study (**Uptime**)–this is a time when a leg movement occurs; and (2) Total energy consumption of the RestEaZe band when compared to a band that is always-on.

Figure 14 shows the distribution of the total **Uptime** for the eight in-home subjects. The median **Uptime** is close to 11%, while the maximum **Uptime** is 20%. Figure 14 show the **Uptime** per subject. The **Uptime** varies from subject to subject depending on how disruptive a subject's sleep is. For instance, subject 7 suffers from chronic insomnia, and hence the **Uptime** for 7 is 4.9 times higher than Subject 2, who is a sound sleeper. Figure 10 shows the number of hours that the band would last on a single charge of the 400 mAh battery as a function of the **Uptime**. With a 10% **Uptime**, the system would last for 95 hours, which is equivalent 4 days of continuous operation. Figure 15 show the average power consumption of RestEaZe for the eight in-home subjects. The overall power consumption system varies from 15.75 mW to 18.18 mW. We can draw two conclusions from the figure. First, the RestEaZe band has a lifetime that varies from 4.5x to 5.2x when compared to an always-on band. Second, we observe that writing to the flash consumes a substantial amount of this power. The system power consumption can be further optimized by caching data in memory and compressing it before it is written into the flash.

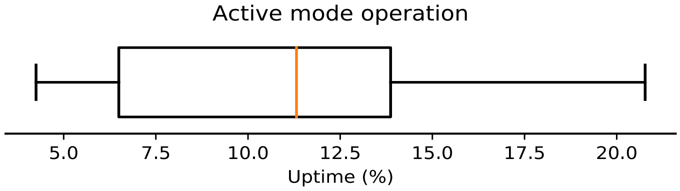


Figure 14: Boxplot of time spent in active mode for eight different subjects.

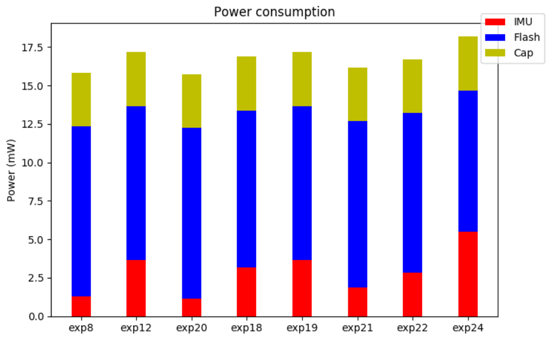


Figure 15: Average power consumption by module of eight different subjects, collected in-home during normal sleep.

6.3. Data Quality Collected by RestEaZe

An important evaluation metric for RestEaZe is the quality of data reconstructed by the system when running in low power mode. We evaluate the data quality by comparing the reconstructed data with the actual raw data from the always-on system as well as comparing the error in the sleep measures calculated by RestEaZe and the always-on system.

Correlating the raw sensor data: The low power version of the system, ideally, should be able to capture all movements for a subject while remaining in the low power mode as long as possible. We compare the output of the always-on system with the reconstructed data from RestEaZe and calculate the Pearson correlation coefficient for the two time series for the sensors on the band that we reconstruct the data for (accelerometer and gyroscope). The resulting correlations for the eight in-home studies is shown in Figure 17. Although one data set has a very high correlation across all sensors, the others tend to have low correlation coefficient values. After careful scrutiny, we found that since the bands were not placed at exactly at the same position and orientation, the raw data, the IMU sensors might have experienced different rotational and linear forces during movements. To validate this observation, we performed a more controlled experiment, where the two regular bands were worn exactly in the same orientation overnight. The result shown in Figure 16 shows high correlations. In spite of the above, in the next section we show that the final values of the sleep measures calculated by the RestEaZe band closely matches the always-on band.

Comparing sleep quality metrics: The RestEaZe system provides several sleep measures as output from the analysis on the leg movement data. These sleep measures are similar to the measures provided an overnight sleep study performed using polysomnograph. We have independently validated the accuracy of the measures calculated by RestEaZe with PSG (not part of this paper). The measures include: (1) `CLMnum:` The total number of Complex Leg Movements; (2) `ARL:` the total number of awakening and micro-arousals during the night; (3) `PLMnum:` the total number of periodic leg movements during the night (dorsiflexions); (4) `WASODur:` Wake after sleep onset duration; (5) `Sleep Efficiency:`; and (6) TST: Total Sleep Time. To evaluate the accuracy of determining these metrics with RestEaZe, we calculate the error in the value of these metrics calculated from the always-on band and RestEaZe. Figure 18 shows the error distribution

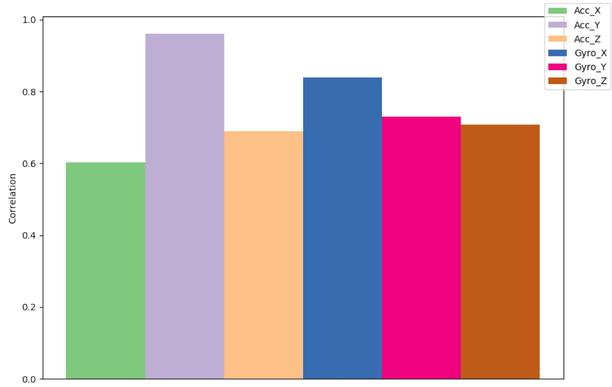


Figure 16: Pearson correlation between data from two regular bands worn over night on the right leg.

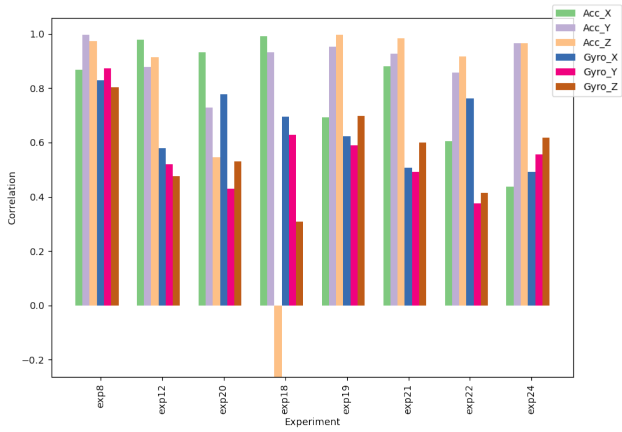


Figure 17: Pearson correlation between data from regular band and low power band.

across all the eight subjects. We observe the median error in calculating these metrics is less than 10%, which is within range of the error when PSG is manually tagged by trained clinicians.

Summary of Results: RestEaZe collects very similar quality of leg movement data (with error in the sleep measures $< 10\%$), while having a lifetime of 5X compared to an always-on sensor.

7. Related Work

RestEaZe builds on previous work on sleep monitors, and studies on the significance of leg movements for sleep. Here we compare and contrast RestEaZe with the most relevant literature.

Sleep Monitoring Devices: There are several devices that perform sleep monitoring and are listed in Table 8. We detail the differences and similarities between the devices in Table 8. Of these, only the RestEaZe device has the sensitivity to accurately identify PLMS and micro-arousals. One other system claims to measure PLMS (not micro-arousals), the PAM-RL, but is 4-5 times more expensive, difficult to use, and cannot assess or compare movement in both legs. The competitive advantages of RestEaZe are in the basic underlying RestEaZe concepts of using leg movements for determining texture of sleep and its use as an aid for diagnostics of sleep disorders. These advantages will persist over the time. RestEaZe provides

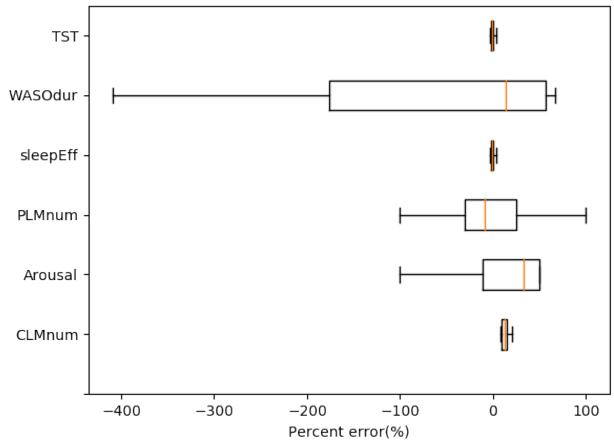


Figure 18: Output of our IMU analytics script contains several parameters. This is the percent error between the regular and low power modes.

System	Location	Leg Activity	PLM	Arousals
Phone apps	Pocket	No	No	No
Fitbit	Wrist	No	No	No
Actitrac	Wrist	No	No	No
PAM-RL	Ankle	Yes	Yes	No
RestEaZe	Ankle	Yes	Yes	Yes

Table 8: The table highlights the major advantages of RestEaZe over existing sleep monitoring systems.

a convenient, accurate, low cost means for diagnosis and monitoring of awakening arousals, micro-arousals, and PLMS in the home setting.

Relevance of Periodic Leg Movements During Sleep (PLMS): High rates of PLMS indicate possible sleep apnea, RLS, or PLMD. PLM detection may also have some future relevance for those with cardiovascular risk factors, given the now well-established relation between each PLM and significant transient blood pressure and heart rate elevations [13, 14], that can be reduced by dopamine treatment [15]. But more significantly, evaluating PLMS for children addresses a currently recognized medical need and role for RestEaZe. PLMS $>$ 5 per hour in children is considered clinically significant [8, 16] particularly when associated with increased arousals and poor sleep [8]. PLMS occur commonly for children with attention deficit hyperactivity disorder [17, 18] and RLS [7]. The PLMS indicate disturbed sleep exacerbating associated problems, e.g. attention deficit hyperactivity disorder (ADHD). PLMS relate to reduced brain (substantia nigra) iron [19]. PLMS in children often occur with low but normal serum ferritin indicating possible functional brain iron deficiency. Children with PLMS and low normal serum iron ($<$ 50-75 mcg/l) can be successfully treated with oral[20, 21] or even IV iron [22]. In these studies, the critical issue was the PLMS, not the sleep complaint or a diagnosis of RLS.

8. Conclusion

In this paper, we present the design, implementation, and evaluation of the RestEaZe system, a sleep monitoring system that uses leg movements as a marker for arousals, restless sleep, and as an aid for diagnostics of sleep-related disorders such as RLS and ADHD. We present the software and hardware architecture for RestEaZe and present a hierarchical system which uses low power textile capacitive sensors to wakeup high power consuming sensors like the IMU. Using evaluation on 4 subjects in a sleep lab and 8 other subjects in a home setting, we show that the RestEaZe sensor has a lifetime of 5X as long as an always-on band while providing similar quality data.

References

[1] I. of Medicine, Sleep Disorders and Sleep Deprivation: An Unmet Public Health Problem, The National Academies Press, Washington, DC, 2006. doi:10.17226/11617.

[2] L. Marie Trotti, D. L Bliwise, S. A Greer, A. Sigurdsson, G. Birna Gudmundsdottir, T. Wessel, L. M Organisak, T. Sigthorsson, K. Kristleifur, T. Sigmundsson, D. B Rye, Correlates of plms variability over multiple nights and impact upon rls diagnosis 10.

[3] R. Nandakumar, S. Gollakota, N. Watson, Contactless sleep apnea detection on smartphones (05 2015).

[4] J. M Kelly, R. Strecker, M. Bianchi, Recent developments in home sleep-monitoring devices 2012 (2012) 768794.

[5] J. Mantua, N. Gravel, R. Spencer, Reliability of sleep measures from four personal health monitoring devices compared to research-based actigraphy and polysomnography 16 (2016) 646.

[6] D. Gabelia, T. Mitterling, B. Högl, G. Wenning, B. Frauscher, Do periodic arm movements during sleep exist in healthy subjects? a polysomnographic study 15.

[7] D. Picchietti, R. Allen, A. S Walters, J. Davidson) Mount, A. Myers, L. Ferini-Strambi, Restless legs syndrome: Prevalence and impact in children and adolescents the peds rest study 120 (2007) 253–66.

[8] C. L Marcus, J. Traylor, P. R Gallagher, L. Brooks, J. Huang, D. Koren, L. Katz, T. B.A. Mason, I. E Tapia, Prevalence of periodic limb movements during sleep in normal children 37 (2014) 1349–52.

[9] E. Stepanski, J. Lamphere, T. Roehrs, F. Zorick, T. Roth, Experimental sleep fragmentation in normal subjects 33 (1987) 207–14.

[10] S. E. Martin, P. Brander, I. J. Deary, N. J. Douglas, The effect of clustered versus regular sleep fragmentation on daytime function 8 (2000) 305–11.

[11] S. E Martin, H. M Engleman, I. J Deary, N. J Douglas, The effect of sleep fragmentation on daytime function 153 (1996) 1328–32.

[12] J. Tartar, C. Ward, J. Mckenna, M. Thakkar, E. Arrigoni, R. McCarley, R. Brown, R. Strecker, Hippocampal synaptic plasticity and spatial learning are impaired in a rat model of sleep fragmentation 23 (2005) 2739–2748.

[13] F. Siddiqui, J. Strus, X. Ming, I. Lee, S. Chokroverty, A. S Walters, Rise of blood pressure with periodic limb movements in sleep and wakefulness 118 (2007) 1923–30.

[14] M.-H. Pennestri, J. Montplaisir, R. Colombo, G. Lavigne, P. Lanfranchi, Nocturnal blood pressure changes in patients with restless legs syndrome 68 (2007) 1213–8.

[15] A. Bauer, W. Cassel, H. Benes, K. Kesper, D. Rye, D. Sica, J. W Winkelman, L. Bauer, F. Grieger, L. Joeres, K. Moran, E. Schollmayer, J. Whitesides, H. C Carney, A. S Walters, W. Oertel, C. Trenkwalder, Rotigotine's effect on plm-associated blood pressure elevations in restless legs syndrome: An rct 86.

[16] M.-H. Pennestri, S. Whittom, B. Adam, D. Petit, J. Carrier, J. Montplaisir, Plms and plmw in healthy subjects as a function of age: Prevalence and interval distribution 29 (2006) 1183–7.

[17] A. Sadeh, L. Pergamin-Hight, Y. Bar-Haim, Sleep in children with attention-deficit hyperactivity disorder: A meta-analysis of polysomnographic studies 10 (2007) 381–98.

[18] D. L Picchietti, H. Stevens, Early manifestations of restless legs syndrome in childhood and adolescence 9 (2007) 770–81.

[19] X. Li, R. Allen, C. J. Earley, H. Liu, T. E. Cruz, R. Edden, P. B. Barker, P. van zijl, Brain iron deficiency in idiopathic restless legs syndrome measured by quantitative magnetic susceptibility at 7 tesla 22.

[20] N. Simakajornboon, D. Gozal, V. Vlasic, C. Mack, D. Sharon, B. M McGinley, Periodic limb movements in sleep and iron status in children 26 (2003) 735–8.

[21] J. Tilma, K. Tilma, O. Norregaard, J. R Ostergaard, Early childhood-onset restless legs syndrome. symptoms and effect of oral iron treatment. 102.

[22] K. Grim, B. Lee, A. Y Sung, S. Kotagal, Treatment of childhood-onset restless legs syndrome and periodic limb movement disorder using intravenous iron sucrose 14.